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DUONG THUY LE
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VOLATILITY IN THE CRUDE OIL AND NATURAL GAS MARKETS

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BY

Dr. Louis Ederington, Chair

Dr. Chitru Fernando

Dr. Xin Huang

Dr. Scott Linn

Dr. Duane Stock

Dr. Wayne Thomas

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ABSTRACT

This dissertation consists of three essays which explore the determinants and properties of actual and implied volatilities in the crude oil and natural gas markets. The first two essays examine the causes and behavior of price volatility in the US crude oil and natural gas markets. I theorize and find that (1) the crude oil and natural gas markets are characterized by volatility persistence, (2) in the crude oil market, a negative shock has more impact on future volatility than an equal positive shock whereas in the natural gas market, predicted volatility increases more following a positive shock than an equal negative shock (3) crude oil volatility is lower at higher prices, (4) there is a day-of-the-week pattern in both markets, (5) OPEC meeting announcements and the Petroleum Status Report releases cause increased volatility in the crude oil market, (6) surprises in the change in natural gas in storage cause increased volatility in the natural gas market, (7) natural gas volatility tends to be higher during and immediately after bid week, (8) there is a month-of-the-year pattern in natural gas volatility, (9) natural gas volatility tends to be higher on winter days when the temperature is lower than normal, and (10) the conditional covariance and correlation between crude oil prices and the value of the dollar vary over time. In these two essays, I develop and employ an improved procedure for testing and quantifying the hypothesized volatility determinants within a GARCH type model.

The third essay examines the structure, characteristics, and determinants of implied volatilities (IVs) calculated from crude oil and natural gas options from September 1999 to June 2006. In several ways, the behavior of IVs in these markets is opposite to that observed in most financial options markets. Crude oil and natural gas

IVs tend to increase as the options approach expiration. There is a positive “skew” pattern in natural gas IVs and long-term crude oil IVs in which IVs tend to be lowest at low strike prices and increase monotonically with strike prices. There is a time-of-the-year pattern in that natural gas IVs tend to be higher for options expiring in winter and crude oil IVs tend to be lower for options expiring in summer. Oil and gas IVs tend to decrease from Friday close to Monday close. After May 2002, natural gas IVs tend to decrease following the release of the Natural Gas Storage Report. A negative futures return has more impact on crude oil IV than an equal positive return while a positive futures return has more impact on natural gas IV than an equal negative return. IV is a fairly efficient forecast of future volatility in these markets but its forecasting power differs across terms-to-maturity and strike prices.

Chapter I. Introduction

This dissertation consists of three essays which explore the determinants and properties of actual and implied volatilities in the crude oil and natural gas markets. The markets for oil and gas derivatives contracts are becoming increasingly important due to the impact of energy on the economy and the high volatility in oil and gas prices. Crude oil and natural gas are two of the most essential energy sources in the U.S., accounting for about 40% and 25% of the nation's energy consumption, respectively. Since OPEC's 1973 decision to regulate its oil price independently, crude oil prices have been subject to dramatic volatility and this large oil price fluctuation tendency has continued in recent years. For example, the crude oil market experienced dramatic volatility in 2008 as prices reached an all-time high level of $145 per barrel in July and then fell sharply to $50 per barrel in November. Natural gas is also one of the most volatile markets, particularly since its evolution from a highly regulated market in which government regulations prescribed everything from prices to who could buy, sell, and transport natural gas and under what conditions to a largely deregulated market in which prices are driven by supply and demand. For example, in 2008, natural gas prices rose sharply from $7.8 per mmBtu in early January to $13.5 per mmBtu in July, which was the highest price level for that time of year. Then starting around the end of July, natural gas prices fell almost as sharply and were approximately $5.5 per mmBtu toward the end of 2008. Crude oil and natural gas prices are more volatile than those in most financial markets. In 2007, the annualized standard deviation of the daily percentage change in prices was 31.33% for crude oil and 49.94% for natural gas. By comparison, that number was only 4.08% for the US dollar-Euro exchange rate, 16.37% for the S&P 500 and 19.10% for the 10-year T-bond interest rate[1].

The high volatility in crude oil prices is likely due to actual and anticipated fluctuations in supply and the short-term inelasticity of demand. Given that crude oil is one of the most essential energy sources, it is very difficult for many oil users to reduce their consumption within a short period of time following a price increase. On the other hand, there is considerable fluctuation in oil supply which depends on a variety of macroeconomic and political factors. For example, in 1997, when the world economy was already in a recession, the Organization of Petroleum Exporting Countries (OPEC), failing to predict the oil demand correctly, increased its production levels which resulted in a huge decrease in oil prices. In June-July 2008, a combination of supply uncertainties in oil producing countries and a falling dollar caused an unprecedented oil price spike. On the reverse, an appreciation of the dollar and signs of worldwide economic slowdown led to a sharp decrease in oil price toward the end of 2008.

The high volatility in the natural gas market is mostly attributable to the short-term inelasticity of supply and demand. Since natural gas supplies are often constrained by storage levels and imports are limited, natural gas suppliers are unable to increase production levels in a short period of time. Also, it is difficult for consumers to quickly reduce their consumption when a sharp increase in natural gas prices occurs, especially during the winter. Since natural gas suppliers cannot rapidly

[1]The data for the crude oil and natural gas prices are from the Energy Information Administration website. The data for the S&P 500, US dollar-Euro exchange rate, and the 10-year T-bond interest rates are from the CRSP database and the Federal Reserve website (http://www.federal reserve.gov).

adjust their production levels to match demand changes, supply and demand imbalances may result in sharp price changes.

This high variability in crude oil and natural gas prices makes it extremely difficult for consumers to forecast their costs and for producers to forecast their profits. The desire to protect market participants against such price fluctuations has led to the creation of and active trading in futures, swaps and options where the market value of the latter depends on volatility. An understanding of the causes and behavior of oil and gas volatility is therefore essential to measuring and managing the risk faced by energy producers and major consumers.

Although it is difficult to forecast the direction of future price changes from past price behavior, the absolute magnitude of price changes, i.e. volatility, has been proven much more predictable in most financial markets and, consequently, has received an immense attention in the literature. However, the vast majority of the research on market volatility has focused on the volatility of financial markets such as the stock, bond, interest rates and foreign exchange futures markets, etc. Despite the fact that crude oil and natural gas markets tend to be more volatile than most financial and commodity markets, research into the determinants and properties of actual and implied volatilities in these markets is relatively sparse.

My first two essays, which explore the determinants of oil and natural gas price volatilities respectively, are motivated by the limited nature of previous research on crude oil and natural gas price volatility. The limited studies on crude oil volatility to date focus solely on volatility persistence, i.e., the relation between current and past volatility, in this market (see, for example, Wilson, Aggarwal and Inclan, 1996; Yang, Hwang and Huang, 2002; Pindyck, 2004; and Kuper and Soest, 2006). Other possible determinants of crude oil volatility, such as a day-of-the-week, levels and announcement effects, are neglected in the literature. Previous studies on natural gas volatility examine several volatility determinants in isolation. Susmel and Thompson (1997), Pindyck (2004) and Murry and Zhu (2004) find that natural gas volatility follows an ARCH-GARCH type process, Linn and Zhu (2004) document that the release of the Weekly Natural Gas Storage Report announcement causes increased natural gas volatility, Murry and Zhu (2004) document that natural gas volatility increases on Monday and on days the Storage Report is released, and Mu (2007) examines the impact of storage and weather conditions on natural gas volatility.

As mentioned above, previous studies on oil and gas actual volatility consider only one or two possible volatility determinants. In other words, they test for volatility persistence, and/or day-of-the-week effects, or announcement effects, or weather effects but not all four. Thus it is possible that the determinant they examine is in fact proxying for another determinant. For instance a day-of-the-week pattern could be due to an announcement pattern. My study extends the research in oil and gas price volatility in several dimensions. First, I simultaneously estimate GARCH, volatility asymmetry, seasonality, announcement and other effects in a single econometric model. This allows me to determine which are the most important volatility determinants in these markets. Second, as explained further in the first two essays, my model affords a cleaner test of seasonality, announcement and other transitory effects than that in previous studies. Third, I test and quantify several possible volatility determinants unexplored heretofore, such as a time-of-the-year pattern and bid week effects for natural gas and asymmetric volatility, levels and announcement effects, and day-of-the-week pattern for crude oil.

My third essay, which explores the determinants and behavior of implied volatilities in both the crude oil and natural gas markets, is also motivated by the fact that research on oil and gas options markets has been quite sparse although energy prices tend to be more volatile than most other prices and that oil and gas options have become more heavily traded. To my knowledge, the only studies to date which include oil and gas implied volatilities (IVs) among other IVs they examine are Day and Lewis (1993), Szakmary, Ors and Kim (2003), Martens and Zein (2004), Mahar, Peterson and Horan (2004), and Doran and Ronn (2006). Day and Lewis (1993), Szakmary et al. (2003), Martens and Zein (2004), and Doran and Ronn (2006) document the forecasting performance of oil and gas IVs, i.e., testing (1) whether IV is an unbiased forecast of future volatility and (2) whether IV predicts future volatility better than historical volatility or a GARCH-type forecast. Mahar, Peterson and Horan (2004) examine the behavior of crude oil IV surrounding OPEC meetings. None of these papers examine other attributes of oil and gas IVs such as whether IVs vary by term-to-maturity or by strike price. This limitation is due to the data sets used in previous studies which only include IVs calculated from nearby at-the-money options. There are also unexplored questions of a possible seasonality pattern in oil and gas IVs and whether oil and gas IVs respond differently to positive and negative return shocks of the underlying futures contracts. In the third essay, I construct a dataset that includes IVs across various strike prices for a range of terms to maturity. This comprehensive data set allows me to compare the behavior of IVs across different strike prices as well as across different terms to maturity and also to address other unexplored issues concerning the determinants of oil and gas IVs. Consequently, results in this study have implications for option traders who need to better understand the behavior of oil and gas IVs for valuation purposes.

As mentioned above, my dissertation consists of three essays. The first two essays examine the causes and behavior of price volatility in the US crude oil and natural gas markets from January 1997 through December 2008. In these essays, I simultaneously test and quantify the hypothesized determinants of actual volatility in these markets using a multiplicative GARCH type model. This model, which separates volatility into a persistent part and a transitory part, allows me to implement a much cleaner study of the determinants of volatility than that used in several previous studies. The third essay explores the structure, characteristics, and determinants of implied volatilities calculated from crude oil and natural gas call options from September 1999 through June 2006.

My most important results and contributions to the literature include the following. One, crude oil and natural gas markets are characterized by volatility persistence where volatile periods are followed by volatile periods and stable periods are followed by stable periods. Two, in the natural gas market, there is evidence of asymmetric volatility in that an unexpected increase in price increases predicted volatility (according to a GARCH type model) more than an equal unexpected decrease in price. Consistent with this evidence, natural gas implied volatility, which supposedly represents the market's expectation of future volatility, also increases more following a positive return shock. This asymmetry pattern which, to my knowledge, is unique to natural gas is likely caused by the hypothesized shape of the supply and demand curves in this market. At low volume and prices, natural gas supply is highly elastic, but once storage limits are reached, supply becomes quite inelastic as natural gas producers, due to infrastructure constraints, are unable to increase their production levels within a short period of time (Krichene, 2002; Burns, 2008). The demand curve for natural gas also contains an elastic portion when prices are low and an inelastic portion when prices are high (Krichene, 2002; Burns, 2008). Given the hypothesized shape of the natural gas supply and demand curves, the same fluctuation in demand when prices are low should cause a smaller change in prices than when prices are high. Thus, a positive price shock which moves the natural gas market up the supply and demand curves is likely to presage higher future volatility than a negative shock moving the market down the curves. To a lesser extent and in an opposite pattern, there is also an asymmetric volatility in the crude oil market where an unexpected decrease in price increases predicted volatility and implied volatility more than an unexpected increase in price of similar magnitude.

Three, oil and gas implied volatilities tend to increase as the options approach expiration and the increasing pattern is consistent across strike prices. This term structure pattern is opposite to that observed for the stock index, T-bond and foreign exchange options markets where IVs tend to decrease as expiration approaches. While inconsistent with the pattern for IV in those financial options markets, the oil and gas IV term structure pattern is consistent with the actual volatility pattern for different maturity futures contracts. Given this term structure pattern, if a financial engineer uses the IV from nearby options, the IV that would normally be calculated, to value longer term options, the latter will tend to be overvalued.

Four, oil and gas IVs tend to differ by strike price. Natural gas IVs exhibit a positive skew pattern in that IVs are higher for out-of-the-money calls than for at- and in-the-money calls. This upward sloping pattern is unique to natural gas options since, to my knowledge, all smile patterns documented to date are either U-shaped or downward sloping. There is no evidence that this positive skew pattern is caused by the characteristics of the underlying futures return distribution. It is apparent that the hedging pressure in this market is at least partly responsible for this pattern. While the skew pattern is consistent across terms to maturity for natural gas, the shape of the cross-sectional pattern changes with term-to-maturity for crude oil. For nearby and second-month crude oil options, IVs are highest for deep in- and out-of-the-money calls and lowest for moderately in-the-money calls. For third- and fourth-month options, IVs are lowest for deep in-the-money calls and increase monotonically with strike prices.

Five, there is a day-of-the-week volatility pattern in oil and gas markets. In both markets, Friday-close-to-Monday-close returns tend to be more volatile than any other weekday return, implying that these markets are impacted by sorts of news occurring during the weekend such as weather news or geo-political events. There is evidence that oil and gas actual volatilities increase on Wednesday and Thursday, respectively, which is attributable to the weekly release of the Petroleum Status Report and the Natural Gas Storage Report on these days. The oil and gas implied volatilities also exhibit a day-of-the-week pattern which is consistent with the pattern in actual volatilities.

Six, there is an announcement effect in oil and gas markets. As mentioned above, crude oil volatility tends to increase on days the Petroleum Status Report is released. There is also significant evidence that news from the OPEC meetings cause an increase in crude oil volatility. In the natural gas market, surprises in storage report news has a significant impact on volatility. In addition, there is strong evidence that natural gas volatility increases during and immediately after the "bid week", the last five trading days of a month, as news about prices and volumes being set in the spot market becomes public.

Seven, both actual and implied volatilities in the natural gas market exhibit a time-of-the-year pattern in which volatility tends to be higher on contracts expiring in the winter months. Consequently, if a financial engineer uses the yearly average volatility to value natural gas options, he or she will tend to overestimate the values of options expiring in summer and underestimate the values of options expiring in winter. Eight, natural gas actual volatility tends to increase on winter days when the temperature is lower than normal. Nine, crude oil volatility tends to be high when oil prices are historically low and low when prices are historically high. Ten, there is strong evidence of a time-varying conditional correlation between crude oil prices and the value of the dollar. Eleven, although the unbiasedness of oil and gas IVs depends on term-to-maturity and moneyness of the options, IV is a fairly efficient forecast of future volatility in these markets. Twelve, I develop and use a variant of the multiplicative GARCH type model outlined in Jones, Lamont and Lumsdaine (1998) and show that a GARCH model which fails to control for seasonality, announcement, and other transitory effects tends to overestimate the impact of a surprise return shock on subsequent volatility.

The dissertation is organized as follows. Chapter II examines the ex-ante determinants of price volatility in the US crude oil market. Chapter III studies the determinants of price volatility in the natural gas market. Chapter IV explores the structure, characteristics, and determinants of oil and gas implied volatilities. As the dissertation consists of separate essays in the format of journal articles, several hypotheses, data descriptions, and analyses in Chapters II, III and IV are similar and overlapping.

Chapter II. Price Volatility in the Crude Oil Market

1. Introduction

This paper examines the causes and behavior of price volatility in the US crude oil market from January 1997 through November 2008. Crude oil is one of the most essential energy sources in the U.S., accounting for about 40% of the nation's energy consumption. Since OPEC's 1973 decision to regulate its oil price independently of large oil companies, crude oil prices have been subject to dramatic volatility. Oil prices increased from less than $3 per barrel in mid-1973 to $36 in early 1981. This large oil price fluctuation tendency has continued in recent years. From less than $11 per barrel in the beginning of 1999, oil prices increased to $38 per barrel in September 2000, decreased to $18 per barrel in January 2002 and went up to $77 per barrel in July 2006. The crude oil market has experienced an unprecedented dramatic volatility in 2008 as crude oil prices reached an all-time high level of $145 per barrel in July and then fell sharply to $50 per barrel in November.

Crude oil prices are more volatile than those in most financial markets. In 2007, the annualized standard deviation of the daily percentage change in prices was 31.33% for crude oil. By comparison, that number was only 4.08% for the US dollar-Euro exchange rate, 16.37% for the S&P 500 and 19.10% for the 10-year T-bond interest rates[2]. Figure 1 depicts crude oil prices and historical volatilities from January 1997 through November 2008 wherein historical volatilities are measured as the annualized rolling 30-day standard deviation of returns. As shown in these graphs, the

[2] The data for the S&P 500, US dollar-Euro exchange rate, and the 10-year T-bond interest rates were collected from CRSP database and the Federal Reserve website (http://www.federalreserve.gov).

crude oil market has undergone notable price fluctuations during the sample period and volatility tends to cluster over time.

The high volatility in crude oil prices is likely due to actual and anticipated fluctuations in supply and the short-term inelasticity of demand. Given that crude oil is one of the most essential energy sources, it is very difficult for most oil users to reduce their consumption within a short period of time following a price increase. On the other hand, there is considerable fluctuation in oil supply which depends on a variety of macroeconomic and political factors. For example, in 1997, when the world economy was already in a recession, the Organization of Petroleum Exporting Countries (OPEC), failing to predict the oil demand correctly, increased its production levels which resulted in a huge decrease in oil prices. In June-July 2008, a combination of supply uncertainties in oil producing countries and a falling dollar caused an unprecedented oil price spike. On the reverse, an appreciation of the dollar and signs of worldwide economic slowdown led to a sharp decrease in oil price toward the end of 2008. This high variability in crude oil prices makes it extremely difficult for consumers to forecast their costs and for producers to forecast their profits. The desire to protect market participants against such price fluctuations has led to the creation of and active trading in futures, swaps and options where the market value of the latter depends on volatility.

Although it is difficult to forecast the direction of future price changes from past price behavior, the absolute magnitude of price changes, i.e. volatility, has been proven much more predictable in most financial markets. It is generally found that highly volatile markets tend to be followed by volatile markets whereas stable markets tend to be followed by stable markets. The vast majority of the research on market volatility has focused on the volatility of financial markets such as the stock, bond, interest rates and foreign exchange futures markets, etc. Despite the fact that crude oil prices, like any other energy prices, tend to be more volatile than most financial prices, research into the cause and behavior of volatility in the crude oil market is limited. For instance, in a well-known and comprehensive study of the volatility literature, Poon and Granger (2003) surveyed 93 articles examining volatility in all sorts of markets; only three of these included crude oil among the markets examined (Day and Lewis, 1993; Szakmary, Ors and Kim, 2003; and Martens and Zein, 2004).

An understanding of the causes and behavior of crude oil volatility is essential to measuring and managing the risk faced by energy producers and major consumers, such as airlines. Also the market value of risk management products such as options depends largely on volatility. However, most research on the crude oil market has focused on the behavior of oil prices rather than on volatility. The limited studies on crude oil volatility to date focus solely on volatility persistence, i.e., the relation between current and past volatility, in this market (see, for example, Wilson, Aggarwal and Inclan, 1996; Yang, Hwang and Huang, 2002; Pindyck, 2004; and Kuper and Soest, 2006). Other possible determinants of crude oil volatility are neglected in the literature. In this study, I attempt to fill this gap in our understanding by simultaneously testing and quantifying several hypothesized ex-ante determinants of crude oil volatility. These determinants consist of volatility persistence, volatility asymmetry, oil price levels, announcement, and seasonality effects.

My most important results and contributions to the literature include the following. One, crude oil volatility is asymmetric in that an unexpected decrease in price increases predicted volatility more than an unexpected increase in price of similar magnitude. Two, crude oil volatility tends to be high when oil prices are historically low and low when prices are historically high. Three, crude oil volatility tends to increase on days the OPEC meetings announcements are released. Four, crude oil volatility is significantly higher on Monday, implying that the crude oil market is impacted by news occurring during the weekend and on Wednesday, possibly because Wednesday is the release day of the Weekly Petroleum Status Report. Five, a model which fails to control for levels, announcement, and seasonality effects tends to overestimate the impact of an unexpected price decrease on predicted volatility. Six, there is strong evidence of a time-varying conditional correlation between crude oil prices and the value of the dollar.

I develop and use a variant of the multiplicative GARCH type model outlined in Jones, Lamont and Lumsdaine (1998). This model, which separates volatility into a persistent part and a transitory part, allows me to implement a much cleaner study of the determinants of volatility than that used in several previous studies on other markets.

To the best of my knowledge, my study is the first comprehensive study of the ex-ante determinants on volatility within a GARCH framework for the crude oil market and also the first study of the time-varying conditional covariance between crude oil prices and the value of the dollar.

The chapter is organized as follows. In Section 2, I propose and develop my hypotheses. The data is presented in Section 3. In Section 4, I analyze the multiplicative GARCH type model to quantify the determinants of crude oil volatility and the bivariate GARCH model for the conditional covariance between crude oil prices and the value of the dollar. Section 5 presents the results and Section 6 concludes the paper.

2. Hypotheses

In this study, I attempt to answer the following questions:

1. *Are crude oil prices characterized by volatility persistence as has been documented in other markets?* It has been observed that in many other markets volatile periods tend to follow volatile periods whereas stable periods tend to follow stable periods. Among numerous studies documenting volatility persistence are: Adrian, Pagan and Schwert (1990), Andersen, Bollerslev, Diebold and Ebens (2001), Wu (2001) and Flannery and Protopapadakis (2002) for the stock market, Ederington and Lee (1993, 1995 and 2001) for interest rates, Harvey and Huang (1991), Ederington and Lee (1993, 1995 and 2001), Andersen and Bollerslev (1998) and Low and Zhang (2005) for the foreign exchange market and Jones et al. (1998) for the Treasury bond market. I hypothesize that similar volatility persistence exists in the crude oil market.

2. *Is there volatility asymmetry in the crude oil market?* That is, do equal positive and negative shocks have different impacts on future volatility? It is generally documented that asymmetric volatility exists in a number of financial markets. French and Roll (1986), French, Schwert and Stambaugh (1987), Campbell and Hentschel (1992), Glosten, Jagannathan and Runkle (1993), Veronesi (1999), Bekaert and Wu

(2000) and Wu (2001) and others found that in the stock market, an unexpected decrease in price has a bigger impact on predicted volatility than an unexpected increase in price of equal magnitude. The asymmetric volatility in the stock market is generally attributed to either a leverage effect and/or a volatility feedback effect[3]. To a lesser extent, Brunner and Simon (1996) and Simon (1997) found similar evidence for the Treasury bond futures and options markets.

While in the stock market negative shocks tend to have more impact on predicted volatility than equal positive shocks, the hypothesized reasons, i.e., leverage and/or volatility feedback effects, would not apply to the crude oil market. There are reasons to expect that due to the elasticity of the supply and demand curves, a positive shock in the energy market could have more impact on predicted future volatility than an equivalent negative shock. The supply and demand curves for crude oil are likely to be more elastic at low prices than at higher prices. Given the hypothesized shape of the supply and demand curves, the same fluctuation in demand when prices are low should cause a smaller change in prices than when prices are high. Thus, a positive price shock which moves the market up the supply and demand curves is likely to presage higher future volatility than a negative shock moving the market down the curves.

3. *Is there levels effect in crude oil volatility?* High oil prices which indicate that the supply and demand curves become inelastic should cause an increase in volatility. However, as depicted in Figure 1, periods of high volatility tend to be associated with low prices and periods of low volatility tend to be associated with high

[3]Wu (2001) provides a survey on the determinants of asymmetric volatility in the stock market.

prices. Therefore, the price levels effect on crude oil volatility is an empirical issue to be explored.

4. *Do the OPEC meetings cause increased volatility in the crude oil market?* The Organization of Petroleum Exporting Countries (OPEC), founded in 1960, produces about 40 percent of the world's crude oil. OPEC nations control approximately 78% of known reserves and export about 55% of the oil traded internationally[4]. The Organization is required by its charter to hold a minimum of two conferences per year, at which each member nation is to be represented. In addition to these regularly scheduled conferences, OPEC holds "extraordinary meetings" on an as-needed basis. During these meetings, the OPEC delegates often consider and ratify future production levels and therefore OPEC meetings are usually the subject of intense media attention.

Disagreement exists in the literature about the OPEC's influence on crude oil prices. Loderer (1985) and Gullen (1996) find that OPEC influenced crude oil prices in the eighties and nineties but not during the seventies and early eighties. Alhajji and Huettner (2000) reject the hypothesis that OPEC has a significant impact on crude oil prices. Conversely, Deaves and Krinsky (1992) find that crude oil prices under-react to bullish outcomes of OPEC meetings and efficiently react to bearish outcomes. Despite the controversial evidence of the OPEC's influence on oil price *levels*, there are reasons to expect that OPEC news impact crude oil *volatility*. On days the OPEC decisions are coming to the market, market participants adjust prices according to new information and thus, the crude oil market should become more volatile. Since the OPEC meetings are generally not open to the press and most valuable news are not

[4]What is OPEC? (OPEC, 2006)

made known to the public until after the meetings[5], I hypothesize that volatility will be higher on days following the OPEC meetings.

5. *Are there seasonal effects in crude oil volatility?*

5.1 Day-of-the-week pattern

Some academic studies find that the volatility of financial asset returns varies across days of the week.[6] In some financial markets, the volatility from Friday close to Monday close is higher than that of a normal one-day period but not as high as that of a three-weekday period presumably because there is not much information coming out during the weekend. In this study, I hypothesize that crude oil volatility tends to be high on Monday (including weekend) since the crude oil market is likely to be affected by news that occurs during the weekend, such as weather or geo-political events. I also hypothesize higher crude oil volatility on Wednesday since this is the release day of the Weekly Petroleum Status Report. This Report, which is compiled and issued by the U.S. Energy Information Administration, is widely considered to be one of the most important news in the crude oil market since it provides timely information on supply and inventory data of crude oil and principal petroleum products in the context of historical information and forecasts.

5.2 Time-of-the-year pattern

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[5] Platts (2002)

[6] The literature on day-of-the-week effect on volatility includes French and Roll (1986), Berument and Kiymaz (2001) for the stock market, Harvey and Huang (1991), Ederington and Lee (1993) for interest rates and the foreign exchange futures market and Jones et al. (1998) for the Treasury bond market.

It has been documented that returns in some markets differ by month of the year[7] but little attention has been given to a seasonal pattern in volatility. In this study, I investigate the possibility of a time-of-the-year pattern in volatility in the crude oil market where part of the demand supposedly depends on weather conditions. For example, the demand for gasoline often increases during the summer driving season and similarly, the demand for heating oil may increase sharply in the winter season. Since gasoline and heating oil are two of the most important products distilled from crude oil[8], an increase in product demand supposedly results in an increase in crude oil demand and if crude oil supply is essentially fixed in the short run, volatility would increase.

6. *Is there evidence of a time-varying conditional covariance between crude oil prices and the value of the dollar?* It is often argued that because oil prices are denominated in dollars, oil prices and the value of the dollar should be negatively correlated. An appreciation (depreciation) of the U.S. dollar would tend to make oil more (less) expensive in non-dollar currencies and would reduce (increase) demand for crude oil thereby possibly lowering (increasing) oil prices in dollars.

The relationship between crude oil prices and the value of the dollar has been examined in prior academic research (see, for example, Amano and Norden, 1998; Sadorsky, 2000; Benassy-Quere, Mignon and Penot, 2007). However, while numerous studies document strong evidence of heteroskedastic covariances among other

[7]See, for instance, Keim (1983), Lakonishok and Smidt (1984) for the stock market and Jordan and Jordan (1991) for the corporate bond market
[8]A 42-U.S. gallon barrel of crude oil provides slightly more than 20 gallons of finished motor gasoline and 10 gallons of heating oil and diesel fuel.

financial assets[9], none of the previous studies on the correlation between crude oil prices and the value of the dollar have explored whether that correlation is constant or time-varying. I hypothesize a time-varying conditional correlation between crude oil prices and the value of the dollar. While an increase (decrease) in the dollar's value implies more (less) expensive oil prices in non-dollar currencies which should result in a downward (upward) pressure on oil demand and hence lower (increase) oil prices in dollars, oil prices are also impacted by international supply-demand shifts not caused by changes in the dollar's value in which case there should be no correlation between oil prices and the dollar's value. Occasionally, there may be forces that simultaneously increase or decrease oil prices and the value of the dollar, resulting in a positive correlation between the two. Hence, I test whether the covariance and correlation between the value of the dollar and oil prices in dollars vary over time.

3. Data and preliminary analysis

These hypotheses are tested using daily closing prices for crude oil futures contracts traded on the New York Mercantile Exchange (NYMEX). Crude oil futures contracts, which began trading on the NYMEX on March 30, 1983, trade in units of 1,000 U.S. barrels. My sample period is January 1, 1997 to November 28, 2008 totaling 2,981 daily observations. Crude oil prices are from the Energy Information Administration[10]. Details on the OPEC meetings are collected from Dow Jones Factiva database.

Futures prices are used in place of spot prices for the following reasons. First, futures prices are the major prices in the crude oil market. The NYMEX crude oil

[9]See, for example, Bollerslev et al. (1988), Harvey (1989), Bodurtha and Mark (1991).
[10]http://tonto.eia.doe.gov

futures contract is the world's most liquid forum for crude oil trading and is used as a principal international pricing benchmark. Crude oil futures prices are also the prices reported in newspapers. Second, the futures market for crude oil is liquid and centralized while spot markets are localized and illiquid. Third, futures prices are the prices normally used in most oil risk management contracts such as swaps and options.

To examine volatility in a GARCH type framework, I utilize daily log returns[11] defined as $r_t=\ln(P_t/P_{t-1})$ wherein P_t is the price of the futures contract on day t and P_{t-1} is the price of the same contract the previous day. As traders often cover their positions on the last trading day of a contract's life, trading volume and open interest decline and price volatility increases substantially. To avoid this "thin market" problem, I replace the return of the nearest contract on the last trading day of each month with that of the second nearest contract in constructing the r_t series.

To proxy for the value of the dollar, I use a trade-weighted average of the foreign exchange value of the U.S. dollar against a subset of the broad index currencies that circulate widely outside the country of issue, including the Euro Area, Canada, Japan, United Kingdom, Switzerland, Australia, and Sweden. The exchange index data is from the Federal Reserve Statistical releases.[12]

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[11]The daily crude oil "returns" are used to measure price changes only. These "returns" are not investment returns since no money is actually invested.

[12]The index value is set 100 in March 1973 and calculated using the formula: $EI_t = EI_{t-1} \times \prod_{j=1}^{N(t)} (e_{j,t}/e_{j,t-1})^{w_{j,t}}$, where EI_t is the value of the index at time t, $e_{j,t}$ and $e_{j,t-1}$ are the prices of the U.S. dollar in terms of foreign currency j at times t and $t-1$, $w_{j,t}$ is the weight of currency j in the index at time t (based on annual data on international trade), $N(t)$ is the number of foreign currencies in the index at time t, and $\sum_j w_{j,t} = 1$.

Table I provides summary statistics for daily crude oil returns on nearby, second- and third-month contracts. The annualized standard deviation of the daily percentage change in nearby crude oil prices over the January 1997-November 2008 period is 38.26%, indicating that this market is characterized by very high volatility. There is evidence that volatility decreases with time-to-maturity of the futures contracts, from 38.26% for the nearby to 34.79% for the second-month and 32.57% for the third-month contracts.

Table I shows preliminary evidence of volatility persistence in that the first-order autocorrelation coefficients for absolute returns are positive and significant at the 0.01 level. For squared returns (not reported), the first-order autocorrelation coefficients are also significantly positive at the 0.001 level. Clearly, the crude oil market, like many others, is characterized by volatility persistence.

4. Model Specification and Analysis

4.1. Ex-ante determinants of crude oil volatility

In order to test and quantify the determinants of crude oil volatility as discussed in section 2, I estimate a model in which the conditional variance follows a multiplicative GARCH type process:

$$r_t = \mu + \varphi_1 r_{t-1} + \varepsilon_t \tag{1}$$

where:

$$\varepsilon_t \sim \mathrm{N}(0, \sigma_t^2) \text{ and } \sigma_t^2 = h_t \cdot s_t \tag{2}$$

$$h_t = \mathrm{Var}(\zeta_t) = \omega + \alpha\zeta_{t-1}^2 + \beta h_{t-1} + \gamma\zeta_{t-1}^2 I_{t-1}, \text{ where } \zeta_t = \varepsilon_t / \mathrm{s}_t^{.5} \tag{3}$$

$$\mathrm{s}_t = \prod_{i=1}^{4} \mathrm{s}_{i,t} \tag{4}$$

$$s_{1,t} = [AP_t/\overline{AP}]^{\kappa} \quad (4.a)$$

$$s_{2,t} = (1+ \delta_{-1}DA_{t-1})(1+ \delta_0 DA_t)(1+ \delta_1 DA_{t+1}) \quad (4.b)$$

$$s_{3,t} = \prod_{i=1}^{4}(1+\lambda_i DW_{i,t}) \quad (4.c)$$

$$s_{4,t} = (1+ \theta_1 DSUM_{i,t})(1+ \theta_2 DWIN_{i,t}) \quad (4.d)$$

r_t is the log percentage change in price of the futures contract on day t, I_{t-1}=1 if ζ_{t-1} >0 and 0 otherwise. My main interest is in the ex-ante determinants of the variance of the surprise oil return, ε_t. I model this variance as a multiplicative function of an asymmetric GARCH function (equation 3), price levels (equation 4.a), announcement effects (equation 4.b), day-of-the-week pattern (equation 4.c) and seasonal effects (equation 4.d).

4.1.1 Volatility Persistence and Asymmetric Volatility

Equation 3 is the asymmetric GARCH model due to Glosten et al. (1993) often referred to as the GJR or TGARCH model. If volatility persistence is an attribute of the crude oil market, α and β should be significantly positive, implying that predicted volatility depends on both unexpected price changes and the previous day's forecast volatility. Asymmetric volatility implies $\gamma \neq 0$ in equation (3); γ >0 implies that a positive shock increases conditional volatility more than an equivalent negative shock.

4.1.2 Levels, Announcement and Seasonality effects

Equation 4, the transitory effects equation, estimates the impact of other determinants on volatility. Equation 4(a) tests the hypothesis that volatility is sensitive to price levels. AP_t is the inflation-adjusted price = $(P_t/CPI_T)100$ where P_t is the crude oil price on day t and CPI_T is the Consumer Price Index for that month. $\overline{AP}$ represents the average inflation-adjusted price over the sample period. κ >0 implies that volatility is higher at high price levels and κ <0 implies that volatility is lower at high price levels.

Equation 4(b) estimates the impact of OPEC meetings announcements on volatility. DA_t is 1 on OPEC meeting days and 0 otherwise. I also include DA_{t-1} and DA_{t+1} as dummies for the days before and after OPEC meeting days because (1) it is often reported in the media that market participants speculate on the OPEC decisions and adjust prices prior to the meetings and (2) important OPEC meetings news are usually not released to the public until the following day. In equation 4(b), δ_i represents the estimated log percentage increase in volatility normally caused by OPEC meetings.

Equations 4(c) and 4(d) estimate the day-of-the-week and time-of-the-year patterns in crude oil volatility. $DW_{i,t}$ are zero-one dummies for Monday (which includes the weekend), Wednesday, Thursday and Friday with Tuesday being the left-out day. λ_i estimates the average percentage difference between volatility on day i and volatility on Tuesday. In other words, assuming that $s_{1,t}=s_{2,t}=s_{4,t}=1$, then the estimated variance on Tuesday is h_t. On Monday, the estimated variance is $h_t(1+\lambda_M)$. On Wednesday, the estimated variance is $h_t(1+\lambda_W)$ and so on for other days. If the crude oil market is impacted by news occurring over the weekend, Monday return (which is a three-day return including the weekend) should be more volatile than any normal weekday return and λ_M >0. I also expect that λ_W > 0 because Wednesday is the release day of the Weekly Petroleum Status Report.

$DSUM_{i,t}$=1 if the futures contract expires in the summer months (from May through August); $DWIN_{i,t}$=1 if the futures contract expires in the winter months (from November through February). θ_1 and/or $\theta_2 \neq 0$ imply a time-of-the-year pattern in crude oil volatility.

4.1.3 Comparison with Previous Models

My model improves on that used in several previous studies for non-oil markets which seek to simultaneously estimate both GARCH and other determinants of volatility. The introduction of a transitory volatility equation s_t into the specification enables me to implement a much cleaner study of the determinants of volatility than when announcement and/or day-of-the-week dummies are added to the variance equation. For instance, Hsieh (1989), Berument and Kiymaz (2001), Ederington and Lee (2001) and Lee (2002) use GARCH type models to examine day-of-the-week effects on volatility in other markets. In those studies, weekday dummies are in the h_t equation (equation 3) and the coefficient estimates reflect how conditional volatility changes across weekdays. Thus, using their model, there is no s_t equation (equation 4) and equation (3) becomes:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \lambda_M DW_{M,t} + \lambda_W DW_{W,t} + \lambda_R DW_{R,t} + \lambda_F DW_{F,t}, \quad (5)$$

In equation 5, since weekday dummies are in the h_t equation, the dummy for any day of the week impacts volatilities on *all* days of the week through the h_{t-1} term on the right hand side of the equation. Suppose, for instance, that day t is Monday. $\partial h_t/\partial DW_{M,t} = \lambda_M$. Now consider the impact of the Monday dummy on volatility on Tuesday (day $t+1$). Since

$h_{t+1} = \omega + \alpha\varepsilon_t^2 + \beta h_t + \lambda_M DW_{M,t+1} + \lambda_W DW_{W,t+1} + \lambda_R DW_{R,t+1} + \lambda_F DW_{F,t+1}$, (5)

$\partial h_{t+1}/\partial DW_{M,t} = (\partial h_{t+1}/\partial h_t)(\partial h_t/\partial DW_{M,t}) = \beta\lambda_M$. Likewise, the Monday dummy impact on the Wednesday's volatility is $\partial h_{t+2}/\partial DW_{M,t} = \beta^2\lambda_M$. Therefore, when weekday dummies are in the h_t equation, as in equation (5), λ_M does not measure how much higher volatility is on Monday than on the omitted day (Tuesday). Indeed, depending on the coefficient pattern, day X which has the highest λ_X coefficient may not be the day with the highest volatility.

In contrast, a specification which separates the variance of returns into a persistent part, equation (3), and a non-persistent part, equation (4), allows me to estimate a model in which any weekday dummy impacts that day's volatility only. For example, λ_M measures how much higher (or lower) in percentage terms the volatility is on Monday than on the omitted day (Tuesday) and λ_W measures how much higher (or lower) the volatility is on Wednesday and so on.

To estimate the announcement impacts on volatility in other markets, several previous studies, for example, Hsieh (1989), Berument and Kiymaz (2001), Ederington and Lee (2001), De Goeij and Marquering (2006), add an announcement dummy to the h_t equation and do not include the s_t equation. Thus, the variance equation becomes:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \delta_0 DA_t, \tag{6}$$

In equation (6), an unscheduled shock on day *t-1* impacts volatility on day *t* through the term $\alpha\varepsilon_{t-1}^2$. However, since an announcement impact is forced to persist on the subsequent days ($\partial h_t/\partial DA_t = \delta_0$, $\partial h_{t+1}/\partial DA_t = (\partial h_{t+1}/\partial h_t)(\partial h_t/\partial DA_t) = \beta\delta_0$,

$\partial h_{t+2}/\partial DA_t = \beta^2\delta_0$ and so on), the impact of a shock due to scheduled announcement on day $t-1$ on volatility on day t includes not only $\alpha\varepsilon_{t-1}{}^2$ but also $\beta\delta_0$. Consequently, models like equation (6) impose much higher persistence for shocks due to scheduled announcements than for equivalent shocks due to unscheduled announcements. In contrast, in my model, the impact of a shock due to scheduled announcement does not persist on the following days ($\partial\sigma_t^2/\partial DA_t = \delta_0$ and $\partial\sigma_{t+1}^2/\partial DA_t = 0$) and therefore, the estimated impact of a shock on day $t-1$ on volatility on subsequent days t is the same for scheduled and unscheduled announcements.

4.2. Bivariate GARCH model of the conditional covariance between crude oil prices and the value of the dollar

I utilize a multivariate GARCH model to test for a time-varying covariance between crude oil prices and the value of the dollar. The development of multivariate GARCH models represents a major step forward in the modeling of volatility. Among various multivariate GARCH models in the literature, the Diagonal VECH model introduced by Bollerslev, Engle and Wooldridge (1988) is one of the most popular. In the general Diagonal VECH model, the conditional covariance follows a multivariate GARCH (1,1) process:

$$H_t = \Omega + A \otimes \boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}^{'} + B \otimes H_{t-1} \tag{7}$$

where the coefficient matrices A, B and Ω are NxN symmetric matrices, and the operator $\otimes$ is the element by element (Hadamard) product.

I hypothesize that the conditional covariance matrix of crude oil and exchange index returns follows a bivariate GARCH process and estimate the following Diagonal VECH model:

$$\mathbf{r}_t = \boldsymbol{\mu} + \boldsymbol{\varepsilon}_t \tag{8}$$
$$\boldsymbol{\varepsilon}_t \sim N(0, H_t)$$

$$H_t = \Omega + A \otimes \boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}^{'} + B \otimes H_{t-1} \tag{7}$$

where $\mathbf{r}_t = (r_{1,t}, r_{2,t})'$ is a (2x1) vector containing crude oil and exchange index returns and H_t is a (2x2) conditional covariance matrix. Let H_t follow the most unrestricted process among all Diagonal VECH models where the parameters in the matrices Ω, A, and B are allowed to vary without any restriction, the model may be written in single equation format as:

$$(H_t)_{ij} = (\Omega)_{ij} + (A_{ij})\varepsilon_{j,t-1}\varepsilon_{i,t-1} + (B)_{i,j}(H_{t-1})_{ij} \tag{9}$$

where, for instance, $(H_t)_{ij}$ is the *i*-th row and *j*-th column of matrix H_t. Ω is a (3x1) parameter vector; *A* and *B* are (3x3) diagonal parameter matrices.

5. Results

5.1. Ex-ante determinants of crude oil volatility

Estimates of the specification (1-4) for returns on nearby futures contracts are presented in the third column of Table II.

5.1.1 Volatility Persistence and Asymmetric Volatility

As expected, there is evidence of volatility persistence in the crude oil market. The estimates of α and β are positive and significant at the 0.001 level, implying that predicted volatility depends on both previous shocks and previous volatilities. Hence, highly volatile periods in the crude oil market tend to be followed by volatile periods in the future and this finding is robust when I control for levels, announcement and seasonality effects. There is also evidence of asymmetric volatility in the crude oil market. The estimated γ is significantly negative, indicating that volatility increases considerably more following a sudden decline in oil prices than following an equal sudden increase in prices.

Figure 2 presents the impact of a two-standard deviation oil return shock on subsequent predicted volatilities. Suppose the conditional variance, $h_{t-1}=\mathrm{Var}(\zeta_{t-1})$ is at its steady-state level and suppose there is a shock such that $\zeta_{t-1}^2 = 4\mathrm{Var}(\zeta_{t-1})$. Figure 2 demonstrates the percentage difference in expected volatility on day $t+x$ and on day $t-1$, $\left[\frac{\mathrm{Var}(\zeta_{t+x})}{\mathrm{Var}(\zeta_{t-1})}-1\right]$, assuming $E(\zeta_{t+x}^2) = \mathrm{Var}(\zeta_{t+x})$ for $x > -1$ and that negative and positive return shocks are equally likely. For example, the conditional volatility is about 14% higher the day after the shock and 7% a week later.

In the second column of Table II, I present estimates of a GJR model without levels, announcement and seasonality effects. In other words, I estimate a model consisting of equations (1-3) assuming that $s_t=1$. A comparison of the estimates of the GJR model (in the second column) and those of the full model (in the third column) indicates that determinants of volatility other than volatility persistence and asymmetry are important when modeling volatility in the crude oil market. The likelihood ratio test statistics is 58.72 with 10 degrees of freedom and therefore, the null hypothesis that there are no levels, announcement and seasonality effects is rejected at the 0.001 level. The estimate of α in the GJR model is significantly higher than that in the full model while the estimates of $(\alpha+\gamma)$ are not significantly different from each other. Figure 3 plots different impacts of equal positive and negative shocks on predicted volatility according to the estimates from the GJR and the full models.

Again, suppose the conditional variance, $h_{t-1}=\mathrm{Var}(\zeta_{t-1})$ is at its steady-state level. According to the estimates in both the GJR and the full models, the conditional variance for day *t* falls 8% if there was no price change on day *t-1* and rises about 17.50% if the price increased 15%. However, if the price fell 15% on day *t-1*, the conditional variance for day *t* increases 43.06% in the GJR model and only 28.52% in the full model. Apparently, failing to control for levels, announcement and seasonality effects leads to an overestimation of the impact of a negative oil shock on predicted volatility and the overestimation is approximately 41.13%[13].

To test whether the omission of levels, announcement or day-of-the-week effects is responsible for this overestimation, I estimate specifications consisting of equations (1-3) and either equation 4(a), 4(b) or 4(c). Results (not reported) indicate that the overestimation caused by a model which fails to control for announcement and day-of-the-week effects is just 2.73% while the overestimation caused by a model which fails to control for levels effects and either announcement or day-of-the-week effects is approximately 40%. Apparently, failing to control for levels effects is the main cause of the overestimation of the impact of a negative oil shock on predicted volatility.

5.1.2 Levels effect

Somewhat consistent with the evidence that a positive oil shock has less impact on predicted volatility than an equivalent negative shock, the estimate for *κ*, the levels effect, is significantly negative, indicating that volatility is high when oil prices

[13]This is measured as 1-(E_{wo}/E_w) where E_{wo} represents the estimate of α from the GJR model where I do not control for seasonality, announcement and levels effects and E_w that from the full model where I do.

are low and low when prices are high. As shown in Figure 1, crude oil volatilities were especially high during the periods 02-07/1998; 11/1998-01/1999; 10/2000-01/2001, 10-12/2001, and 10-11/2008 which were accompanied by low prices. In contrast, the periods 02/2007-07/2007 and 06-08/2008 are characterized by both high prices and low volatilities.

This finding for the crude oil market is opposite to the evidence in the interest rates market that volatility is high (low) when interest rates are high (low). One possible explanation for this difference is that in most studies on interest rates market, the measure of interest rate volatility is the volatility of the rate change while in this study, the measure of crude oil volatility is the volatility of the log percentage change in price.

5.1.3 OPEC meetings

As indicated by the parameter estimates in Table II, decisions made at the OPEC meetings tend to contain important information for the crude oil market. On the day after OPEC meetings, the standard deviation of crude oil returns increases by 24.29%[14]. This concurs with the observation that news from OPEC meetings are not made known to the market until the following days. Contrary to media assertions that market participants adjust prices in speculation of OPEC decisions, there is apparently no significant evidence that crude oil volatility increases on or before the OPEC meeting days.

5.1.4 Seasonality

5.1.4.1 Day-of-the-week pattern

[14]This is calculated as: $(1+.5447)^{1/2}-1= 24.29\%$

Since Tuesday is the left-out dummy, the coefficients in Table II measure the difference between average volatility on each weekday and on Tuesday. Contrary to the findings in some other markets[15], there is no significant evidence that crude oil volatility increases on Friday. This may be due to the fact that in other markets, important economic news is often released on Friday whereas this is not the case in the crude oil market.

As expected, the Monday returns (including weekend) tend to be more volatile than any normal weekday return. The standard deviation of the Friday-close-to-Monday-close return is 18.49%[16] higher than that on Tuesday and the difference between Monday and Tuesday volatilities is significant at the 0.001 level.

Crude oil volatility tends to increase on Wednesday in that the standard deviation of Wednesday return is 15.15% higher than that of Tuesday return and the difference is significant at the 0.001 level. The higher Wednesday volatility is likely caused by the release of the Weekly Petroleum Status Report which is widely considered as one of the most important announcements in the petroleum market. This report provides timely information about current supply and demand conditions in the petroleum market and is therefore followed closely by market participants.

5.1.4.2 Time-of-the-year pattern

Contrary to my earlier hypothesis, there is no significant evidence that crude oil volatility increases during either the summer driving season or the winter heating

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[15]For example, Harvey and Huang (1991) reported higher volatility in interest rate and foreign exchange futures market on Friday. Ederington and Lee (1993) further supported these results. Jones et al. (1998) and Berument and Kiymaz (2001) found similar evidence for the bond and stock markets.

[16]This is calculated as: $(1+.3663)^{1/2}-1= 16.88\%$

season.[17] Apparently crude oil volatility is less likely to be determined by the fluctuations in demand for petroleum products.

To further explore a month-of-the-year pattern in crude oil volatility, I re-estimate specification (1-4) with equation 4(d) expanded to include 11 monthly dummies. Results from this expanded specification[18] indicate that September and October are the two least volatile months in a year. As the summer driving season ends and the winter does not arrive, this is the period of low crude oil demand. This slowdown in demand is often coupled with an increase in supply as numerous oil producing countries increase production and shipping of oil before their ports ice over during the winter.

5.1.5 Ex-ante determinants of volatility across terms to maturity

The last two columns of Table II report estimation results of the specification (1-4) for returns on second- and third-month futures contracts. There is evidence of volatility persistence for returns on these contracts. However, there is no evidence of asymmetric volatility for returns on third-month futures contracts.

The impact of OPEC announcements on crude oil volatility is more pronounced for longer term-to-maturity contracts than for nearby contract. On the days following OPEC meetings, the standard deviation of nearby returns increases by 24.29% while the increases for second- and third-month are 30.77% and 29.51%. Since announcements from OPEC meetings mostly contain information regarding

[17] I also estimate the specification (1-4) using gasoline and heating oil data during the sample period and find significant evidence that gasoline volatility increases during the summer months and heating oil volatility increases during the winter months.
[18] Results are available upon request.

crude oil production levels, this sorts of information is likely to have more impact on prices of longer term-to-maturity contracts than on nearby contracts.

There also exists a day-of-the-week pattern in volatilities for longer term contracts. The increase in Monday volatility (including weekend) is less sizable for third-month returns than for nearby and second-month. Apparently, news which occurs during the weekend such as weather or geo-political events tends to have more implication for crude oil prices in the short term than in the long term. In contrast, the increases in Wednesday volatility do not significantly differ across terms to maturity, implying that the Petroleum Status Report is viewed by the market as having similar impact on crude oil prices in the short run and in the long run.

5.2. Bivariate GARCH model for crude oil and exchange index returns

It is often argued that oil prices in dollars and the value of the dollar should be negatively correlated. An appreciation (depreciation) of the U.S. dollar would tend to make oil more (less) expensive in non-dollar currencies and would reduce (increase) demand for crude oil thereby possibly lowering (increasing) oil prices in dollars.

I hypothesize that the correlation between crude oil prices and dollar value varies over time. While an increase (decrease) in the dollar’s value implies more (less) expensive oil prices in non-dollar currencies which should result in a downward (upward) pressure on oil demand and hence lower (increase) oil prices in dollars, oil prices are also impacted by international supply-demand shifts not caused by changes in the dollar’s value in which case there should be no correlation between oil prices and the dollar’s value. Occasionally, there may be forces that simultaneously increase or decrease oil prices and the value of the dollar, resulting in a positive correlation between the two. Hence, I test whether the covariance and correlation between the value of the dollar and oil prices in dollars vary over time.

Estimation results from specification (7-8) are presented in the fourth column of Table III. In order to provide some intuition on the bivariate model parameters, I present the estimates of the univariate GARCH(1,1) specification for exchange index and crude oil volatilities in the second and third columns of Table III. Results from Table III indicate that the bivariate GARCH estimates of volatility persistence for exchange index and crude oil returns are close to, and not significantly different from, the univariate GARCH (1,1) estimates.

The estimate of $\Omega(1,2)$, the unconditional mean of the covariance between crude oil and exchange indices returns, is negative and significant at the 0.05 level, which is consistent with the observation of a negative correlation between crude oil prices and the value of the dollar. The estimates of $A(1,2)$ and $B(1,2)$ (the ARCH and GARCH terms in the covariance equation) are both positive and significant at the 0.01 level, implying that the covariance between crude oil prices and the value of the dollar tends to cluster over time.

The positive estimate for $A(1,2)$, the ARCH term, means that shocks to oil prices and exchange rates of the same sign affect the conditional covariance positively, while shocks of opposite signs affect the forecasted covariance negatively. Given that the unconditional mean of the covariance, $\Omega(1,2)$, is significantly negative, two shocks of the same sign would decrease and two shocks of opposite signs would increase the predicted covariance in absolute value terms. A significantly positive estimate of $A(1,2)$ also indicates that causes of the correlation between oil prices and the dollar's value tend to persist. If on one day the change in the dollar price of oil is largely due to a change in the dollar's value, there is a tendency for the next day's change in oil prices to be primarily caused by changes in the dollar's value as well. On the other hand, if on one day the change in the dollar price of oil is caused primarily by factors other than the dollar's value, there is a tendency for those to be the primary causes of changes in the dollar price of oil on subsequent days.

To examine whether the time variability in the covariance of crude oil and exchange index returns is solely due to variation in the two variances, I calculate the conditional correlation coefficient at time *t+1*, $\rho_{12,t+1}$:

$$\rho_{12,t+1} = \frac{Cov_t\{r_{1,t+1}, r_{2,t+1})}{\sqrt{Var_t(r_{1,t+1})Var_t(r_{2,t+1})}}$$

If $\rho_{12,t+1}$ is constant over time, the variability in covariance is solely due to variation in variances. To test the null hypothesis of a constant correlation coefficient, I estimate the Constant Conditional Correlation (CCC) model and test the Diagonal VECH model against the CCC model. The likelihood ratio test statistics is 9.8 with 2 degrees of freedom and significant at the 0.01 level. Therefore, the Constant Conditional Correlation hypothesis is rejected, implying that the correlation between oil prices and the value of the dollar tends to change over time.

Figures 4 and 5 present the plots of the conditional covariance forecasts and the estimated correlation coefficient over time, based on the estimation results of the diagonal VECH model as presented in Table III. The figures show that the conditional covariance and the correlation coefficient vary considerably over time.

6. Summary and Conclusions

The contribution this study makes is to provide an empirical examination of the causes and behavior of price volatility in the crude oil market. Daily returns data from January 1997 through November 2008 are used to estimate a multiplicative GARCH type model. The crude oil market is characterized by volatility persistence where highly volatile periods are followed by highly volatile periods and stable periods are followed by stable ones. I find that a negative crude oil shock has more impact on predicted volatility than an equivalent positive shock. A somewhat surprising result is that crude oil volatility is low when prices are high and high when prices are low. The OPEC meetings cause increased crude oil volatility on days the meetings announcements are released. There is a day-of-the-week pattern in the crude oil market in that Monday return (including weekend) is more volatile than any normal weekday return. The high weekend/Monday volatility is mainly due to the accumulation of information over the weekend. Crude oil volatility tends to increase on Wednesday since this is the announcement day of the Petroleum Status Report. In contrast to the findings for some financial markets, there is no evidence of higher Friday volatility in this market. I also document time-varying conditional covariance and correlation between crude oil prices and the value of the dollar.

In this study, I use a multiplicative asymmetric GARCH type model which separates volatility into a persistent part and a non-persistent part. This model allows me to implement a much cleaner study of the ex-ante determinants on volatility than that used in some previous studies.

Chapter III. Price Volatility in the Natural Gas Market

1. Introduction

This paper examines the causes and behavior of price volatility in the US natural gas market from January 1997 through December 2008. Natural gas is one of the most essential energy sources in the U.S., accounting for about 25% of the nation's energy consumption. Trading activity in the natural gas market has increased significantly in recent years. In October 2006 the New York Mercantile Exchange (NYMEX) reported that the daily trading of natural gas futures reached 54,213 contracts. By December 2007, the number had nearly tripled to 158,525 and subsequently increased to a record high of 403,106 contracts on July 24, 2008[19].

The natural gas market has undergone revolutionary changes since the early 1990s. From a highly regulated market in which government regulations prescribed everything from prices to who could buy, sell, and transport natural gas and under what conditions, the natural gas market has evolved into a largely deregulated market in which prices are driven by supply and demand. Since then, natural gas has been one of the most volatile markets. For example, from less than $2.5 per million British thermal units (mmBtu) in July 2002, natural gas prices increased to $9.5 per mmBtu in February 2003. This large price fluctuation tendency has continued in recent years. In 2008, natural gas prices rose sharply from $7.8 per mmBtu in early January to $13.5 per mmBtu in July, which was the highest price level for that time of year. Then starting around the end of July, natural gas prices fell almost as sharply and were approximately $5.5 per mmBtu toward the end of 2008. According to the U.S. Energy

[19]Natural Gas Year-In-Review 2007, Energy Information Administration and NYMEX Holdings releases.

Information Administration (EIA), this decline in natural gas price resulted from a combination of a larger-than-expected increase in domestic gas production and a drop in oil prices.

Natural gas prices are more volatile than those in most financial markets. In 2007, the annualized standard deviation of the daily percentage price change was 49.94% for natural gas. By comparison, that number was only 4.08% for the US dollar-Euro exchange rate, 16.37% for the S&P 500, 19.10% for the 10-year T-bond interest rates, and 31.33% for crude oil[20]. Figure 6 depicts prices and historical volatilities of the nearby natural gas futures contract from January 1997 through December 2008 wherein historical volatilities are measured as the annualized rolling 30-day standard deviation of returns. As shown in these graphs, the natural gas market has undergone notable price fluctuations during the sample period and there is a time-of-the-year pattern in which volatility tends to increase in winter.

The high volatility in natural gas prices is likely due to the short-term inelasticity of supply and demand. Since natural gas supplies are often constrained by storage levels and imports are limited, natural gas suppliers are unable to increase production levels in a short period of time. Also, it is difficult for consumers to quickly reduce their consumption when a sharp increase in natural gas prices occurs, especially during the winter. As natural gas suppliers cannot rapidly adjust their production levels to match demand changes, supply and demand imbalances may result in sharp price changes. This high variability in natural gas prices makes it extremely difficult for consumers to forecast their costs and for producers to forecast

[20]The data for the S&P 500, US dollar-Euro exchange rate, and the 10-year T-bond interest rates were collected from CRSP database and the Federal Reserve website (http://www.federalreserve.gov).

their profits. The desire to protect market participants against such price fluctuations has led to the creation of and active trading in futures, swaps and options where the market value of the latter depends on volatility. An understanding of the causes and behavior of natural gas volatility is therefore essential to measuring and managing the risk faced by market participants.

Although it is difficult to forecast the direction of future price changes from past price behavior, the absolute magnitude of price changes, i.e. volatility, has been proven much more predictable in most financial markets. It is generally found that highly volatile periods tend to be followed by volatile periods whereas stable periods tend to be followed by stable periods. The vast majority of the research on market volatility has focused on the volatility of financial markets such as the stock, bond, interest rates and foreign exchange futures markets, etc. Despite the fact that natural gas prices tend to be more volatile than most financial and commodity prices, research into the causes and behavior of volatility in the natural gas market is limited.

The limited studies on natural gas volatility to date examine several determinants of natural gas volatility in isolation. Susmel and Thompson (1997), Pindyck (2004) and Murry and Zhu (2004) find that natural gas volatility follows an ARCH-GARCH type process, Linn and Zhu (2004) document that the release of the Weekly Natural Gas Storage Report announcement causes increased natural gas volatility, Murry and Zhu (2004) document that natural gas volatility increases on Monday and on days the Storage Report is released, and Mu (2007) examines the impact of storage and weather conditions on natural gas volatility. In this study, I combine these volatility determinants into a single econometric model and also test and quantify other hypothesized determinants of natural gas volatility such as asymmetric volatility, bid week effect and month-of-the-year volatility pattern.

My most important results and contributions to the literature include the following. One, natural gas volatility is asymmetric in that an unexpected increase in price increases predicted volatility more than an unexpected decrease in price of similar magnitude. To my knowledge, this asymmetry pattern is unique to natural gas. Two, natural gas volatility is significantly higher on Monday, implying that the natural gas market is impacted by news occurring during the weekend and on Thursday, which is attributable to the fact that Thursday is the release day of the Natural Gas Weekly Update. Three, surprises in the change in natural gas in storage tend to cause increased volatility. Four, there is a month-of-the-year pattern in natural gas volatility in that volatility tends to increase in the winter months. Five, volatility tends to be high on winter days when the temperature is lower than normal. Six, volatility tends to increase during bid week, the last five trading days of a month, and on days immediately following bid week. Seven, a model which fails to control for seasonality, announcement, weather and bid week effects tends to overestimate the impact of a surprise return shock on subsequent volatility.

I develop and use a variant of the multiplicative GARCH type model outlined in Jones, Lamont and Lumsdaine (1998). This model, which separates volatility into a persistent part and a transitory part, allows me to implement a much cleaner study of the determinants of volatility than that used in several previous studies on other markets as well as on the natural gas market. To the best of my knowledge, my paper is the first comprehensive study of the determinants of volatility within a GARCH framework for the natural gas market.

The chapter is organized as follows. In Section 2, I review the most relevant literature and develop additional hypotheses. The data is presented in Section 3. I analyze the multiplicative GARCH type model to quantify the determinants of natural gas volatility in Section 4 and present the results in Section 5. Section 6 presents results from the robustness check. Section 7 concludes the paper.

2. Hypotheses and other research on natural gas volatility

Several of the natural gas volatility determinants that I consider have been examined before individually. Susmel and Thompson (1997), Murry and Zhu (2004), and Mu (2007) have estimated ARCH-GARCH type models of natural gas volatility and have consistently found evidence of volatility persistence - that volatile periods tend to follow volatile periods whereas stable periods tend to follow stable periods.

Susmel and Thompson (1997) find that a negative shock in the natural gas market has more impact on predicted volatility than a positive shock of the same magnitude while Murry and Zhu (2004) and Mu (2007) find no evidence of asymmetric volatility in this market. Contrary to the findings in Susmel and Thompson (1997), Murry and Zhu (2004), and Mu (2007), there are good reasons to expect that a positive shock in the natural gas market could have more impact on predicted future volatility than an equivalent negative shock. My reasoning for this hypothesis is based on the likely shape of the natural gas supply and demand curves. At low volume and prices, natural gas supply is highly elastic, but once storage limits are reached, supply becomes quite inelastic as natural gas producers, due to infrastructure constraints, are unable to increase their production levels within a short period of time (Krichene, 2002; Burns, 2008). The inelasticity of natural gas supplies is also caused by the fact that the U.S. gas market, although tightly integrated with the Canadian gas market, is relatively isolated from overseas natural gas supplies[21]. The demand curve for natural gas also contains an elastic portion when prices are low and an inelastic portion when prices are high (Krichene, 2002; Burns, 2008). Given the hypothesized shape of the natural gas supply and demand curves, the same fluctuation in demand when prices are low should cause a smaller change in prices than when prices are high. Thus, a positive price shock which moves the natural gas market up the supply and demand curves is likely to presage higher future volatility than a negative shock moving the market down the curves.

Regarding the day-of-the-week volatility pattern, Murry and Zhu (2004) find higher volatility on Monday which is attributable to the accumulation of information over the weekend, and on Wednesday which is explained by the fact that the American Gas Association (AGA) released its Weekly Natural Gas Storage Report on Wednesday throughout most of their sample period from November 1997 to August 2003. The Storage Report, which "provides an estimate of the change in inventory levels for working gas in storage facilities across the United States"[22], is widely considered to be one of the most important information for the natural gas market (Linn and Zhu, 2004). Linn and Zhu (2004) find that the release of the Storage Report causes increased volatility in the natural gas market for about 30 minutes following the announcement. In this study, I attempt to simultaneously test for the day-of-the-week

[21] U.S. Natural Gas Markets: Mid-Term Prospects for Natural Gas Supply, EIA, 2001.
[22] Issue Brief 2001-03, Policy Analysis Group, American Gas Association.

effect and storage announcement effect on volatility. If an increase in volatility on a certain day of the week is caused by the storage announcement, that pattern should disappear when I control for the impact of the storage surprise on volatility (Andersen and Bollerslev, 1998).

Although it is generally argued that natural gas prices are weather-sensitive, (Fleming, Kirby and Ostdiek, 2006; Chiou-Wei, Linn and Zhu, 2007; Mu, 2007), to my knowledge, a possible time-of-the-year natural gas volatility pattern has not been explored in the literature. I expect natural gas volatility to display a time-of-the-year pattern which is possibly caused by periodic imbalances between supply and demand during the winter months. The demand for natural gas often displays a substantial fluctuation in winter and occasionally spikes during a cold snap. At the same time, however, the supply of natural gas is essentially fixed in winter due to storage capacity and limited imports (EIA Publication, 2007). Therefore, possible supply and demand imbalances in winter may cause large price swings in the natural gas market. This observation motivates my hypothesis of high natural gas volatility in the winter months.

Consistent with the argument that natural gas prices are weather-sensitive, Mu (2007) finds that weather surprise (the deviation of temperatures from normal) has a significant effect on the conditional volatility of natural gas prices. In this study, I hypothesize that the impact of weather on natural gas volatility is still robust after controlling for the time-of-the-year volatility pattern.

Another seasonality pattern that I examine is the behavior of volatility during the last five trading days of a month, which is known as “bid week” in the natural gas market. Although the daily spot market is active for natural gas and gas transactions are done in terms of volume per day, the standard market practice is to deal for a month at a time and the majority of gas trading occurs during the bid week. During these five trading days, buyers and sellers arrange for the purchase and sale of physical natural gas to be delivered throughout the coming month and the average prices set during bid week are commonly the prices used in spot contracts over the coming month.[23]

I anticipate that during bid week, as the bids of marketers for natural gas to be delivered for the coming month are revealed and spot contracts are signed, this sort of news will contain information which is relevant to the futures market. This is akin to an announcement effect as documented in Ederington and Lee (1993, 1995) for the T-bond, interest rates and foreign exchange markets, in Flannery and Protopapadakis (2002) for the stock market, and in Linn and Zhu (2004) for the natural gas market, among others. However, "bid week" information is different from scheduled announcements in that while the latter arrives in the market at the same time, news about prices and volumes being set tends to leak out from many spot contract signings. I hypothesize that natural gas volatility will be higher during bid week. As documented in Ederington and Lee (1993, 1995) and others, volatility tends to increase when lots of new information is coming to the market. In addition, the first three trading days of the bid week is the period when the nearby futures contract is expiring and traders are having to reverse their positions and therefore, could be characterized by high volatility.

[23]Understanding Natural Gas Markets, API, 2006.

I hypothesize that volatility will continue to increase for the day following bid week. Previous studies on scheduled announcement effect (Ederington and Lee, 1993, 1995; Jones, Lamont and Lumsdaine, 1998, Flannery and Protopapadakis, 2002, Linn and Zhu, 2004, among others) have consistently found evidence that prices tend to complete adjusting to new information within the announcement day and subsequently, volatility tends to fall back to near normal level the following day. However, as mentioned above, information about prices and volumes being set in the spot market differs from that in scheduled announcements in that while the latter is available to all market participants at the same expected time, part of “bid week” news, which leak from contract signings, is not public knowledge until the following day. Therefore, volatility could increase on the day following bid week as all “bid week” news becomes public.

As noted above, previous studies on natural gas volatility consider only one or two possible determinant types. In other words, they test for volatility persistence and/or day-of-the-week, for announcement effect or weather effect but not all four. My study extends the research in natural gas volatility in several dimensions. First, I simultaneously estimate GARCH, seasonality, announcement and weather effects as well as testing for a possible volatility asymmetry in one single econometric model. Second, as explained further in Section 4, my model affords a cleaner test of seasonality, announcement and weather effects than that in previous studies. Third, I test and quantify several unexplored determinants of natural gas volatility such as a time-of-the-year and bid week volatility patterns.

3. Data and preliminary analysis

3.1 Natural gas prices

This study examines natural gas volatility using daily prices of the NYMEX nearby futures contracts from January 02, 1997 to December 31, 2008. The daily trading data is obtained from the Commodity Research Bureau. Natural gas futures contracts, which began trading on the NYMEX on April 3, 1990, trade in units of 10,000 million British thermal units (mmBTu).

Futures prices are used in place of spot prices for the following reasons. First, the NYMEX natural gas futures price is widely used as a national benchmark price. Natural gas futures prices are also the prices reported in newspapers. Second, the futures market for natural gas is liquid and centralized while spot markets are localized and illiquid. Third, futures prices are the prices normally used in most risk management contracts such as swaps and options.

I use two measures of daily natural gas volatility in this study. The first volatility measure is based on a GARCH type model. In this framework, I use daily log returns[24] defined as $r_t = \ln(P_t/P_{t-1})$ wherein P_t is the closing price of the nearby futures contract on day t and P_{t-1} is the price of the same contract the previous day. As traders often cover their positions on the last trading day of a contract's life, trading volume and open interest decline and price volatility increases substantially on that day. To avoid this "thin market" problem, I replace the return of the nearest contract on the last trading day of each month with that of the second nearest contract in constructing the r_t series.

[24]The daily natural gas "returns" are used to measure price changes only. These "returns" are not investment returns since no money is actually invested.

To check the robustness of the GARCH type estimation results, I utilize a second volatility measure which is the extreme value estimator developed by Parkinson (1980) and used in numerous studies including Wiggins (1992), Martens and Van Dijk (2007) and Cao, Chang and Wang (2008), among others. In the extreme value method, intraday volatility on day *t* is calculated as:

$$Variance_t = \frac{\left(\ln(High_t) - \ln(Low_t)\right)^2}{4\ln(2)},$$

where $High_t$ and Low_t denote the highest and lowest prices of the nearby futures contract on day *t*, respectively. As Parkinson (1980) shows, this measure can be used as an estimator of the variance of the price if the latter follows a random walk with zero drift.[25]

Table IV provides summary statistics for daily returns and extreme value estimator of volatility on natural gas nearby futures contracts. The annualized standard deviation of the daily percentage change in nearby natural gas prices over the January 1997-December 2008 period is 62.19%, indicating that this market is characterized by very high volatility. Table IV shows preliminary evidence of volatility persistence in that the first-order autocorrelation coefficients for absolute returns and for extreme value estimator of volatility are positive and significant at the 0.01 level. For squared returns (not reported), the first-order autocorrelation coefficient is also significantly positive at the 0.001 level. Clearly, the natural gas market, like many others, is characterized by volatility persistence.

[25]Wiggins (1991, 1992) document that the efficiency of the extreme value estimator significantly exceeds that of the close-to-close estimator of volatility.

3.2 Natural gas storage data

I collect the actual storage announcement data from various issues of the Weekly Natural Gas Storage Report issued by the U.S. Energy Information Administration (EIA). The Storage Report was compiled and released by the American Gas Association (AGA) prior to April 10, 2002 and by the EIA since then. The report contains the actual level of natural gas in storage and change in the level in storage in three regions, consuming east, consuming west, and producing region, as of each Friday. The report was released on Wednesday (prior to May 06, 2002) or Thursday (after May 06, 2002) of the subsequent week.

Several years after the first storage report in 1994, analysts from the consulting industry, production companies and investment banks began providing their weekly forecasts of storage changes and the implied storage levels to be released in the storage report. To facilitate the public dissemination of these analyst forecasts, Bloomberg, a major market information vendor, solicits forecasts from analysts, computes a consensus estimate and publishes this information electronically in advance of the release of the storage report[26]. The Bloomberg survey of predicted changes in storage is generally regarded as the best available amongst practitioners and represents the forecasts that are most readily available to market participants (Chiou-Wei, Linn and Zhu, 2007 and Gay, Simkins and Turac, 2007). Following

[26]The Bloomberg survey procedure is summarized in Gay, Simkins and Turac (2007) as follows. By Tuesday of each week, a Bloomberg employee calls each analyst or receives an email containing the analyst’s forecast. Many analysts provide a range for their estimated change in storage. In these cases, Bloomberg uses the midpoint of the range. Bloomberg then computes a “consensus estimate” based on the arithmetic average of the analyst forecasts. The first Bloomberg estimate of each week is typically prepared and released on Tuesday morning when at least one half of the analysts have reported. Updates are released if additional forecasts are received.

Chiou-Wei et al. (2007) and Gay et al. (2007), I assume that the natural gas market participants condition their expectation of the weekly storage change to equal the Bloomberg consensus analyst forecast. Consequently, I use the survey data available on Thursday morning prior to the release of the EIA report as a proxy for the market's expectation of natural gas storage change before the announcement.

3.3 Weather data

Weather data are obtained from the National Climatic Data Center (NCDC), a division of the National Oceanographic and Atmospheric Administration (NOAA), Department of Commerce. Following the industry convention I control for weather conditions using two measures. A Cooling Degree Day (CDD) is one for which the actual temperature minus 65 degrees F is greater than zero. The calendar day is assigned the value of the difference when this is the case and 0 otherwise. A Heating Degree Day (HDD) occurs when 65 degrees F minus the actual temperature is greater than zero. The calendar day is assigned the degree difference when this condition is met and 0 otherwise. Therefore, each day receives both a CDD measure and a HDD measure. My dataset contains variables measuring daily actual temperature and the data on normal condition which is defined as the previous 30 years' average temperature as of the date of relevance. Weather data are obtained from the weather reporting stations in the following main consumption regions: Chicago, New York, Atlanta, and Dallas.

4. Model Specification and Analysis

In order to test and quantify the determinants of natural gas volatility as discussed in section 2, I estimate a model in which the conditional variance follows a multiplicative GARCH type process:

$$r_t = \mu + a_1 Oilret_t + a_2 CddDif_t + a_3 HddDif_t^{\{+\}} + a_4\, HddDif_t^{\{-\}} + a_5 SRFE_t + \sum_{i=1}^{4} \vartheta_i DW_{i,t} + \varepsilon_t \tag{10}$$

where

$$\varepsilon_t \sim \mathrm{N}(0, \sigma_t^2) \text{ and } \sigma_t^2 = h_t \cdot s_t \tag{11}$$

$$h_t = Var(\zeta_t) = \omega + \alpha \zeta_{t-1}^{\ 2} + \beta h_{t-1} + \gamma \zeta_{t-1}^{\ 2} I_{t-1}, \text{ where } \zeta_t = \varepsilon_t / s_t^{.5} \tag{12}$$

$$s_t = \prod_{i=1}^{5} s_{i,t} \tag{13}$$

$$s_{1,t} = \prod_{i=1}^{4} (1 + \lambda_i DW_{i,t}) \tag{13.a}$$

$$s_{2,t} = (SR_t)^{\kappa} \tag{13.b}$$

$$s_{3,t} = \prod_{i=1}^{11} (1 + \theta_i DM_{i,t}) \tag{13.c}$$

$$s_{4,t} = (1 + \psi W_t) \tag{13.d}$$

$$s_{5,t} = (1 + \delta_0 BW_t)(1 + \delta_1 ABW_t) \tag{13.e}$$

The purpose of equation 10 (the mean equation) is to remove predictable changes in natural gas returns thereby obtaining the surprise return ε_t whose volatility is examined in the study. The specification of the mean equation is motivated by Chiou-Wei et al. (2007) and Mu (2007) who find that (1) changes in natural gas prices are statistically significantly and positively related to changes in crude oil prices (2) weather shock, which is a proxy for natural gas demand, tends to have some impact on natural gas prices, and (3) natural gas prices strongly react to the "surprise" component in the natural gas storage report.

In equation 10, r_t is the log percentage change in price of the nearby natural gas futures contract on day t; $Oilret_t$ is the log percentage change in price of the nearby crude oil futures contract on day t; $CddDif_t$ is the difference between the actual Cooling Degree Day measure and the 30-year average CDD measure for day t; $HddDif_t$ is the difference between the actual Heating Degree Day measure and the 30-year normal HDD measure for day t, $HddDif_t^{\{+\}} = HddDif_t$ if $HddDif_t > 0$ and 0 otherwise, $HddDif_t^{\{-\}} = HddDif_t$ if $HddDif_t < 0$ and 0 otherwise; $SRFE_t$ is the surprise in the change in storage which is defined as the actual storage change as reported in the EIA storage survey minus the consensus expected storage change as reported by Bloomberg prior to the EIA report release; $DW_{i,t}$ are zero-one dummies for Monday (which includes the weekend), Wednesday, Thursday and Friday with Tuesday being the left-out day.

The mean equation is not the focus of the paper. My main interest is in the determinants of the variance of the surprise natural gas return, ε_t. I model this variance as a multiplicative function of an asymmetric GARCH function (equation 12), day-of-the-week pattern (equation 13.a), storage announcement effect (equation 13.b), month-of-the-year pattern (equation 13.c), temperature impact (equation 13.d), and bid week effect (equation 13.e).

4.1 Volatility Persistence and Asymmetric Volatility

Equation 12 is the asymmetric GARCH model due to Glosten et al. (1993) often referred to as the GJR or TGARCH model in which I_{t-1}= 1 if ζ_{t-1} <0 and 0 otherwise. If volatility persistence is an attribute of the natural gas market, α and β should be significantly positive, implying that predicted volatility depends on both unexpected price changes and the previous day's forecast volatility. Asymmetric volatility implies $\gamma \neq 0$ in equation 12; $\gamma < 0$ implies that a positive shock increases conditional volatility more than an equivalent negative shock.

4.2 Seasonality patterns, storage announcement, weather, and bid week effects

Equation 13, the transitory effects equation, estimates the impact of other hypothesized determinants on volatility.

Equation 13(a) estimates the day-of-the-week pattern in natural gas volatility. $DW_{i,t}$ are zero-one dummies for Monday (which includes the weekend), Wednesday, Thursday and Friday with Tuesday being the left-out day. λ_i estimates the average percentage difference between volatility on day i and volatility on Tuesday. In other words, assuming that $s_{2,t}= s_{3,t}= s_{4,t}= s_{5,t}= 1$, then the estimated variance on Tuesday is h_t. On Monday, the estimated variance is $h_t(1+\lambda_M)$. On Wednesday, the estimated variance is $h_t(1+\lambda_W)$ and so on for other days. If the natural gas market is impacted by news occurring over the weekend, Monday return (which is a three-day return including the weekend) should be more volatile than any normal weekday return and λ_M >0. Also, if the Natural Gas Storage Report contains price moving information, volatility should be higher on days the report is released. I do not include a separate dummy variable for storage report announcement days in equation 13 because, since this announcement is released weekly, I cannot separate its impact from other possible weekly factors. When testing for day-of-the-week volatility pattern, I anticipate that this weekly announcement will be part of the reason for the pattern.

Equation 13(b) tests the hypothesis that natural gas volatility is sensitive to the surprise in the change in natural gas in storage. The level of natural gas in storage and the change in natural gas in storage often receive a high amount of attention because they are widely considered as a measure of supply and demand balance in the market (EIA Publication, 2007; Mu, 2007). For example, a low inventory of working gas than the market's expectation may create a perception of supply tightness, which places upward pressure on prices. Chiou-Wei, Linn and Zhu (2007) find an inverse relation between the change in storage surprise (actual change minus expected change) and futures price change on the days of the EIA storage announcement.

Following Balduzzi, Elton and Green (2001), and Andersen, Bollerslev, Diebold and Vega (2003), I define the standardized change in storage surprise as: $SSRFE_t = \frac{|SRFE_t|}{s_{SR}}$ where $SRFE_t$ is the surprise in the change in storage = the actual storage change (reported in the EIA report) - the consensus expected storage change (reported by Bloomberg prior to the EIA report release) and s_{SR} is the sample standard deviation of $|SRFE_t|$. I do not include separate variables for positive surprise and negative surprise because Chiou-Wei et al. (2007) find no evidence that natural gas prices respond differently to positive surprises as compared to negative surprises. The variable SR_t is then defined as: $SR_t = SSRFE_t$ on days the storage report announcement is released and SR_t = 1 on other days since Chiou-Wei et al. (2007) find that the market's assessment of the level of natural gas in storage (as measured by the difference between the consensus Bloomberg forecast and the 5-year average volume) is unrelated to the price change on non-announcement days. If larger storage surprises are associated with larger futures price changes, κ should be > 0.

In equation 13(c), $DM_{i,t}$=1 if the futures contract observed on day *t* expires in month *i*. $\theta_i \neq 0$ imply a month-of-the-year volatility pattern. In equation 13(d), W_t= 1 if the difference between the actual Heating Degree Day measure and the 30-year normal HDD measure for day t ($HddDif_t$) is < 0 and W_t= 0 otherwise. I do not include dummy variables for days when $CddDif_t \neq 0$ or when $HddDif_t$ > 0 since results from the mean equation do not indicate that $CddDif_t$ and $HddDif_t^{\{+\}}$ have significant impact on natural gas prices.

Equation 13(e) estimates the behavior of natural gas volatility around bid week. BW_t is 1 if day *t* is one of the last five trading days in a month and 0 otherwise. I hypothesize above that δ_0 >0. I also include ABW_t as dummy for the day after the bid week. If prices and volumes set during bid week leak from contract signings rather than being available to market participants at the same time as for scheduled announcements, part of the bid week information is not public knowledge until right after bid week. Therefore, volatility should increase when all information becomes public and δ_1 >0.

4.3 Comparison with Previous Models

My model improves on that used in several previous studies for natural gas and other markets which seek to simultaneously estimate both GARCH and other determinants of volatility. The introduction of a transitory volatility equation s_t into the specification enables me to implement a much cleaner study of the determinants of volatility than when announcement and/or day-of-the-week dummies are added to the variance equation. For instance, Hsieh (1989), Berument and Kiymaz (2001), Ederington and Lee (2001) and Lee (2002) use GARCH type models to examine day-of-the-week effects on volatility in the foreign exchange, stock, and interest rates markets and Murry and Zhu (2004) in the natural gas market. In those studies, weekday dummies are in the h_t equation (equation 12) and the coefficient estimates reflect how conditional volatility changes across weekdays. Thus, using their model, there is no s_t equation (equation 13) and equation 12 becomes:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \lambda_M DW_{M,t} + \lambda_W DW_{W,t} + \lambda_R DW_{R,t} + \lambda_F DW_{F,t}, \quad (14)$$

In equation 14, since weekday dummies are in the h_t equation, the dummy for any day of the week impacts volatilities on *all* days of the week through the h_{t-1} term on the right hand side of the equation. Suppose, for instance, that day t is Monday. $\partial h_t/\partial DW_{M,t} = \lambda_M$. Now consider the impact of the Monday dummy on volatility on Tuesday (day $t+1$). Since

$$h_{t+1} = \omega + \alpha\varepsilon_t^2 + \beta h_t + \lambda_M DW_{M,t+1} + \lambda_W DW_{W,t+1} + \lambda_R DW_{R,t+1} + \lambda_F DW_{F,t+1}, \quad (14)$$

$\partial h_{t+1}/\partial DW_{M,t} = (\partial h_{t+1}/\partial h_t)(\partial h_t/\partial DW_{M,t}) = \beta\lambda_M$. Likewise, the Monday dummy impact on the Wednesday's volatility is $\partial h_{t+2}/\partial DW_{M,t} = \beta^2\lambda_M$. Therefore, when weekday dummies are in the h_t equation, as in equation 14, λ_M does not measure how much higher volatility is on Monday than on the omitted day (Tuesday). Indeed, depending on the coefficient pattern, day X which has the highest λ_X coefficient may not be the day with the highest volatility.

In contrast, a specification which separates the variance of returns into a persistent part, equation 12, and a non-persistent part, equation 13, allows me to estimate a model in which any weekday dummy impacts that day's volatility only. For example, λ_M measures how much higher (or lower) in percentage terms the volatility is on Monday than on the omitted day (Tuesday) and λ_W measures how much higher (or lower) the volatility is on Wednesday and so on.

To estimate the announcement impacts on volatility, several previous studies, for example, Hsieh (1989), Berument and Kiymaz (2001), Ederington and Lee (2001), De Goeij and Marquering (2006) for other markets and Mu (2007) for the natural gas market, add an announcement dummy to the h_t equation and do not include the s_t equation. Thus, the variance equation becomes:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} + \delta_0 DA_t, \tag{15}$$

In equation 15, an unscheduled shock on day $t-1$ impacts volatility on day t through the term $\alpha\varepsilon_{t-1}^2$. However, since an announcement impact is forced to persist on the subsequent days ($\partial h_t/\partial DA_t = \delta_0$, $\partial h_{t+1}/\partial DA_t = (\partial h_{t+1}/\partial h_t)(\partial h_t/\partial DA_t) = \beta\delta_0$, $\partial h_{t+2}/\partial DA_t = \beta^2\delta_0$ and so on), the impact of a shock due to scheduled announcement on day $t-1$ on volatility on day t includes not only $\alpha\varepsilon_{t-1}^2$ but also $\beta\delta_0$. Consequently, models like equation 15 impose much higher persistence for shocks due to scheduled announcements than for equivalent shocks due to unscheduled announcements. In contrast, in my model, the impact of a shock due to storage announcement does not persist on the following days $\ln(\partial\sigma_t^2/\partial SR_t) = \kappa$ and $\ln(\partial\sigma_{t+1}^2)/\partial SR_t = 0$ and therefore, the estimated impact of a shock on day *t-1* on volatility on subsequent days *t* is the same for scheduled and unscheduled announcements.

5. Results

Since the data of analysts' forecast of natural gas storage is available in Bloomberg starting May 03, 2002, I estimate the specification (10-13) without storage surprise variables in the mean and variance equations for the sample period January 1997-December 2008 and estimate the full specification (10-13) for the sub-period May 2002-December 2008. The last three columns of Panel A and Panel B in Table V present the results for the 1997-2008, 1997-2002 and 2002-2008 periods, respectively.

5.1 The mean equation

Consistent with the findings in Chiou-Wei et al. (2007) and in Mu (2007), natural gas returns are statistically significantly and positively related to crude oil returns. There is no significant evidence that departure from normal weather conditions in the summer (*CddDif*) and on winter days when the temperature is higher than normal ($HddDif^{\{+\}}$) have significant impact on natural gas prices. However, departure from the norm on winter days when the temperature is lower than normal ($HddDif^{\{-\}}$) tends to have a negative impact on natural gas prices. For the period 05/2002-12/2008, the estimated coefficient for $SRFE_t$ is negative and significantly different from zero at the 0.001 level, implying that natural gas prices tend to increase on days the EIA releases news of a lower than expected gas in storage and tend to decrease on news of a higher than expected gas in storage. This result is consistent with the findings in Chiou-Wei et al. (2007) and in Mu (2007). There is no significant evidence of a day-of-the-week effect in natural gas prices for the sample period 1997-

2008 but for the sub-period 05/2002-12/2008, natural gas prices tend to decline on Thursday and Friday.

5.2 Volatility Persistence and Asymmetric Volatility

As expected, there is evidence of volatility persistence in the natural gas market. The estimates of α and β are positive and significant at the 0.001 level, implying that predicted volatility depends on both previous shocks and previous volatilities. Hence, highly volatile periods in the natural gas market tend to be followed by volatile periods in the future and this is consistent with the findings in Murry and Zhu (2004) and Mu (2007). However, while Murry and Zhu (2004) and Mu (2007) find no evidence of asymmetric volatility in the natural gas market, the estimated γ in my model is significantly negative, indicating that volatility increases considerably more following a sudden increase in natural gas prices than following an equal sudden decrease in prices. As hypothesized earlier, the behavior of natural gas volatility could mostly be explained by the likely shape of the supply and demand curves. Since the same fluctuation in demand when prices are low should cause a smaller change in prices than when prices are high, a positive price shock which moves the natural gas market up the supply and demand curves is likely to presage higher future volatility than a negative shock moving the market down the curves.

Figure 7(a) plots different impacts of equal positive and negative shocks on predicted volatility according to the estimates from the model (10-13) presented in the third column of Panel B in Table V. Suppose that the conditional variance, $h_{t-1}=\mathrm{Var}(\zeta_{t-1})$ is at its steady-state level. According to the estimates in the model, the conditional variance for day t falls 8% if there was no price change on day $t-1$, increases 5.97% if the price fell 15%, and increases 21.03% if the price increased 15%.

Figure 8 presents the impact of a two-standard deviation natural gas return shock on subsequent predicted volatilities. Suppose the conditional variance, $h_{t-1}=\mathrm{Var}(\zeta_{t-1})$ is at its steady-state level and there is a shock such that $\zeta_{t-1}^2 = 4\mathrm{Var}(\zeta_{t-1})$. Figure 8 demonstrates the percentage difference in expected volatility on day $t+x$ and on day t-1, $\left[\frac{\mathrm{Var}(\zeta_{t+x})}{\mathrm{Var}(\zeta_{t-1})}-1\right]$, assuming $E(\zeta_{t+x}^2) = \mathrm{Var}(\zeta_{t+x})$ for $x > -1$ and that negative and positive return shocks are equally likely. For example, the conditional volatility is about 14% higher the day after the shock and 7% a week later.

In the second column of Panel B in Table V, I present estimates of a GJR model as it would normally be estimated, i.e., without storage announcement, seasonality, bid week and weather effects. In other words, I estimate a model consisting of equations (10-12) only. A comparison of the estimates of the GJR model (in the second column) and those of the full model (in the third column) indicates that determinants of volatility other than volatility persistence and asymmetry are important when modeling volatility in the natural gas market. The likelihood ratio test statistics is 338.174 with 18 degrees of freedom and therefore, the null hypothesis that there are no announcement, seasonality, bid week and weather effects is rejected at the 0.001 level. In addition, the estimates of α and $(\alpha+\gamma)$ in the GJR model are significantly higher than those in the full model. Apparently, failing to control for announcement, seasonality, bid week and weather effects leads to overestimation of the impact of a surprise return shock on subsequent volatility, and the estimate of the resulting percentage overestimation is 78.76%. (Assuming negative and positive shocks are equally likely, the estimated average impact of a day t return shock on volatility on day t+1 is α+.5γ. The overestimation is measured as: (E_{wo}/ E_w)-1 where E_{wo} represents the estimates of α+.5γ in the second column of Table V where I do not control for these effects and E_w those in the third column where I do).

Figure 7(b) plots different impacts of equal positive and negative shocks on predicted volatility according to the estimates from the GJR and the full models. Again, suppose the conditional variance, $h_{t-1}=\mathrm{Var}(\zeta_{t-1})$ is at its steady-state level. According to the estimates in the GJR model, the conditional variance for day t increases 20.25% if the price fell 15%, and increases 25.20% if the price increased 15% while according to the estimates in the full model, the increase in conditional variance for day t are 5.97% and 21.03%, respectively.

To test whether the omission of announcement, seasonality, bid week or weather effects is responsible for this overestimation, I estimate the full model (10-13) dropping equation 13.b and just one of the equations (13.a, 13.c, 13.d or 13.e). When I estimate the model dropping equation 13.c, the estimates of equation 12 are virtually unchanged from those in the second column and the overestimation of the impact of a surprise return shock on subsequent volatility is roughly 60%. Therefore, failing to control for a month-of-the-year pattern in natural gas volatility is the main cause of the overestimation.

5.3 Day-of-the-week and Storage announcement

The null hypothesis that $\lambda_{Monday}=\lambda_{Wednesday}=\lambda_{Thursday}=\lambda_{Friday}$ is rejected at the 0.01 level with the χ^2 test statistics of 108.90 and 3 degrees of freedom, implying a significant day-of-the-week pattern in natural gas volatility. Since Tuesday is the left-out dummy, the coefficients in Panel B of Table V measure the difference between average volatility on each weekday and on Tuesday. Contrary to the findings in some other markets[27], there is no significant evidence that natural gas volatility increases on Friday. This may be due to the fact that important economic news for other markets is often released on Friday whereas this is not the case in the natural gas market. Indeed, Friday tends to be the lowest volatility day of the week in this market.

As expected, Monday return (including weekend) tends to be more volatile than any normal weekday return. During the 1997-2008 period, the variance of the Friday-close-to-Monday-close return is 87.72% higher than that of Tuesday return at the 0.001 level. Apparently, the natural gas market is impacted by sorts of news occurring during the weekend such as weather news.

Thursday has the second-highest coefficient estimate during the 1997-2008 period. Since the Natural Gas Storage Report was released on Wednesdays before May 06, 2002 (by the American Gas Association) and on Thursdays (by the EIA) since then, I examine the day-of-the-week volatility pattern before and after May 06, 2002. Results in the fourth column of Panel B in Table V indicate that during the 01/1997-05/2002 sub-period, Thursday is associated with the second-highest coefficient estimate. The variance of Thursday return is 28.48% higher than that of Tuesday at the 0.05 level. Apparently, although Wednesday is the release day of the Storage Report in this period, there is no significant evidence that natural gas volatility is higher on Wednesday than on other days of the week. This is explained by the fact

[27]For example, Harvey and Huang (1991) reported higher volatility in interest rate and foreign exchange futures market on Friday. Ederington and Lee (1993) further supported these results. Jones et al. (1998) and Berument and Kiymaz (2001) found similar evidence for the bond and stock markets.

that prior to March 2, 2000, the AGA Storage Report was announced after the close of NYMEX trading on Wednesday and from March 2000 to May 2002 it was released at the interval of 2:00-2:15 pm on Wednesday during NYMEX trading hours. Therefore, even though the Storage Report was announced on Wednesday prior to March 2000, apparently storage news from the report did not arrive in the market until the following day.

Results in the fifth column of Panel B in Table V indicate that during the 05/2002-12/2008 sub-period, the variance of Thursday return is 67.60% higher than that of Tuesday at the 0.01 level. Linn and Zhu (2004) and Murry and Zhu (2004) find that the high Thursday volatility is caused by the Natural Gas Storage Report announcement which is released on Thursday (except for holidays) since May 2002. However, if the Storage Report is the only cause of the increased volatility on Thursday, estimates from specification (10-13) should indicate no evidence of higher volatility on Thursday as the specification also controls for the impact of storage report on volatility (Andersen and Bollerslev, 1998). Therefore, evidence of both higher Thursday volatility and significant impact of storage report implies that the market is impacted by other news on Thursday other than that from the storage report. Since May 2002, the EIA releases the Natural Gas Weekly Update at 2:00 pm in addition to the Storage Report (which is released at 10:30 am), both on Thursday. The Weekly Update summarizes weather conditions, spot and futures prices and other market trends over the preceding week. Apparently, certain news in the Weekly Update such as rig counts or transportation update is relevant to the natural gas market.

As mentioned above, the level of working gas in storage often receives a high amount of attention in the natural gas market since it is widely considered as a measure of supply and demand balance in the market (Linn and Zhu, 2004; Chiou-Wei et al., 2007). Consistent with the findings in Chiou-Wei et al. (2007) regarding the impact of storage surprises on natural gas prices, results in the last column of Panel B in Table V indicate that storage surprise has a significantly positive impact on natural gas volatility. During the winter months (withdrawal season), news about a storage level which is lower (higher) than the market's expectation indicates a low (high) natural gas supply which causes upward (downward) pressure on market prices. During the refill season, news about a storage level which is lower (higher) than the market's expectation may increase (decrease) uncertainty regarding whether storage supplies will be sufficient to meet peak demand needs over the following winter. While not surprising given the findings in Linn and Zhu (2004) and in Chiou-Wei et al. (2007), results in my estimation show a significant evidence of increased natural gas volatility in response to storage surprise when I control for the higher Thursday volatility often associated with storage announcement.

5.4 Time-of-the-year pattern and Weather effect

Consistent with my earlier hypothesis, natural gas volatility exhibits a strong seasonality (Figure 9). The null hypothesis that $\theta_{Jan}= \theta_{Feb}=\theta_{March}=\theta_{April}=\theta_{May}= \theta_{July}= \theta_{August}=\theta_{Sept}=\theta_{October}=\theta_{November}=\theta_{December}$ is rejected at the 0.01 level with the χ^2 test statistics of 23.93 and 10 degrees of freedom, implying that natural gas volatility significantly differs by month of the year.

Volatility tends to be highest from October through February. As heating needs dominate the market from December through February (Fleming, Kirby and Ostdiek, 2006), demand for natural gas may rise sharply during these months and at the same time, natural gas supply is essentially fixed due to storage constraint. Consequently, the inelasticity of natural gas supply and demand can cause large price swings in order to balance supply and demand in cold winter. As November is the first month of the heating season[28], decisions made during this month tend to impact the volumes in storage for the rest of the upcoming heating season. Since natural gas suppliers are uncertain about the supply and demand later in the winter whose overall severity is unknown this early in the withdrawal season, fluctuations in demands are not necessarily met readily with working gas in storage (EIA's Publication, 2007). Consequently, price spikes may occur during this month.

Surprisingly October tends to have the highest volatility in a year. During October, the last month of the injection season, storage capacity owners may be competing heavily to inject natural gas for the winter season. This increased competition from storage facilities looking to meet injection refill goals is often coupled with uncertainty regarding whether or not there will be sufficient supplies to meet heating needs in the upcoming heating season (EIA's Publication, 2007).

The more mild spring and summer months exhibit the lowest average levels of natural gas volatility. During March and April, the peak winter demand is generally complete and thus, there is less uncertainty regarding supply and demand imbalance (EIA's Publication, 2007). Although winter-like temperatures sometimes persist into

[28]Using data reported in the EIA's Natural Gas Weekly Storage Report (various issues), I determine that natural gas withdrawals normally begin in November and end in March.

April, it is during this month that natural gas activities tend to switch from storage withdrawals towards storage injection[29].

Overall, there is a strong month-of-the-year pattern in natural gas volatility. During the winter months, both supply and demand are relatively inelastic and therefore, natural gas prices tend to swing more in order to balance supply and demand. Given that natural gas supplies may not keep pace with the increased demand or a prediction of high demand may not materialize because of mild weather during winter season, months with higher levels of market tightness and/or market uncertainty often exhibit higher volatility.

The coefficient estimate of κ is positive and significant at the 0.01 level implying that natural gas volatility tends to be higher on winter days when the average temperature in the main consumption regions falls below the 30-year average and this result is robust after controlling for month-of-the-year pattern.

5.5 Bid week effect

There is strong evidence that volatility in the natural gas futures market increases during bid week. For the 1997-2008 period, the estimated average volatility increase during the last five trading days of the month relative to other days is 65.92%, which is significant at the 0.01 level. As hypothesized above, this increased volatility during bid week is attributable to two reasons. First, as the bids of marketers for natural gas to be delivered for the coming month are revealed and spot contracts are signed, this sort of news contains information which moves prices in the futures market. Second, the first three trading days of the bid week could be a high volatility

[29]Using data reported in the EIA's Natural Gas Weekly Storage Report (various issues), I determine that natural gas injections normally begin in April.

period for the futures market as the nearby futures contract is expiring and traders are having to reverse their positions.

There is also significant evidence that natural gas volatility increases on the day following bid week (the first trading day of a month). As mentioned above, bid week news differs from scheduled announcement in that while the latter is available to all market participants at the same expected time, prices and volumes being set during bid week leak from contract signings and therefore, part of this information may not be public knowledge until the following day. Therefore, volatility could continue to be higher following bid week as this information becomes public. Results from an expanded specification with dummy variables for both the first and the second trading days of a month (not reported) show no significant evidence that volatility continues to increase on the second day. Apparently, all bid week news arrive in the futures market and market participants complete price adjustments by the end of the first trading day of a month.

6. Robustness check

The results documented in sections 5 are obtained from the estimation of a GARCH-type specification. To test the validity of these results, I use a different measure of volatility, the extreme value estimator developed by Parkinson (1980) and used in numerous studies including Wiggins (1992), Martens and Van Dijk (2007) and Cao, Chang and Wang (2008), among others. The extreme value estimator of volatility on day t is calculated as: $Variance_t = \frac{\left(\ln(High_t) - \ln(Low_t)\right)^2}{4\ln(2)}$, where $High_t$ and Low_t denote the highest and the lowest prices on day t, respectively.

From the hypotheses in Section 2, I develop the following specification:

$$Std_t = \omega^{'} + \sum_{i=1}^{5} \alpha_i Std_{t-i} + \gamma_1 \varepsilon_{t-1}^{\{+\}} + \gamma_2 \varepsilon_{t-1}^{\{-\}} + \sum_{j=1}^{4} \lambda_j^{'} DW_{j,t} + \kappa^{'} SR_t + \sum_{k=1}^{11} \theta_k^{'} DM_{k,t}$$
$$+ \psi^{'} W_t + \delta_0^{'} BW_t + \delta_1^{'} ABW_t + \rho OilStd_t + e_t \quad (16)$$

$Std_t = \frac{|\ln(High_t) - \ln(Low_t)|}{2\sqrt{\ln(2)}}$, $High_t$ and Low_t denote the highest and the lowest prices of the nearby natural gas futures contract on day *t*, respectively. $r_t = \ln(P_t/P_{t-1})$ where P_t is the price of the nearby futures contract on day *t* and P_{t-1} is the price of the same contract the previous day. $\varepsilon_{t-1}^{\{+\}} = \varepsilon_{t-1}$ if $\varepsilon_{t-1} > 0$ and 0 otherwise; $\varepsilon_{t-1}^{\{-\}} = \varepsilon_{t-1}$ if $\varepsilon_{t-1} < 0$ and 0 otherwise and ε_t is the residual from the mean equation, equation 10:

$$r_t = \mu + a_1 Oilret_t + a_2 CddDif_t + a_3 HddDif_t^{\{+\}} + a_4 HddDif_t^{\{-\}} + a_5 SRFE_t + \sum_{i=1}^{4} \vartheta_i DW_{i,t} + \varepsilon_t \quad (10)$$

$DW_{j,t}$ are zero-one dummies for Monday, Wednesday, Thursday and Friday with Tuesday being the left-out day. $SR_t = \frac{|SRFE_t|}{s_{SR}}$ on days the storage report announcement is released and 0 otherwise where $SRFE_t$ is the surprise in the change in storage = the actual storage change (reported in the EIA report) - the consensus expected storage change (reported by Bloomberg prior to the EIA report release) and s_{SR} is the sample standard deviation of $|SRFE_t|$. $DM_{k,t}$=1 if the futures contract observed on day t expires in month *k*. W_t = 1 if the difference between the actual Heating Degree Day measure and the 30-year normal HDD measure for day t ($HddDif_t$) is < 0 and W_t= 0 otherwise. BW_t is 1 if day *t* is one of the last five trading days in a month and 0 otherwise. ABW_t =1 if day *t* is the first trading day in a month.

$OilStd_t = \frac{|\ln(OilHigh_t) - \ln(OilLow_t)|}{2\sqrt{\ln(2)}}$, $OilHigh_t$ and $OilLow_t$ denote the highest and the lowest prices of the nearby crude oil futures contract on day *t*, respectively.

Equation (16) is estimated by OLS with Newey and West (1987) correction for both heteroskedasticity and autocorrelation. Results are presented in Table VI. Consistent with the results in Section 5.2, there is significant evidence of volatility persistence when volatility is estimated by the extreme-value method. The coefficients of the five lagged *Std* are positive and significant at the 0.05 level, indicating that high volatility days tend to be followed by high volatility days and low volatility days tend to be followed by low volatility days. There is evidence that a positive return shock leads to higher *Std* at the 0.05 level but there is no significant evidence that a negative shock leads to higher *Std*, indicating that natural gas volatility is more responsive to previous positive shocks than to negative shocks.

The null hypotheses that $\lambda'_{Monday} = \lambda'_{Wednesday} = \lambda'_{Thursday} = \lambda'_{Friday} = 0$ and $\theta'_{Jan} = \theta'_{Feb} = \theta'_{March} = \theta'_{April} = \theta'_{May} = \theta'_{July} = \theta'_{August} = \theta'_{Sept} = \theta'_{Oct} = \theta'_{Nov} = \theta'_{Dec} = 0$ are both rejected at the 0.01 level, indicating a day-of-the-week and time-of-the-year patterns in natural gas volatility as documented in Section 5. There is no significant evidence that Monday is the highest volatility day when volatility is measured by the extreme value method. Apparently, the high Monday/weekend volatility as documented in Section 5.3 is mainly attributable to the accumulation of information over the weekend. Thursday tends to be the most volatile day of the week which is consistent with the fact that Thursday is the release day of the storage report after May 2002 and was the day news about storage report came into the market before April 2000. Over the 1997-2008 sample period, there is significant evidence at the 0.05 level that natural gas volatility, as measured by the extreme value method, is higher on winter days with a lower than normal temperature and on days during the bid week. However, there is no significant evidence that volatility is higher on days immediately following the bid week. Consistent with the findings in Section 5, natural gas volatility tends to be high for futures contracts expiring in the months from September to March. There is significant evidence that volatility in the crude oil market has a positive impact on natural gas volatility which is consistent with the findings above that crude oil prices is a significant predictor of natural gas prices.

The last two columns in Table VI present the estimation results for the May 2002- December 2008 sub-period and these results are similar to those for the entire sample period. The coefficient estimate of κ' is positive and significant at the 0.01 level, which is consistent with the findings above that surprises in the change in natural gas in storage has a positive impact on volatility.

7. Summary and Conclusions

The contribution this paper makes is to provide an empirical examination of the causes and behavior of price volatility in the natural gas market. Daily returns data from January 1997 through December 2008 are used to estimate a multiplicative GARCH type model. This model, which separates volatility into a persistent part and a non-persistent part, allows me to implement a much cleaner study of the determinants of natural gas volatility than that used in some previous studies.

The natural gas market is characterized by volatility persistence where highly volatile periods are followed by highly volatile periods and stable periods are followed by stable ones. I find that a positive shock in the natural gas market has more impact on predicted volatility than an equivalent negative shock. There is a day-of-the-week pattern in natural gas volatility. Monday return (including weekend) is more volatile than any other weekday return. The high weekend/Monday volatility is mainly due to the accumulation of information over the weekend. In contrast to the findings for some financial markets, Friday is the lowest volatility day in this market. Volatility tends to increase on Thursday which is attributable to the announcement of the Weekly Natural Gas Storage Report and Natural Gas Update. The "surprise" news about the level of natural gas in storage has a significantly positive impact on natural gas volatility.

There is a strong time-of-the-year volatility pattern in that volatility tends to be highest from October through February, which is likely caused by the inelasticity of natural gas supply and demand during winter. Volatility also tends to be high on winter days when the temperature is lower than normal. Natural gas volatility tends to increase during bid week as news on prices and volumes being set in the spot market leaks to the futures market and continues to be higher on the day immediately following the bid week when all bid week news becomes public.

To check the robustness of the above findings, I estimate a different specification wherein volatility is measured by the extreme-value method. Results from the robustness check indicate that (1) natural gas volatility is significantly determined by volatility level on previous days, (2) a positive return shock has a significantly positive impact on volatility, (3) there are day-of-the-week and time-of-the-year patterns in volatility, (4) "surprise" news about the change in natural gas in storage has a significantly positive impact on volatility, (5) volatility tends to increase during bid week and (6) crude oil volatility has a significantly positive impact on natural gas volatility.

Chapter IV. Implied Volatility in the Crude Oil and Natural Gas Markets

1. Introduction

This paper explores the structure, characteristics, and determinants of implied volatilities calculated from crude oil and natural gas call options traded on the New York Mercantile Exchange (NYME) from September 1999 through June 2006. According to financial theory, implied volatility, the volatility that equates the theoretical price of an option according to an option pricing formula with the observed market price, reflects the market's expectation of future volatility over the life of the option and therefore, an understanding of the cause and behavior of implied volatility is essential to market participants.

The markets for crude oil and natural gas derivatives contracts are becoming increasingly important due to the impact of energy on the economy and the high volatility in oil and gas prices. Crude oil and natural gas are two of the most essential energy sources in the U.S., accounting for about 40% and 25% of the nation's energy consumption, respectively. Since OPEC's 1973 decision to regulate its oil price independently, crude oil prices have been subject to dramatic volatility. Natural gas is also one of the most volatile markets, particularly since its evolution from a highly regulated market to a largely deregulated market in which prices are driven by supply and demand. In 2007, the annualized standard deviation of the daily percentage change in prices was 31.33% for crude oil and 49.94% for natural gas. By comparison, that number was only 4.08% for the US dollar-Euro exchange rate, 16.37% for the

S&P 500 and 19.10% for the 10-year T-bond interest rates[30]. This high variability in crude oil and natural gas prices makes it extremely difficult for consumers to forecast their costs and for producers to forecast their profits. The desire to protect market participants against such price fluctuations has led to the creation of and active trading in oil and gas risk management products such as swaps and options.

The empirical properties associated with implied volatility calculated from option prices have been a subject of intense research activity in recent decades. The vast majority of the research on implied volatility has focused on financial options markets such as the stock, stock index, interest rate, Eurodollar, T-Bond futures and foreign exchange options markets. In contrast to the literature on equity and other financial options, research on crude oil and natural gas options markets has been quite sparse despite the fact that energy prices tend to be more volatile than most other prices and that oil and gas options have become more heavily traded. For instance, in a well-known and comprehensive study of the volatility literature, Poon and Granger (2003) survey 52 articles examining implied volatilities in all sorts of options markets; only 3 of these include crude oil among the volatilities they examine (Day and Lewis, 1993; Szakmary, Ors and Kim, 2003 and Martens and Zein, 2004). Szakmary et al. (2003) is the only study on natural gas implied volatility in that survey.

My study is motivated by the limited nature of previous research on crude oil and natural gas implied volatilities. Day and Lewis (1993), Szakmary, Ors and Kim (2003), Martens and Zein (2004), and Doran and Ronn (2006) focus on the forecasting

[30]The data for the crude oil and natural gas prices are from the Commodity Research Bureau. The data for the S&P 500, US dollar-Euro exchange rate, and the 10-year T-bond interest rates are from the CRSP database and the Federal Reserve website (http://www.federal reserve.gov).

performance of oil and gas IVs, i.e., testing (1) whether IV is an unbiased forecast of future volatility and (2) whether IV predicts future volatility better than historical volatility or GARCH-type forecast. Mahar, Peterson and Horan (2004) examine the behavior of crude oil IV surrounding OPEC meetings. None of these papers examine other attributes of crude oil and natural gas IVs such as whether IVs vary by strike price, by day-of-the-week or by time-of-the-year. This limitation is due to the data sets used in previous studies which only include IVs calculated from nearby at-the-money options. On the contrary, in this study, I construct a dataset that includes IVs across various strike prices for a range of terms to maturity. This comprehensive data set allows me to compare the behavior of IVs across different strike prices and terms to maturity and also to address other unexplored issues concerning the determinants of oil and gas IVs. Consequently, results in this study have implications for option traders who need to better understand the behavior of oil and gas IVs for valuation purposes.

My results and contributions to the literature include the following. One, there is a term structure in crude oil and natural gas implied volatilities in that IVs tend to increase as the options approach expiration and this pattern is consistent across strike prices. This term structure pattern is opposite to that observed for the stock index, T-bond and foreign exchange options markets where IVs tend to decrease as expiration approaches. While opposite to the pattern for IV in those financial options markets, the oil and gas IV term structure pattern is consistent with the actual volatility pattern for different maturity futures contracts. There is no evidence of a mean-reversion in oil and gas futures prices which could cause IVs to decline with maturity. Given this term structure pattern, if a financial engineer uses the IV from nearby options, the IV that would normally be calculated, to value longer term options, the latter will tend to be overvalued.

Two, crude oil and natural gas IVs tend to differ by strike price. Natural gas IVs exhibit a positive skew pattern in that IVs are higher for out-of-the-money calls than for at- and in-the-money calls. While the shape of the cross-sectional pattern is consistent across terms-to-maturity for natural gas options, it changes with term-to-maturity for crude oil. For nearby and second-month crude oil options, IVs are highest for deep in- and out-of-the-money calls and lowest for moderately in-the-money calls. For third- and fourth-month options, IVs are lowest for deep in-the-money calls and increase monotonically with strike prices. The positive skew pattern in natural gas options and in longer term-to-maturity crude oil options is a rough mirror image of the negative skew pattern in post-1987 stock index options. Contrary to the theory that the "smile" and "smirk" patterns observed in Black-Scholes IVs (1973) are due to erroneous assumptions in the B-S model regarding the returns distribution, I find that the "smile" and positive "skew" patterns in crude oil and natural gas IVs are not caused by excess kurtosis or skewness in oil and gas return distribution. The hedging pressure hypothesis – in particular, hedgers buying out-of-the-money call options to protect against a sharp price increase, could partially explain the positive "skew" pattern in natural gas IVs. However, there is no evidence that the cross-sectional IV pattern in crude oil options is caused by hedging pressures in that market.

Three, there is a time-of-the-year pattern in oil and gas IVs. I find that natural gas IVs are significantly higher on options expiring in the winter months than on those expiring in other months. This seasonality effect is consistent with the high actual volatility in winter when demand for natural gas may increase dramatically and supply of natural gas is essentially fixed. Consequently, if a financial engineer uses the yearly average volatility to value natural gas options, he or she will tend to overestimate the values of options expiring in summer and underestimate the values of options expiring in winter. To a lesser extent, crude oil IVs are lower on options expiring in the summer months than on those expiring in other months.

Four, crude oil and natural gas IVs exhibit a day-of-the-week pattern. Consistent with the findings for oil and gas actual volatilities, (1) IV significantly decreases from Friday close to Monday close indicating that weekend/Monday returns is more volatile than any weekday returns, and (2) after May 2002, natural gas IV tends to decline from Wednesday close to Thursday close, which is likely caused by the release of the Weekly Natural Gas Storage Report on Thursday. Contrary to earlier findings for actual volatilities, there is no significant evidence that crude oil IV declines following the release of the Petroleum Status Report and that natural gas IV declines following the release of the Storage Report prior to May 2002.

Five, crude oil and natural gas IVs respond asymmetrically to positive and negative futures return shocks[31]. Crude oil IV tends to increase more following an unexpected negative return than a positive return of equal magnitude while natural gas IV tends to increase more following an unexpected positive return than an equal negative return. While it is left unexplained why crude oil IV increases more following a negative return shock, the finding that natural gas IV increases more

[31]The futures “returns” are used to measure price changes throughout this study. These “returns” are not investment returns since no money is actually invested.

following a positive return shock is attributable to the hypothesized shape of the supply and demand curves which are likely to be inelastic at high volumes and prices. Given this inelasticity, the same fluctuation in demand when prices are low should cause a smaller change in prices than when prices are high and therefore, a positive price shock which moves the market up the supply and demand curves is likely to presage higher future volatility than a negative shock moving the market down the curves.

Six, although the unbiasedness of crude oil and natural gas IVs depends on term-to-maturity and moneyness of the options, IV is a fairly efficient forecast of future volatility in these markets. While the forecasting performance of oil and gas IVs from nearby at-the-money options has been the subject of previous research, I expand this strand in the literature by examining IV's unbiasedness and efficiency across strike prices for a range of terms to maturity. This enables me to consequently explore the differences in the forecasting power of oil and gas IVs by strike price and maturity. Regression results indicate that the common practice of using IVs calculated from at-the-money options to represent the volatility expectations of market participants is justifiable for oil and gas nearby options but not for longer term options.

The chapter is organized as follows. The hypotheses are developed in the next Section. The data and sampling procedure are presented in Section 3. The term structure and the smile patterns are documented in Section 4. Section 5 presents the time-of-the-year and day-of-the-week patterns in implied volatility. Section 6 documents the asymmetric impact of positive and negative return shocks on implied volatility. The forecasting performance of implied volatility is reported in Section 7. Section 8 concludes the paper.

2. Hypotheses

In this study, I attempt to answer the following questions:

First, is there a term structure pattern in crude oil and natural gas implied volatilities and, if so, what is the pattern and why? Several studies have examined the term structure of implied volatilities in the stock index, T-bond and currency options markets. It has been documented that IVs on stock index futures options generally decrease as the options get closer to expiration. Park and Sears (1985) find that IVs on NYSE and S&P 500 options generally decline over the lives of the options, yielding higher volatilities for longer term-to-maturity options. Becker and Tucker (1991) document that IVs on S&P 100 options tend to decrease until the last week before expiration and increase thereafter. Consistent with these findings, Dumas, Fleming and Whaley (1998) report that IVs on S&P 500 options differ by term-to-maturity where IVs for the 17-day options are lower than for the 45-day options which are, in turn, lower than for the 80-day options. Xu and Taylor (1994) show that the slope of the term structure of IVs on foreign exchange options traded on the Philadelphia Stock Exchange changed frequently during the 1985-1989 period. Campa and Chang (1995) also find that the term structure of IVs on currency options changes the slope over time. On the contrary, Backus, Foresi and Wu (2004) find that IVs on at-the-money options on major foreign currencies increase, on average, with maturity. Tompkins (2003) finds that for options on T-bond futures, longer term options have higher IVs than shorter term options.

Different hypotheses have been developed to account for the term structure pattern in financial options markets. Park and Sears (1985) argue that the longer the time to maturity of a given stock index futures contract, the higher the uncertainty and hence, volatility, of futures returns which is impounded in option prices. Stein (1989) posits that the IV term structure pattern is attributable to a strongly mean-reverting process in volatility. Therefore, if IV on a short-term option is higher than the average volatility, IV on a longer-term option should be somewhat lower than the average volatility and conversely, if IV on a short-term option is lower than the average volatility, the longer-term option should have a higher IV. This hypothesis is supported by the empirical evidence in the currency options markets as documented in Xu and Taylor (1994) and Campa and Chang (1995). However, Backus et al. (2004) explain the tendency for average ATM IVs on currency options to rise with maturity by the changes in the underlying return distribution by term-to-maturity. They argue that as a call option's maturity approaches infinity, skewness and excess kurtosis approach zero and call prices approach the Black-Scholes formula.

Contrary to the evidence for the stock index, bonds, and foreign exchange options markets, there are reasons to expect that average oil and gas IVs increase as the options approach expiration. Since IV is generally considered as the forecast of actual future volatility, the term structure pattern of IV should be consistent with that of the underlying asset's actual volatilities. Consequently, if actual volatilities of oil and gas futures returns increase as the futures contracts approach expiration, there should be a similar pattern in IVs. In his seminal article, Samuelson (1965) formulates the proposition that the volatility of futures returns increases as the contract approaches expiration. The Samuelson hypothesis (more recently termed the "maturity effect") is predominantly explained by associating futures returns volatility with the amount of information available in a market. That is, little information is known regarding distant contracts compared to contracts closer to expiration and as maturity approaches, the amount of information reflecting the fundamentals of the asset increases, causing large changes in the futures prices and consequently intensifying volatility. There has been a wide range of research documenting the existence of the maturity effect in various commodities markets (see, for example, Castelino and Francis, 1982; Milonas, 1986; Galloway and Kolb, 1996). Compared to findings for commodity futures, the evidence of the maturity effect in financial futures markets seems weaker (see, for example, Grammatikos and Saunders, 1986; Han and Misra, 1990; Galloway and Kolb, 1996; Han, Kling and Sell, 1999). In the area of energy futures, Serletis (1992) finds support for the Samuelson hypothesis in NYMEX energy futures for the period 1987 to 1990. Walls (1999) and Mu (2007) also find strong evidence of the maturity effect in energy futures.

An analysis of crude oil and natural gas futures returns indicates that oil and gas actual volatilities tend to go up as the futures contracts get closer to expiration. The annualized standard deviations of futures daily returns over the 1999-2006 sample period are 38.59%, 35.27%, 32.84% and 31.78% for nearby, second-, third-, and fourth-month futures contracts, respectively, in the crude oil market. In the natural gas market, the numbers are: 63.11%, 57.69%, 53.43%, and 47.45%. Therefore, as IV is widely considered the forecast of future volatility, the term structure pattern of IVs should be consistent with that of actual futures volatilities and average IVs on short-term options should be higher than on long-term options.

An alternative explanation for the hypothesized declining IVs with maturity is the likely mean-reversion in oil and gas prices. The presumption underlying most option pricing models, such as Black-Scholes (1973), is that price movements are independent so that the annualized volatility should be the same whether return is estimated from weekly, monthly, or quarterly data. However, that seems unlikely to be the case for oil and gas prices which are found to be mean-reverting. Intuitively, if oil or gas price runs up one month, supply tends to go up and demand fall so that price tends to decrease the following month. For example, Bessembinder, Coughenour, Seguin and Smoller (1995) find that investors anticipate mean reversion in prices of 11 commodities including crude oil. Indeed, the magnitude of the estimated mean reversion is large for crude oil in that 44 percent of a typical oil price shock is expected to be reversed over the subsequent eight months. Furthermore, Bessembinder, Coughenour, Seguin and Smoller (1996) argue that the maturity effect is more likely to be explained by the mean reversion in assets prices than by the information clustering towards a futures contract's expiry date as stated in Samuelson (1965). The evidence in Bessembinder et al. (1995) is further supported by Litzenberger and Rabinowitz (1995), Schwartz (1997) and Pindyck (2001). Consequently, if oil and gas prices are mean-reverting as found in previous studies, volatility of futures returns should decline with term to maturity of the futures contracts: Var (A+B)= $\left\lfloor \mathrm{Var(A)} + \mathrm{Var(B)} + 2\rho\sqrt{\mathrm{Var(A)Var(B)}} \right\rfloor$ < Var(A) + Var(B) as

ρ <0 where Var(A) and Var(B) are variances over one-month period and Var (A+B) is the variance over two-month period.

Second, is there a "smile" pattern in crude oil and natural gas implied volatilities and, if so, what causes IVs to be different across strike prices? As the Black-Scholes IVs calculated from different strike options with the same expiration date supposedly represent the market's expectation of volatility over the same period, there should be no significant difference in those IVs. However, contrary to this hypothesis, previous studies document sizable and persistent cross-sectional differences in IV in various markets. IVs calculated from stock and stock index options, for example, form a "smile" pattern prior to the October 1987 market crash where options that are deep in the money or out of the money have higher IVs than at-the-money options. After the crash, a negative skew or "smirk" pattern appears in the stock and stock index options where IVs decrease monotonically as the exercise price increases (see, for example, Canina and Figlewski, 1993; Rubinstein, 1994; Dumas, Fleming and Whaley, 1998; Das and Sundaram, 1999; Ederington and Guan, 2005). Many studies on the foreign exchange options market, including Rosenberg (1996), Malz (1996), Campa, Chang, and Reider (1997), Backus, Foresi and Wu (2004), and Carr and Wu (2007) document that the time-series average of IVs on currency options display a smile pattern where IVs are lowest for ATM options. There is also a smile pattern for bond futures options (Belongia and Gregory, 1984 and Tompkins, 2003) and for interest rate options. (Jarrow, Li, and Zhao, 2007 and Deuskar, Gupta and Subrahmanyam, 2008).

The most popular explanation of the "smile" or “smirk” pattern observed in Black-Scholes IVs is that the pattern is due to erroneous assumptions in the B-S model regarding the return distribution. The B-S model makes the parsimonious assumption that stock returns are normally distributed with known mean and variance. However, it has been documented that stock return distributions are kurtotic (before the 1987 stock market crash) and skewed (after the crash) relative to a normal distribution. Hull and White (1987), Stein and Stein (1991), and Heston (1993) show that the “smile” or other cross-sectional patterns in IVs are caused by the kurtosis and skewness in the underlying assets’ return distribution. For bond and currency options, Heston (1993) documents that while kurtosis in the return distribution affects the pricing of near-the-money versus far-from-the-money options, skewness affects the pricing of in-the-money options relative to out-of-the-money options. Similarly, it is argued that the negative skewness in S&P 500 index returns causes the B-S model to overprice low-strike options and underprice high-strike options (see, for example, Corrado and Su, 1996). For foreign exchange options, Bates (1996) documents that the “smile” pattern results from the leptokurtic unconditional distribution of log-differenced exchange rates.

An alternative explanation for the implied volatility “smile” or “smirk” pattern is the hedging pressure hypothesis by Ederington and Guan (2002) and Bollen and Whaley (2004). According to Bollen and Whaley (2004), it is the net buying pressure of the options market that drives the index options prices to be higher. Hence, the IVs calculated from options prices become non-constant across exercise prices. Specifically, they contend that, in the S&P 500 index options market, institutional investors usually purchase large quantities of out-of-the-money index put options in hedging their underlying cash positions. Since the demand is strong in this segment of the index options market, to mitigate risk, the market makers would raise the index put options prices (particularly the OTM put) higher. As a result, the IVs increase, which results in the inverse relation between IV and exercise price. Bollen and Whaley (2004) show that the evidence from the S&P 500 index options is consistent with their net buying pressure hypothesis. Subsequently, Chan, Chen and Lung (2004), Ederington and Guan (2005), Han (2008) and Deuskar, Gupta and Subrahmanyam (2008), among others, document evidence to support the hedging pressure hypothesis in Bollen and Whaley (2004).

Although the literature is replete with studies on the implied volatility "smile" or "smirk" pattern for various financial options markets, none of the previous studies, to the best of my knowledge, have explored the possible pattern for any commodity, including crude oil or natural gas, futures options. Again, this is due to the limited dataset in previous studies on commodity options which only examine ATM options (see, for example, Szakmary, Ors and Kim, 2003). In this study, I attempt to fill this gap in our understanding by exploring whether there is a smile pattern in crude oil and natural gas implied volatilities. If a pattern is found, I will explore the reasons.

Third, is there a month-of-the-year pattern in crude oil and natural gas implied volatilities and, if so, why? Fleming, Kirby and Ostdiek (2006) posit that natural gas prices are among the most sensitive to weather conditions. The U.S. typically consumes twice as much natural gas in winter as in summer (due to space heating) while the supply of natural gas is essentially fixed in winter because the U.S.

natural gas production is relatively constant throughout the year and imports is very limited. Therefore, natural gas prices can spike during peak periods in winter in order to balance supply and demand. As noted in Doran and Ronn (2008), natural gas volatility displays a pronounced seasonality pattern. Consistent with Doran and Ronn (2008), in an earlier paper on actual volatility in the natural gas market, I find that the average variance of nearby futures returns is 58.45% higher for futures contracts expiring in the winter months (from November through February) than in other months.

Consequently, I hypothesize that average natural gas IVs should be higher on options expiring in the winter months than in other months. As the market participants expect higher natural gas volatility in winter, that expectation should be impounded in IV calculated from options expiring in winter. In addition, given large price swings in winter, there may be more natural gas users buying call options to hedge against price increases leading to higher prices and IVs on call options expiring in winter. The findings of higher IVs for options with winter expiry would be meaningful for option valuation. If a financial engineer uses the yearly average volatility to value natural gas options, he or she will tend to overestimate the values of options expiring in summer and underestimate the values of options expiring in winter.

While there are reasons to expect higher natural gas IV for options expiring in the winter months, the answer is less obvious for crude oil IV. According to Fleming, Kirby and Ostdiek (2006), crude oil prices are not typically weather sensitive because over 90% of U.S. oil consumption is for transportation and industrial uses which are not sensitive to the weather. Therefore, the issue concerning a seasonal pattern in crude oil IV is subject to empirical evidence.

Fourth, is there a day-of-the-week pattern in crude oil and natural gas implied volatilities and, if so, why? Many studies have documented an intraweek pattern in various options markets. In a study of the S&P 100 index options, Harvey and Whaley (1992) report that the IV (calculated based on calendar days) tends to increase on Mondays and decrease on Fridays[32] and they hypothesize that the weekday pattern is due to buying/selling pressure as traders open position on Monday and close them on Friday. Fleming, Ostdiek and Whaley (1995) report that although the CBOE Market Volatility Index (VIX) calculated using calendar days increases significantly on Mondays and decreases throughout the week, this intraweek pattern disappears when the VIX is calculated using trading days. Ederington and Lee (1996) also show that in the T-Bond and Eurodollar markets, Monday IVs tend to be high when they are computed based on calendar days, and this Monday effect disappears with trading-day adjusted IVs. In addition, Ederington and Lee (1996) provide evidence that the scheduled announcements could explain the IV intraweek pattern in that IVs tend to decline on Fridays with scheduled announcements, but not on Fridays without announcements. Kim and Kim (2003) document that foreign exchange IVs calculated based on trading days tend to be low on Mondays (Friday close to Monday close) and high on Wednesdays for all currencies.

Murry and Zhu (2004) and Mu (2007) document that the natural gas actual volatility is higher for Friday-close-to-Monday-close returns than for any other

[32]However, it is unclear whether this pattern still holds if trading day is used instead of calendar day as the discount factor in calculating the implied volatility using Black-Scholes (1973) formula.

weekday returns. In my earlier papers, I also document the high volatility of weekend/Monday futures returns in both oil and gas markets. In addition, I find that actual volatility tends to increase on Wednesday (for crude oil) and on Thursday (for natural gas) which is likely caused by the announcements of the Petroleum Status Report and the Natural Gas Storage Report. These announcements are reportedly among the most important scheduled news influencing the oil and gas markets (see, for example, Susmel and Thompson, 1997 and Linn and Zhu, 2004).

In this paper, I examine whether IV calculated from crude oil and natural gas options differs by day of the week. Consistent with the findings in my earlier papers on oil and gas actual volatilities, I hypothesize that weekend/Monday actual volatility is higher than any other weekday's volatility and therefore, the IV should decline from Friday to Monday. Since Friday's IV includes the expected weekend/Monday's volatility whereas Monday's IV does not, Monday's IV should drop because the period over which it is calculated no longer includes the anticipated high weekend/Monday volatility. Similarly, if the announcements of the Petroleum Status Report and the Natural Gas Storage Report significantly impact oil and gas prices, IV should decrease following the release of these announcements. As documented in Ederington and Lee (1996), in the T-Bond and Eurodollar markets, IV tends to fall following the release of important scheduled announcements. Since the pre-release IV impounds the anticipated impact of important releases on volatility, IV will normally decline post-release as this uncertainty is resolved.

Fifth, do positive and negative futures return shocks have an asymmetric impact on crude oil and natural gas implied volatilities and, if so, what possibly *explains the asymmetry?* In the equity markets, as demonstrated by Black (1976), Christie (1982), and French et al. (1987), there exists a negative relationship between stock returns and changes in volatility. Schwert (1989, 1990) documents the asymmetric relationship between stock returns and expected volatility changes in that the expected volatility is more sensitive to negative than positive equity returns. Under the assumption that implied volatility proxies for future volatility, Fleming et al. (1995) show that CBOE Market Volatility Index (VIX), an average of the S&P 100 option implied volatilities, is inversely related to the contemporaneous S&P 100 index returns. They find that both daily and weekly VIX changes are more sensitive to the negative than positive stock market moves. Dumas et al. (1998) report the similar findings between the implied volatility from the S&P 500 index and the index itself. Conditional volatility asymmetry in the equity market is generally attributed to either a leverage and/or volatility feedback effect. However, Simon (1997) reports the same IV asymmetry in the Treasury bond market, where there is no leverage or volatility feedback effect, indicating that conditional volatility asymmetry exists more broadly and results from more general factors than financial leverage or volatility feedback. Contrary to the findings in the equity and bond markets, Kim and Kim (2003) find no evidence of asymmetric IV in the foreign exchange markets.

Previous studies have explored whether there exists a conditional volatility asymmetry in the crude oil and natural gas markets (Susmel and Thompson, 1997; Murry and Zhu, 2004; and Mu, 2007) and find no evidence of such asymmetry in these markets. To my knowledge, the impact of positive and negative return shocks on oil and gas IVs has not been explored in the literature. Contrary to the findings in earlier studies, I hypothesize that positive and negative returns in the energy market have different impacts on expected future volatility. My reasoning for this hypothesis is based on the likely shape of the supply and demand curves in this market. At low volume and prices, the supply is highly elastic, but once storage limits are reached, supply becomes quite inelastic as producers, due to infrastructure constraints, are unable to increase their production levels within a short period of time. The demand curve may also have an elastic portion when prices are low and an inelastic portion when prices are high. Given the hypothesized shape of the energy supply and demand curves, the same fluctuation in demand when prices are low should cause a smaller change in prices than when prices are high. Thus, an unexpected price increase which moves the market up the supply and demand curves is likely to presage higher future volatility than a negative shock moving the market down the curves.

In my earlier chapters which use an expanded GARCH type model to examine oil and gas actual volatilities, I find that positive and negative return shocks tend to have asymmetric impacts on forecast volatility in these markets. There is evidence that in the crude oil market, predicted volatility increases more following a negative return shock than an equal positive return shock while in the natural gas market, predicted volatility increases more following a positive return shock than an equal negative return shock. Therefore, as IV supposedly represents the market participants' forecast of future volatility, unexpected positive and negative returns should have asymmetric impacts on oil and gas IVs.

Sixth, how well do crude oil and natural gas implied volatilities predict future volatility across different strike prices and terms to maturity? Furthermore, I examine whether IV calculated from a moneyness and maturity group is an unbiased and/or efficient forecast of actual volatility.

The volatility implied in an option's price is widely regarded as the market's forecast of future volatility over the remaining life of the option. If option markets are efficient, IV should be an efficient forecast of future volatility, i.e., IV should subsume all other information in explaining future volatility. The literature is replete with studies on whether IV predicts future volatility and whether it does so efficiently in various markets, including the stock and stock index options market[33], foreign exchange options market[34], futures options markets[35], Eurodollar options market[36], etc.

For the energy markets, Day and Lewis (1993) and Martens and Zein (2004) find that crude oil IV outperforms historical volatility in forecasting future volatility and Szakmary et al. (2003) document that IV calculated from crude oil and natural gas options is biased but still efficient forecast of future volatility. However, the results in Day and Lewis (1993), Szakmary et al. (2003) and Martens and Zein (2004) are limited to IVs calculated from nearby at-the-money options. In this study, I use a comprehensive data set to (1) examine the forecasting power of IV across strike prices and terms to maturity and (2) explore whether IV from any group is the best forecast of future volatility. This study is motivated by the findings in Ederington and Guan (2005) who, contrary to the conventional notion of at-the-money IVs being the most informative, find significant evidence that for stock index options, IVs calculated from

[33]See, for example, Day and Lewis (1993), Lamoureux and Lastrapes (1993). Canina and Figlewski (1993), Christensen and Prabhala (1998), etc.
[34]Jorion (1995)
[35]See, Day and Lewis (1993), Martens and Zein (2004), Szakmary, Ors and Kim (2003)
[36]Amin and Ng (1997)

moderately high strike options are both unbiased and efficient predictors of future volatility whereas those from at-the-money options are biased and less efficient.

3. Data and Sampling procedure

Actual and implied volatilities are calculated from daily closing prices of crude oil and natural gas futures and call options on futures traded on the New York Mercantile Exchange from September 01, 1999 through June 30, 2006. An advantage of using options on futures is that I can avoid the nonsynchronous data problem. Since futures and futures' options are both traded on the NYME, both closing prices are observed at the same time[37]. The trading volumes of crude oil and natural gas options are extracted from the Dow Jones Factiva database.

Two exclusionary criteria are applied to the data. First, I eliminate options with less than one week or more than 4 months to expiration. The shorter-term options have relatively small time premiums, so a one-tick change (perhaps due to bid-ask bounce) leads to a jump in IVs calculated from very short term options imparting noise in the IVs. Second, I exclude options with $\{C - [F\text{-PV}(X)]\} \leq 10$ cents where C is the call price, F is the underlying futures price and PV(X) is the present value of the strike price. If, for an option, $\{C - [F\text{-PV}(X)]\} \leq 10$ cents, trading in that option is likely light and its IV is sensitive to a minimal change in its price, especially for short time-to-expiration options. Since the price changes in 1-cent increments, if $\{C - [F\text{-PV}(X)]\} \leq 10$ cents, the price and IV either change by more than 10% or not at all whereas they should be continuous. Also, when $\{C - [F\text{-PV}(X)]\} \leq 10$ cents, if the equilibrium price

[37]Hentschel (2003) documents that for stock index options, a large error typically comes from using closing prices for the options and index that are measured 15 minutes apart.

and IV are unchanged but the transaction price changes by 1 cent due to bid-ask bounce, the IV will appear to change by more than 10%.

This exclusion process left a total of 74,604 observations for crude oil call options and 79,162 observations for natural gas call options. For each market, the sample is broken into four maturity groups corresponding to options' term-to-maturity: near-, second-, third- and fourth- month. Each maturity group is then divided into "moneyness" bins corresponding to the amount the options are in or out of the money. The extent to which the options are in or out of the money is represented by the "moneyness" which is defined as *X*/*F-1*, where *X* is the call option's strike price and *F* is the underlying futures price on any given day.

I denote the "moneyness" bin as GIk or GOk, where "I" or "O" indicates whether the option is in or out of the money and k reports the moneyness where 1 is the closest to the money and 15 is the furthest in- or out-of-the-money. GOk represents out-of-the-money options whose strike prices are in the interval, $F \cdot \left\{1 + \frac{4(k-1)}{100}\right\}$, $F \cdot \left\{1 + \frac{4k}{100}\right\}$ and closest to $F \cdot \left\{1 + \frac{4(k-1)}{100}\right\}$ where *F* is the underlying futures price that day. Thus GO1 represents the options whose strike prices are just above the current underlying futures prices but not more than 4% higher than *F*. GO5 represents the options whose strikes are at least 16% and not more than 20% above *F*. Similarly, GIk indicates in-the-money options whose strikes are in the interval $F \cdot \left\{1 - \frac{4(k-1)}{100}\right\}$, $F \cdot \left\{1 - \frac{4(k-1)}{100}\right\}$ and closest to $F \cdot \left\{1 - \frac{4(k-1)}{100}\right\}$.

I do not necessarily have a price observation in each "moneyness" group each day, because (1) trading is light in far in- and out-of-the-money options and (2) exclusionary process has eliminated options whose implied volatilities are very sensitive to price changes.

Using Black's (1976) model for options on futures, day *t* closing prices for both the futures and futures' call options, and 3-month T-bill rates, I solve for the implied standard deviation, $ISD_{i,j,t,C}$ on each option (*i*,*j*) observed on day *t*, where *i* denotes the maturity group and *j* denotes the "moneyness" bin in each maturity group, and *C* is the number of calendar days to expiration.[38]

As pointed out by Ederington and Lee (1996), if Friday's ISD is calculated using *C* calendar days, Monday's ISD is calculated using *C*-3 calendar days. This assumes that the variance of returns from Friday's close to Monday's close is three times the normal weekday close-to-close variance. The evidence in financial markets such as stock, stock index, T-Bond, Eurodollar does not support this assumption (see, for example, French and Roll, 1986; Fleming et al., 1995, Ederington and Lee, 1996). In my previous studies on oil and gas actual volatilities, I find that the three-day weekend return variances are 18.32% and 46.56% higher than the average weekday variance for crude oil and natural gas, respectively, which is still not as large as the calendar day assumption implies.

[38]While Black's (1976) model is for European options, crude oil and natural gas futures options are American. However, like the S&P 500 futures options, early exercise is rare for crude oil and natural gas options. Also the bias in implied volatility due to the use of a European option model for American options is small (Jorion, 1995).

Consequently, I adjust $ISD_{i,j,t,C}$ to a trading day basis. In particular, I follow Ederington and Lee (1996) and calculate $ISD_{i,j,t,T} = ISD_{i,j,t,C}\sqrt{T_c / T_m}$ where $ISD_{i,j,t,T}$ and $ISD_{i,j,t,C}$ are the trading-day and calendar-day ISDs, T_c and T_m are calendar days and trading days to expiration. As noted in Fleming et al. (1995), this trading-day adjustment of ISD is more appropriate than simply using the number of trading days in valuing the option. The time-to-expiration parameter affects an option's value not only through total volatility, but also through the expected rate of appreciation in the underlying asset's value and through the length of time over which the option's expected payoff is discounted to the present. Both of these latter factors are more appropriately measured using calendar days. I use $ISD_{i,j,t,T}$ throughout this study and omit the subscript *T* for simplicity.

Table VII reports the summary statistics of crude oil and natural gas ISDs for the entire sample and for each year from 1999 through 2006.

I measure the actual realized volatility over the life of the option observed on day t, $\sigma_{i,j,t}$, as the annualized standard deviation of returns over the period from day *t* through the expiration date $t+\tau$ for option *i,j*.

$$\sigma_{i,j,t} = \sqrt{252 \cdot \left[\frac{1}{\tau_{i,j} - 1} \sum_{s=t+1}^{t+\tau_{i,j}} (R_s - \overline{R})^2 \right]} . \tag{17}$$

where $R_s = \ln(F_s / F_{s-1})$, F_s is the closing price of the underlying futures contract on day *s*, F_{s-1} is the closing price of the same futures contract on day *s*-1, and $t+\tau_{i,j}$ is the expiration date of option *i,j*.

4. The implied volatility surface

4.1. The implied volatility term structure

I hypothesized above that average oil and gas implied volatilities increase as the options approach expiration either due to the likely mean reversion in oil and gas prices or because the actual oil and gas volatility is greater for shorter than for longer term futures. Results in Table VIII are consistent with this term structure pattern hypothesis. As indicated in the second and the third columns of Panel A in Table VIII, all-strike average IVs (across all options with $-.2 \le (X / F - 1) \le .2$ where X is the option's strike price and F is the underlying futures price[39]) and average at-the-money IVs on nearby options tend to be higher than those on second-month options which are higher than those on third-month options, etc. Apparently oil and gas IVs tend to increase as the options approach expiration, yielding lower IVs from options at longer term to maturity. This findings would be meaningful for option valuation. Since the IVs that are normally reported are IVs from nearby options, if a financial engineer uses these nearby IVs to value options, he or she will tend to overestimate the value of longer-term options.

As presented in Panel B of Table VIII and Figure 10, the declining IV term structure pattern is consistent across all moneyness groups (the only exception is the natural gas GI6 group). This term structure pattern is opposite to that in the stock index options as documented in Park and Sears (1985), Becker and Tucker (1991) and Dumas, Fleming and Whaley (1998) and in the foreign exchange and bond futures options as documented in Xu and Taylor (1994), Campa and Chang (1995), Tompkins

[39]Deep in- and out-of-the-money options are not actively traded in the market so even a small change in call price may result in a big variation in the option's IV.

(2003), and Backus, Foresi and Wu (2004). In each moneyness group, the difference in average IV from nearby, second-, third-, and fourth-month options is significant at the .01 level. As can be seen in Figure 10, while the slope of the IV term structure pattern is consistent across strike prices for natural gas, it tends to be steepest for in- and out-of-the-money call options than for near-the-money options for crude oil.

IVs across different terms to maturity do not represent the market's expectation of future volatility over the same period of time. For example, IV from nearby options represents the market's forecast of future volatility over an average 15-day period whereas IV from second-month options represents the forecast of future volatility over an average 45-day period. To compare IVs on a more consistent basis, I calculate forward IVs on options expiring in two, three and four months. On a given day, if the ISD from an option expiring in t_1 days is x, and that from an option in the same "moneyness" group maturing in t_2 days is y ($t_2 > t_1$), the forward implied standard deviation over the period from day t_1+1 through day t_2 is calculated as $\left(y - \frac{t_1}{t_2}x\right) \Big/ \left(\frac{t_2 - t_1}{t_2}\right)$. In the "Forward ISD" column of Panel A in Table VIII, the second-month forward ISD, which is the average of forward ISDs calculated from ISDs on nearby and second-month options with $[-.2 \le (X/F-1) \le .2]$, represents the market's expectation of future volatility over the period from the nearby option's expiry to the second-month option's expiry. Likewise, the third-month forward ISD, which is the average of forward ISDs calculated from ISDs on second-month and third-month options with $[-.2 \le (X/F-1) \le .2]$, represents the market's expectation of future volatility over the period from the second-month option's expiry to the third-month option's expiry.

As indicated in the "Forward ISD" column of Panel A in Table VIII, the average forward volatility from oil and gas options consistently decreases with time to maturity, and the declining slope in the forward ISD pattern is steeper than in the ISD pattern. Consider the natural gas forward ISDs. According to these forward IVs, the market expects that average natural gas volatility is 57.2% for the first month, 51.5% for the second month, 46.25% for the third month and 41.8% for the fourth month where the first month ends on the nearby option's expiry, the second month is from the nearby option's expiry to the second month option's expiry and so on.

As hypothesized above, the declining pattern in IV term structure may be attributable to two possible reasons. First, if oil and gas prices are mean-reverting as documented in Bessembinder et al. (1995), Litzenberger and Rabinowitz (1995), Schwartz (1997) and Pindyck (2001), returns in successive periods should be negatively correlated and therefore, volatility over a 2-month period will be less than the sum of volatilities over the first and the second months; $\mathrm{Var}(A+B) = \mathrm{Var}(A) + \mathrm{Var}(B) + 2\rho\sqrt{\mathrm{Var}(A)\mathrm{Var}(B)} < \mathrm{Var}(A) + \mathrm{Var}(B)$ as $\rho < 0$. However, in the oil and gas futures markets, as shown in Panel C of Table VIII, the relation between monthly returns over different periods of time is more complicated where monthly returns tend to be positively correlated at the lag of one but negatively at some other lags, although the coefficient estimates are not significant.

Panel D of Table VIII presents the volatility of returns on nearby futures contracts when returns are measured over different periods of time. The "1-month returns" row presents the annualized standard deviations of returns on nearby futures contracts over the 1-month period (from the day the contract becomes the nearby contract to the day the contract expires). The "2-month returns" row presents the annualized standard deviations of returns on the same futures contracts over the 2-month period (from the day the contract becomes the second-month contract to the day the contract becomes the nearby contract) and so on for other rows. As shown in this Panel, volatility of the nearby futures returns generally increases with length of the period over which the returns are measured, implying that Var(A+B) = Var(A) + Var(B) + $2\rho\sqrt{\text{Var(A)Var(B)}}$ > Var(A) + Var(B) and therefore, there is no evidence that $\rho < 0$ in these markets.

The results in Panels C and D of Table VIII are somewhat consistent with Geman (2007) who shows statistical evidence that there is a mean-reversion in crude oil and natural gas prices before 1999 but since 2000, prices in both markets follow a random walk (arithmetic Brownian motion) model. Consequently, with no significant evidence of a mean-reversion in oil and gas prices as indicated in Panels C and D of Table VIII and in Geman (2007), it is unlikely that the declining IV term structure pattern is caused by a mean-reversion in oil and gas prices.

Since oil and gas options are options on futures and not on cash prices, there would seem to be another possible explanation for the declining IV term structure pattern. As IV is widely considered as the forecast of future actual volatility, the term structure pattern of IVs from futures options should be consistent with that of actual futures volatilities. Therefore, if volatility of oil and gas futures returns goes up as the futures contracts get closer to expiration, that tendency could explain the IV term structure pattern. As reported in the "Different futures contracts volatility" column in Panel A of Table VIII, the volatility of oil and gas futures returns tends to increase as the contract approaches expiration. Volatility of nearby futures returns tends to be higher than that of the second-month futures returns which is higher than that of the third-month futures returns and so on. As the IV on an *x*-month futures option should be consistent with the actual volatility of the *x*-month futures contract and there is evidence of an increase in actual volatility when the futures contracts get closer to expiration, this would explain the term structure pattern in oil and gas IVs.

This term structure pattern in the oil and gas futures markets is consistent with the “maturity effect” hypothesis in Samuelson (1965) which is supported by the findings in Serletis (1992) and Walls (1999). Samuelson (1965) argues that as the futures contract approaches expiration, the amount of information reflecting the fundamentals of the asset increases, causing large changes in futures prices and consequently increasing volatility. In addition, certain news in futures markets is likely to have more impact on near-term contracts than on longer-term ones, causing larger price changes for the former. For example, in the previous paper on natural gas futures volatility, I find that sorts of news occurring over the weekend such as weather news tends to have more impact on nearby contracts than on longer-term ones in this market.

Backus et al. (2004) argue that the tendency for average at-the-money IVs from currency options to rise with maturity is attributable to the changes in the underlying return distribution by term-to-maturity. Specifically, they argue that as the maturity of an option approaches infinity, the skewness and excess kurtosis of the underlying return distribution approach zero and the option’s price approaches the value given by the Black-Scholes formula. However, this hypothesis does not hold for oil and gas futures return distribution. As indicated in Panel B of Table IX, there is no evidence that the skewness and kurtosis of oil and gas return distributions consistently decline by term to maturity.

As mentioned in Section 2, many studies find that IVs from stock index, bonds and foreign exchange options generally decrease as the options get closer to expiration, which is opposite to the evidence regarding the term structure pattern in oil and gas IVs. This difference is likely explained by two possible reasons. First, oil and gas options are options on futures and futures price volatility may differ from spot price volatility. Second, as stated in Grammatikos and Saunders (1986), Han and Misra (1990), Galloway and Kolb (1996), and Han, Kling and Sell (1999), the evidence of a maturity effect is weaker for financial futures than for commodity futures.

4.2. The implied volatility smile

Since an implied volatility supposedly represents the market's expectation of likely volatility over the life of an option, the calculated IVs should be the same for all options expiring on the same date and observed at the same time if the option pricing model is correct. In many markets, however, IVs calculated from options with the same expiration date according to Black-Scholes (1973) model tend to differ across exercise prices, often displaying a persistent "smile" or "skew" pattern on a graph. These "smile" or "skew" patterns are documented in, among others, Canina and Figlewski (1993), Rubinstein (1994), Dumas, Fleming and Whaley (1998), Das and Sundaram (1999) and Ederington and Guan (2005) for stock index options markets, in Rosenberg (1996), Malz (1996), Campa, Chang, and Reider (1997), Backus, Foresi and Wu (2004), and Carr and Wu (2007) for currency options market, in Belongia and Gregory (1984) and Tompkins (2003) for options on bond futures, and in Jarrow, Li, and Zhao (2007) and Deuskar, Gupta and Subrahmanyam (2008) for interest rate options market. To my knowledge, all cross-sectional patterns documented in the literature to date are either U-shaped or downward-sloping.

The oil and gas IV cross-sectional patterns are reported in Table IX and Figure 11. For each option *j* in maturity group *i* on day *t*, I calculate both the implied standard deviation $\text{ISD}_{i,j,t}$, and the relative percentage "moneyness" of option *j* measured as $\left(X_{i,j,t}/F_{i,t}-1\right)$ where $X_{i,j,t}$ is option *j*'s strike price and $F_{i,t}$ is the underlying futures price on day *t*. The ISDs are then grouped into different bins according to the option's "moneyness". Each bin is denoted GIk or GOk, where "I" or "O" indicates whether the option is in or out of the money and k reports the option's "moneyness" where 1 is the closest to the money and the higher *k* is, the further the option is in or out of the money. Thus GO1 represents call options whose strike prices are just above the current underlying futures prices but no more than 4% higher than F. GO2 represents call options whose strikes are at least 4% and not more than 8% above F. Similarly, GI1 contains options whose lowest strike is 4% lower than F and highest strike is F. To obtain a complete shape of the smile, I include options in all "moneyness" bins across terms to maturity until a bin's trading becomes too light, i.e., a "moneyness" bin is not included if the number of observations in that bin falls below 50.

Time series means of ISDs across all "moneyness" bins are reported in Panel A of Table IX. Since the number of observations in each bin varies, the mean ISDs for different bins could differ because they are calculated over different samples. To correct for this, I follow Ederington and Guan (2005) and calculate the mean ISD ratio for each "moneyness" bin. For each day *t*, I calculate the average ISD, $ISD_{a,i}$, of the two nearest-the-money bins GO1 and GI1 in the maturity group *i*. For each moneyness bin observed on day *t*, I then calculate the ratio: $R_{i,j,t} = ISD_{i,j,t} / ISD_{a,i,t}$. Time series means of this ratio are reported in the "Mean ISD Ratio" columns of Panel A in Table IX and graphed against each maturity in Figure 11.

As shown in Figure 11, the cross-sectional pattern in natural gas options is consistent across all four maturity groups in that IVs are lowest when strikes are low and increase monotonically with strikes. To my knowledge, this upward-sloping pattern is unique to natural gas options since, as mentioned above, all cross-sectional patterns documented in the literature to date are either U-shaped or downward-sloping. For example, this positive "skew" pattern is opposite to the "sneer", or "smirk" pattern in the stock and stock index options markets where IVs monotonically decrease with strikes.

It is worth noting that the curvature of the "skew" pattern in natural gas IVs tends to be consistent across terms to maturity. For most financial options markets, the degree of curvature of the IV "smile" or "skew" pattern varies by options' maturity. As noted in Das and Sundaram (1999), it appears indisputable that the IV smile in most markets is deepest at short maturities and flattens out monotonically as maturity increases. In the post-1987 stock index options market, the IVs decrease monotonically as the exercise price rises, with the rate of decrease increasing for options with shorter time to expiration (see, for example, Dumas et al., 1998 and Doran, Peterson and Tarrant, 2007). Similarly, for foreign exchange and bond futures options markets, Bates (1996), Tompkins (2003) and Backus et al. (2004), among others, document that the degree of curvature in volatility smile is more extreme when the options are closest to expiration.

While the cross-sectional pattern is consistent across terms to maturity for natural gas, it varies by term to maturity for crude oil. For crude oil nearby group, IVs are lowest when options are near the money and increase as call options become increasingly in or out of the money. For the second-month group, IVs are lowest for moderately low strike (ITM calls) options (GI1 to GI5) and increase for out-of-the-money (OTM) and deep in-the-money (ITM) call options. The IVs in the third- and fourth-month groups exhibit a positive skew pattern where IVs are lowest for deep ITM calls and increase as the option strikes increase. The only other options market that displays a change in the shape of the IV smile pattern, to my knowledge, is the interest rates options market. Deuskar, Gupta and Subrahmanyam (2008) show that long-term options in this market display more of a ‘smirk’’ than a smile as in short-term ones.

The most popular explanation of the "smile" or “smirk” pattern observed in Black-Scholes IVs is that the pattern is due to the B-S model’s assumption that returns are normally distributed with known mean and variance. Hull and White (1987), Stein and Stein (1991), and Heston (1993) show that the smile or “smirk” patterns in IVs are often attributed to the kurtosis and skewness in the underlying assets return distribution. While kurtosis affects the pricing of near-the-money versus far-from-the-money options, skewness affects the pricing of in-the-money relative to out-of-the-money options. For example, there is evidence that the negative skewness in the S&P

500 index returns causes the B-S model to overprice low-strike options and underprice high-strike options (Corrado and Su, 1996). Similarly, the “smile” pattern in foreign exchange options is attributable to the leptokurtic unconditional distribution of log-differenced exchange rates (Bates, 1996 and Backus et al., 2004). Moreover, Bates (1996) and Backus et al. (2004) document that the excess kurtosis of log-differenced exchange rates increases rapidly as the option approaches expiration which results in a less sharply curved smile in long term options.

If the “smile” and “skew” patterns in oil and gas IVs are mainly caused by the excess kurtosis and skewness in the underlying return distributions, I expect to find the following. First, since natural gas options display a positive skew pattern in all expiries, natural gas futures returns should be positively skewed across terms to maturity. Second, as the slope of the cross-sectional pattern in crude oil IVs differs by term to maturity, the skewness in oil futures returns distribution should differ across terms to maturity.

Panel B in Table IX reports descriptive statistics for crude oil and natural gas daily returns from September 01, 1999 to June 30, 2006. The Kolmogorov-Smirnov *D*-statistics all exceed 0.026 and therefore, the null hypothesis of normality is rejected at the 0.01 level for oil and gas returns across all maturities. Oil and gas daily return series show leptokurtic behavior in that the level of kurtosis differs from the level of normal kurtosis by approximately five times the standard error (under the assumption of asymptotic normality) across all maturities. Sample statistics for skewness (two-tailed) also indicate the presence of significant skewness at the 5 percent level for oil and gas returns at all maturities.

While the crude oil IV pattern changes from a “smile” pattern for nearby and second-month series to a positive “skew” pattern for third- and fourth-month series, the existence of significant excess kurtosis and negative skewness is consistent across maturities for crude oil returns. Moreover, the significant negative skewness in longer-term crude oil futures returns would imply a negative skew pattern in oil IVs (similarly to the argument for the “sneer” pattern in the stock index options market) while, in fact, the opposite pattern is observed. For natural gas options, while the positive “skew” pattern and the degree of curvature in gas IVs are consistent across maturities, the underlying return statistics show a significant positive skewness for nearby and second-month series and a significant negative skewness for third- and fourth-month series. Therefore, there is no evidence that the excess kurtosis and skewness in oil and gas return distribution are responsible for the “smile” and “skew” patterns observed in oil and gas IVs.

An alternative explanation for the “smile” or “smirk” pattern is the hedging pressure hypothesis by Bollen and Whaley (2004) and Ederington and Guan (2002) who argue that it is the net buying pressure of the options market that drives the index options prices to be higher. Specifically, they contend that, in the stock index options market, demand for out-of-the-money puts to hedge against stock market declines pushes up implied volatilities on low strike options.

The positive skew pattern across terms to maturity in natural gas options may be attributable to hedging pressures in this market. Given that demand for natural gas can increase dramatically in winter while natural gas production is essentially fixed, there are often large price swings in winter. However, it is extremely difficult for consumers to quickly reduce their consumption when a sharp increase in natural gas prices occurs. Therefore, there may be more natural gas users hedging against a natural gas increase than there are natural gas sellers hedging against a price decrease, leading to higher prices and implied volatilities on high strike call options. If this hedging pressure theory holds for the natural gas market, IVs of high strike call options whose prices are supposedly impacted heavily by hedging pressures should be less representative of the market's volatility expectation than IVs calculated from options with lower strikes whose prices should be less subject to hedging pressures.

Panel C in Table IX and Figure 12 present the average daily trading volume of crude oil and natural gas call and put options during the sample period. For natural gas, the average daily OTM call volume is higher than the average daily OTM put volume across terms to maturities, indicating that there tends to be more natural gas users hedging against a price increase by buying OTM calls than natural gas sellers hedging against a price decrease by buying OTM puts.

The regression results regarding the information content of IVs, which are presented in detail in Section 7, are somewhat consistent with the view that hedging pressures are largely responsible for the skew pattern in natural gas IV. While natural gas IVs calculated from near-the-money options, specifically strikes ranging from 8% below to 4% above the underlying futures price, are both unbiased and efficient predictors of future volatility, IVs calculated from high strikes (OTM calls) are biased predictors of future volatility and significantly less informative. This pattern implies that prices of high strike options are heavily determined by demand for those options for hedging purposes in the natural gas market and that IVs at high strikes are partially influenced by factors other than the market's expectation of future volatility.

However, there is no evidence that the smile pattern in crude oil options is consistent with the hedging pressures argument. As presented in Figure 11, crude oil IVs, except for nearby options, tend to be lowest for low strike options and increase monotonically with strike prices. If the positive skew pattern in longer term crude oil options is caused by hedging pressures in this market, IVs of high strike options whose prices are supposedly impacted heavily by hedging pressures should be less representative of the market's volatility expectation than IVs calculated from lower strike options whose prices should be less subject to hedging pressures. Conversely, the regression results regarding the information content of crude oil IVs in Section 7 are opposite to this prediction. For second-, third-, and fourth-month groups, high strike IVs are the best forecast of future volatility while low strike IVs are the least informative. In addition, Panel C in Table IX shows that for crude oil options, there is no evidence that trading is higher in OTM calls than in OTM puts across terms to maturity.

5. Seasonality

5.1. Month-of-the-year IV pattern

A unique winter effect likely exists in the natural gas market due to the dependence of gas prices on weather conditions. The demand for natural gas may increase dramatically in winter, especially when the weather is severe. At the same time, the supply of natural gas may not increase accordingly because gas supplies are constrained by storage capacity and imports are limited. Consequently, supply and demand imbalances in the natural gas market during winter may cause large price swings. I hypothesized above that the average natural gas IV is higher for options expiring in the winter months than for those expiring in other months because (1) the market expects higher volatility in winter, and (2) there may be more users buying call options to hedge against a price spike in winter which could result in higher prices and IVs on options expiring in the winter months.

Results in Table X and Figure 13 are consistent with the winter effect hypothesis. The average natural gas ISDs display a U-shaped curve in which ISDs are significantly higher on options expiring in the winter months than in other months and this time-of-the-year pattern is consistent across all maturities. Consequently, if a financial engineer uses the yearly average volatility to value natural gas options, he or she will tend to overestimate the values of options expiring in summer and underestimate the values of options expiring in winter. The IV time-of-the-year pattern documented in Table X is consistent with the evidence in my earlier paper that the average variance of natural gas nearby futures returns increases by 58.45% in the winter months (from November through February).

While there are reasons to expect a strong seasonality pattern in natural gas IVs, it is interesting that there is also a month-of-the-year effect in crude oil IVs, although the pattern in the oil market is less pronounced than in the gas market. For example, the all-strike average IVs (across all options with $-.2 \le (X / F - 1) \le .2$ where X is the option's strike price and F is the underlying futures price) from nearby natural gas options expiring in the winter peak (January) is approximately 63.75% higher than that in the summer trough (May) whereas for crude oil options, the peak (February) is

19.21% higher than the trough (September). Apparently IV tends to be lower on crude oil options expiring in the summer months despite the fact that the demand for gasoline, a distilled product from crude oil, often increases during the summer driving season.

The null hypothesis that average ISDs from options expiring each month are equal is rejected at the 0.01 level for both crude oil and natural gas markets. For the natural gas market, there is significant evidence that the average ISD is higher on options expiring in the winter months than on options expiring in other months wherein winter is defined as the period from November through February[40]. Similarly, for the crude oil market, there is significant evidence that the average ISD is lower on options expiring in the summer (from May through September) than on options expiring in other months.

5.2. Day-of-the-week IV pattern

Table XI reports the mean values of the log percentage change in the ISDs, $\ln(ISD_{a,t}/ISD_{a,t-1})$, where $ISD_{a,t}$ is the average of the two nearest-the-money options GO1 and GI1 in the nearby group on day *t* and the sample is stratified by day-of-the-week. As mentioned earlier, the ISDs are calculated based on a trading-day basis.

In both markets, there is a significant tendency for the ISD to decline from Friday close to Monday close. This evidence likely implies the market's expectation that the volatility of nearby futures returns from Friday close to Monday close is higher than that of a normal weekday returns. Consider the change in the ISD from the

[40]My definition of winter months is based on the months in which natural gas is withdrawn from storage and therefore supply is constrained. Using data reported in various issues of the Weekly Natural Gas Storage Report, I determine that natural gas withdrawals normally start in November and end in early March.

close on Friday to the close on Monday. On Friday, it is known that the market is more volatile over the three days ending on Monday and therefore, the anticipated weekend/Monday volatility is impounded in Friday's ISD. However, this anticipated weekend/Monday volatility is dropped from Monday's ISD since Monday's ISD reflects the market's expectation of volatility from Tuesday to the options' expiration date. Consequently, the ISD will tend to decline from Friday close to Monday close because the period over which Monday's ISD is calculated will no longer include the (anticipated) high weekend/Monday volatility.

The result that the ISDs decline from Friday close to Monday close in the crude oil and natural gas options markets is consistent with the findings in my earlier papers for oil and gas actual volatilities. In these papers, I find that Friday-close-to-Monday-close returns are more volatile than any other weekday returns for crude oil and particularly for natural gas.

I hypothesized earlier that oil and gas IVs fall following the release of the Petroleum Status Report and the Natural Gas Storage Report, which are considered one of the most important announcements impacting these markets (see, for example, Susmel and Thompson, 1997 and Linn and Zhu, 2004). As documented in Ederington and Lee (1996), in the T-Bond and Eurodollar markets, IV tends to fall following the release of important scheduled announcements. Ederington and Lee (1996) argue that since the pre-release IV impounds the anticipated impact of important releases on volatility, IV declines post-release as this uncertainty is resolved.

The Natural Gas Storage Report was released on Wednesdays before May 06, 2002 and on Thursdays since then. Consequently, I examine the behavior of natural gas ISDs before and after May 06, 2002. Results are in the last two columns of Table XI. There is evidence that the behavior of Thursday natural gas ISD differs before and after May 2002. After May 06, 2002, when Thursday became the release day of the Storage Report, the mean percentage change in Thursday ISD is negative and significantly lower than that for other weekdays at the 0.01 level while not significant before. However, there is no significant evidence that before May 2002, natural gas ISD declines from Tuesday close to Wednesday close although Wednesday is the release day of the Storage Report during this period. These results imply that the release of the Storage Report has a stronger impact on natural gas prices after May 2002. For crude oil ISD, contrary to the evidence in my earlier paper that actual volatility tends to increase on Wednesday, the release day of the Petroleum Status Report, there is no significant evidence that oil ISD declines from Tuesday close to Wednesday close.

6. Implied Volatility Asymmetry

I hypothesized above that positive and negative return shocks have an asymmetric impact on oil and gas IVs. This hypothesis is motivated by the findings that IVs from stock index and Treasury bond futures options have an asymmetric response to returns of the underlying assets (see, for example, Fleming et al., 1995; Simon, 1997 and Dumas et al., 1998) and by the findings in my earlier papers that positive and negative return shocks have asymmetric impact on predicted volatility in the oil and gas markets.

To explore the impact of positive and negative return shocks on oil and gas IVs, I examine the times series of ISDs from the nearby nearest-the-money options. Specifically, I use the following model:

$$\Delta ISD_{a,t} = \alpha_0 + \sum_{i=1}^{4} \alpha_i D_i + \sum_{j=-1}^{0} \delta_j \left[R_{t+j}^{\{+\}} \Big/ \left(ISD_{a,t+j-1} / \sqrt{252} \right) \right] + \sum_{j=-1}^{0} \kappa_j \left[R_{t+j}^{\{-\}} \Big/ \left(ISD_{a,t+j-1} / \sqrt{252} \right) \right]$$
$$+ u_t \qquad (19)$$

where $\Delta ISD_{a,t}$ is the change in average ISDs of the two nearby nearest-the-money options, GI1 and GO1. $R_t = \ln(F_t/F_{t-1})$ where F_t is the price of the nearby futures contract on day t and F_{t-1} is the price of the same contract on day t-1. $^{\{+\}}$ and $^{\{-\}}$ denote positive and negative returns, and u_t is an error term. The positive and negative returns are scaled by lagged ISD on the previous days, expressed on a daily basis by dividing the lagged ISD by the square root of 252 (the number of trading days in a year). Equation (19) is specified similarly to the asymmetric GARCH model due to Glosten et al. (1993) (often referred to as the GJR model) which is used in my earlier papers on oil and gas price volatility.

In this model, the change in ISD from the close of day t-1 to the close of day t is driven by day-of-the-week effects, separate variables for positive and negative scaled returns from day t-1 to day t and lagged of those variables. Separate variables for positive and negative returns are included to determine whether ISD responds differently to positive and negative returns. $R_t^{\{+\}}$ ($R_t^{\{-\}}$) can be thought of as the actual returns times a dummy variable =1 if the return is positive (negative) and 0 otherwise. As stated in Simon (1997), the reason for scaling returns, R_t, is that market participants should revise their forecasts of volatility more, and, consequently, ISD changes should be greater when the magnitude of returns diverges from that predicted by ISD the previous day. For example, a larger-than-expected return of a given size should result in greater ISD increases when smaller absolute price changes, reflected by low ISD, are expected. Also noted by Simon (1997), if the daily returns are normally distributed with a mean equal to zero and a standard deviation equal to estimated ISD expressed on a daily basis, then $R_t/(ISD_{a,t-1}/\sqrt{252}) \sim N(0,1)$. If a contemporaneous unexpected increase in both positive and negative returns (in absolute value) causes a higher ISD, δ_0 should be significantly positive and κ_0 should be significantly negative. If ISD increases more in response to contemporaneous unexpected positive returns than to unexpected negative returns, $|\delta_0| > |\kappa_0|$.

Equation 19 differs from that in Simon (1997) in that I include dummy variables to control for the day-of-the-week effects discussed in Section 5 and lagged values of scaled returns since Kim and Kim (2003) document that IVs also respond to lagged returns.

Equation 19 is estimated using an ARMA (2,1) model. Results in Table XII indicate that unexpected positive and negative futures returns lead to higher ISD at the 0.05 significance level in both crude oil and natural gas markets. Consistent with my hypothesis above, unexpected positive and negative returns have asymmetric impacts on oil and gas ISDs. Crude oil ISD is more responsive to unexpected negative returns than to positive returns of equal magnitude while natural gas ISD is more responsive to unexpected positive returns than to negative returns of equal magnitude. The null hypotheses that $\delta_0+\kappa_0 = 0$ and $\delta_0-\kappa_0 = 0$ are both rejected at the 0.01 level. In addition, $|\kappa_0| > |\delta_0|$ for crude oil| and $|\delta_0| > |\kappa_0|$ for natural gas, both at the 0.01 significance level. For crude oil, a 1% unexpected positive return results in a 0.27% increase in ISD while a 1% unexpected negative return results in a 0.81% increase in ISD. For natural gas, a 1% unexpected positive return causes a 2.7% increase in ISD while a 1% unexpected negative returns only causes a 0.74% increase in ISD. The null hypothesis that (δ_0+ δ_1) + (κ_0+κ_1) =0 is rejected at the 0.001 level for natural gas and at the 0.1 level for crude oil.

The results regarding the asymmetric impact of unexpected positive and negative returns on IV are consistent with the findings in my earlier papers. Using the GJR model, I find that a negative return shock in the crude oil market tends to have more impact on predicted volatility than an equal positive shock. On the contrary, a positive shock in the natural gas market tends to have more impact on predicted volatility than an equal negative shock. While it is left unexplained why crude oil volatility increases more following a negative return shock, the findings that natural gas volatility increases more following a positive return shock is likely attributable to the inelasticity of the supply and demand curves at high prices in this market. Consequently, as the same fluctuation in demand when prices are low should cause a smaller change in prices than when prices are high, a positive price shock which moves the natural gas market up the supply and demand curves is likely to presage higher future volatility than a negative shock moving the market down the curves.

To test the possibility that the pronounced IV asymmetry with respect to unexpected positive and negative returns may be caused by extreme returns, I re-estimate the model in Equation 19 with separate variables for positive and negative scaled returns that are more than two standard errors from the mean absolute scaled returns.

The expanded model is:

$$\Delta ISD_{a,t} = \alpha_0 + \sum_{i=1}^{4} \alpha_i D_i + \sum_{j=-1}^{0} \delta_j \left[R_{t+j}^{\{+\}} \Big/ \left(ISD_{a,t+j-1} / \sqrt{252} \right) \right] + \delta_1 \left[R_t^{\{+\}} \Big/ \left(ISD_{a,t-1} / \sqrt{252} \right) \right]$$
$$* Tail_t + \sum_{j=-1}^{0} \kappa_j \left[R_{t+j}^{\{-\}} \Big/ \left(ISD_{a,t+j-1} / \sqrt{252} \right) \right] + \kappa_1 \left[R_t^{\{-\}} \Big/ \left(ISD_{a,t-1} / \sqrt{252} \right) \right] * Tail_t + u_t \quad (20)$$

where $Tail_t$ is a dummy variable =1 when the absolute magnitude of scaled return is more than 2 standard errors away from the mean, and 0 otherwise. If the asymmetric impact of positive and negative returns on ISD is caused by the tails of the return distributions, (1) positive and negative scaled returns in the central part of the distribution should have the same effect on ISD, and therefore δ_0 should be > 0, κ_0 should be < 0, and these coefficients should be of the same magnitude; (2) positive and negative scaled returns in the tails of the distribution have an incrementally greater effect on ISD than those that are not, and therefore δ_1 should be significantly positive and κ_1 should be significantly negative.

The results from this expanded specification (not reported) indicate that while δ_0 is significantly positive and κ_0 is significantly negative, the estimates of δ_1 and κ_1 are insignificantly different from 0, implying that the asymmetric impact of unexpected positive and negative futures returns on IV is not caused by extreme returns.

7. The Forecasting Performance of Implied Volatility

If markets are efficient and the option pricing model is correct, then the implied volatility calculated from an option's price should represent the average forecast of the underlying asset's future volatility over the remaining life of the option. Consequently, IVs should be unbiased forecasts of future volatility and should fully impound all available information, including the asset's price history. The information content of IV is typically determined by estimating one or both of the following specifications, which are known as the Mincer-Zarnowitz regression (Mincer and Zarnowitz, 1969) in the forecasting literature (see, for example, Canina and Figlewski, 1993; Jorion, 1995; Christensen and Prabhala, 1998; Szakmary et al., 2003; Ederington and Guan, 2005).

$$\sigma_{j,t} = \alpha + \beta_1 \cdot ISD_{j,t} + u_{j,t} \quad , \ (21) \qquad \text{and}$$

$$\sigma_{j,t} = \alpha' + \beta_1' \cdot ISD_{j,t} + \beta_2' \cdot HIS_{j,t} + u_{j,t} \quad , \ (22)$$

where $\sigma_{j,t}$ denotes the realized volatility from day t through the expiration of option j, $ISD_{j,t}$ denotes the implied volatility (normally the standard deviation) on option j observed on day t, and $HIS_{j,t}$ is a measure of historical volatility (usually either the standard deviation of returns over some recent period or a forecast based on GARCH-type estimation).

If IV is an unbiased forecast of realized volatility, we should find that $\alpha = 0$ and β_1=1 in Equation 21 and $\alpha' = 0$, β_1'=1 in Equation 22. If IV efficiently impounds all available information included in historical volatility, β_2' should be zero in Equation 22. Virtually all studies find that 0<β_1<1 and 0<β_1'<1 and most find that α>0 (Ederington and Guan, 2005). Thus, the evidence in most options markets implies that IV is a biased predictor of realized volatility. There is mixed evidence on whether IV is efficient, i.e., on whether β_2' is significant in Equation 22[41].

[41]Canina and Figlewski (1993), Day and Lewis (1993), Ederington and Guan (2002) and Martens and Zein (2004) observe significant values for β_2' in Eq. (3) in at least some data sets

I estimate the following specifications on each "moneyness" bin across all four maturity groups.

$$\sigma_{i,t}(\tau) = \alpha + \beta_1 \cdot ISD_{i,j,t} + u_{i,j,t} \quad , \ (21) \qquad \text{and}$$

$$\sigma_{i,t}(\tau) = \alpha' + \beta_1' \cdot ISD_{i,j,t} + \beta_2' \cdot HIS_{i,j,t} + u_{i,j,t} \quad , \ (22)$$

where $ISD_{i,j,t}$ is the implied standard deviation computed on day t from the option in maturity group i and "moneyness" group j, and $u_{i,j,t}$ represents the regression error. I include ISDs from all "moneyness" bins across terms to maturity until a bin's number of observations falls below 500. $\sigma_{i,t}(\tau)$ is the realized volatility of log returns over the period between t and $t+\tau$, the option's expiration date, annualized by multiplying the standard deviation calculated per day by $\sqrt{252}$. Log return is defined as: $R_t = \mathrm{Ln}\left(\frac{F_t}{F_{t-1}}\right)$ where F_t is the price of the underlying futures contract on day t and F_{t-1} is the price of the same futures contract on day t-1.

A common problem in most studies on the forecasting power of implied volatility is that due to considerable overlap in the data set, the forecast errors $u_{i,j,t}$ are serially correlated. On any day t, $ISD_{i,j,t}$ represents expected volatility from day t+1 to day $t+\tau$, the day the option expires. Likewise, on day t+1, $ISD_{i,j,t+1}$ represents expected volatility from day t+2 to day $t+\tau$. Observations on realized volatility $\sigma_t(\tau)$ and $\sigma_{t+1}(\tau)$ have $\tau - 1$ days in common, observations on $\sigma_t(\tau)$ and $\sigma_{t+2}(\tau)$ have $\tau - 2$ days in common, etc. which cause serious autocorrelation. When the data set

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while Christensen and Prabhala (1998), Fleming (1998), Blair et al. (2001), Szakmary et al. (2003), and Corrado and Miller (2003) find no evidence that historical volatility or GARCH forecasts contain additional information.

contains overlapping observations, ordinary least squares (OLS) regression coefficient estimates are still unbiased but OLS estimates of the coefficients' standard errors are biased downward. To correct for serial correlation, I employ Hansen's correction, the most common procedure in the literature[42].

Define X_n as the row vector of the independent variables for observation *n* in the sample; that is $X_n = (1 \quad \text{IV})_n$ $[X_n = (1 \quad \text{IV} \quad \text{HIS})_n$ for regressions based on Equation 22]. X is the $N \times 2$ matrix of the X_n. [X is the $N \times 3$ for regressions based on Equation 22]. Let u_n be the regression error for observation *n*, and let *u* denote the N vector of the u_n. Following Hansen (1982) and others, I compute

$$\hat{\Psi} = \sum_{n=1}^{N} (\hat{u}_n)^2 X'_n X_n + \sum_{k=1}^{N} \sum_{n=k+1}^{N} Q(k,n) \hat{u}_k \hat{u}_n (X'_n X_k + X'_k X_n), \qquad (23)$$

where u_k and u_n are the regression residuals for observations *k* and *n* from the OLS regression. $Q(k,n)$ is an indicator function taking the value 1 if there is an overlap between the periods to expiration for the two options, and 0 otherwise.

The corrected variance-covariance matrix for the estimated coefficients is

$$\hat{\Omega} = (X'X)^{-1} \hat{\Psi} (X'X)^{-1}, \quad (2\ \ )$$

7.1. Bias and information content differences across maturities and moneyness

Estimations of Equation 21 for oil and gas IVs are reported in Table XIII and Figures 14 and 15. Apparently, the patterns of the parameter estimates differ by time to expiration. Consider the results for crude oil ISDs. For the nearby group, the

[42]Examples are Canina and Figlewski (1993), Jorion (1995), Ederington and Guan (2005) and others.

intercepts, $\hat{\alpha}$'s, are not significantly different from zero for all "moneyness" bins except for the deep ITM call options. For the second- and third-month groups, $\hat{\alpha}$'s are only indistinguishable from zero for deep OTM call options.

Of more interest are the ISD coefficients. For the nearby group, $\hat{\beta}_1$'s, the ISD coefficients, are close to and insignificantly different from 1.0 for all "moneyness" bins except for the deep ITM calls. For the second-, third- and fourth-month groups, $\hat{\beta}_1$'s are significantly less than 1.0.

I plot $\hat{\beta}_1$ for crude oil options as a function of "moneyness" in Figure 14. For the nearby group, $\hat{\beta}_1$'s display a "frown" image[43] that is approximately a reverse image of the volatility smile where $\hat{\beta}_1$'s are highest for near-the-money options. However, for longer term groups, $\hat{\beta}_1$ pattern is not a reverse image of the volatility smile as $\hat{\beta}_1$'s are generally highest for deep OTM calls.

For natural gas options, the intercepts, $\hat{\alpha}$'s, are not significantly distinguishable from zero in most "moneyness" bins of the nearby and second-month groups. $\hat{\alpha}$'s are significantly different from zero for the third-month group and ITM calls in the fourth-month group. The slope coefficients $\hat{\beta}_1$'s are close to and insignificantly different from 1.0 for near-the-money nearby options and for most options in the second-month subsamples.

As exhibited in Figure 14, the ISD coefficients for natural gas nearby options also displays a "frown" pattern where $\hat{\beta}_1$ is highest for the near-the-money groups. $\hat{\beta}_1$

[43]The information "frown" is first explored in Ederington and Guan (2005).

is less variable in the second-month group. For the third- and fourth-month subsamples, $\hat{\beta}_1$ is generally higher for OTM options.

As shown in Table XIII, adjusted R^2 statistics pattern also varies by time to expiration. Adjusted R^2 statistics for nearby crude oil options display a frown pattern in that they are small at deep ITM or OTM calls and peak at near-the-money calls. For the longer term crude oil options, adjusted R^2 generally increases with strike price. For natural gas nearby and second-month options, adjusted R^2 statistics are generally higher for ITM options and decreases with strike prices. For natural gas third- and fourth-month groups, adjusted R^2 is highest for ATM options.

As noted in Ederington and Guan (2005), comparing R^2 across different "moneyness" groups is problematic in that the samples differ somewhat. On a given day there might be an observation for ATM group but not for ITM or OTM so R^2 could be different because one "moneyness" group is observed on a day with small error and another on a day with a large error. To compare the information content of ISDs from different "moneyness" groups on a more consistent basis, I follow Ederington and Guan (2005) and calculate the relative forecasting power for each "moneyness" group. First I form an un-weighted average $ISDa_{i,t}$ of the ISDs for the two ATM subsamples: GI1 and GO1 in maturity group i on day t. $\sigma_{i,t}(\tau)$ is then regressed on $ISDa_{i,t}$. Let $u(\text{ATMa})_{i,t}$ be the residual from this regression on day t and $u_{i,j,t}$ be the residual from one of the individual "moneyness" regressions in Table XIII, I then form the ratio $Y_{i,j} = \sum u(\text{ATMa})_{i,t}^2 \big/ \sum u_{i,j,t}^2$ where both summations are over only those daily observations where both $u(\text{ATMa})_{i,t}$ and $u_{i,j,t}$ are observed. So $Y_{i,j}$ measures the relative explanatory power of an individual ISD from "moneyness" group j versus the average ISD of the two ATM options. If $Y_{i,j}$ <1, the average ATM ISDs predicts future volatility over the life of the option better than the individual ISD. If $Y_{i,j}$ >1, the individual ISD predicts future volatility better than the ATM average.

As reported in Table XIII and graphed in Figure 15, *Y* pattern varies by time-to-maturity. For crude oil nearby options, relative R^2's are highest for ATM options. However, for longer term crude oil options, R^2's are generally higher for OTM options. For natural gas nearby options, relative R^2's are highest for moderately low strike options in the “moneyness” bins GI1, GI2 and GI3. For longer term natural gas options, relative R^2's are higher for ATM options than for ITM or OTM options.

In summary, the information content in oil and gas IVs varies considerably by time-to-maturity and by options’ “moneyness”. For crude oil options, the most informative in terms of predicting future volatility are ISD’s calculated from the prices of nearby group, except for deep ITM options. For natural gas options, the most informative in terms of forecasting future volatility are ISD’s calculated from the prices of near-the-money options in the nearby group and of most options in the second-month group. For these “most informative” options, the regression evidence in Table XIII is consistent with the hypothesis that IVs are unbiased predictors of actual volatility in that the slope coefficients, $\hat{\beta}_1$'s are close to and insignificantly different from 1.0 and the intercepts, $\hat{\alpha}$'s are close to and insignificantly different from zero. For other options groups, the hypothesis that the ISD’s are unbiased predictors of future volatility is rejected. Thus, ISDs on other options are influenced by something other than the market’s volatility expectation.

Both academic researchers and market participants normally use IV calculated from ATM options to represent the volatility expectations of market participants. However, results in Table XIII indicate that while that practice is justifiable for natural gas options and for nearby crude oil options, it is problematic for longer term crude oil options.

7.2. Efficiency

Next I test whether oil and gas IVs efficiently impound all the historical information by estimating Equation 22 where a measure of historical volatility is added to the equation. For historical volatility, I use the volatility forecast over the life of the options generated by the GJR model[44]. Results are reported in Table XIV. For the three far ITM crude oil nearby groups (GI3, GI4, GI5), $\hat{\beta}_2^{'}$s, the coefficients of historical volatility forecast, are significantly different from zero and relatively sizable, implying that the ISDs for these groups are influenced by factors other than the market's volatility expectation. Except for these three groups, $\hat{\beta}_2^{'}$s are insignificantly different from zero across all other options groups, implying that crude oil and natural gas implied volatilities generally impound information in historical volatility fairly efficiently.

The evidence that IV from oil and gas options is a fairly efficient forecast of future volatility is consistent with the findings in Christensen and Prabhala (1998),

[44] I use a GJR model to forecast historical volatility over the life of the option. The GJR specification is $h_t = \omega + \gamma_1 \varepsilon_{t-1}^2 + \gamma_2 h_{t-1} + \gamma_3 \eta_t \varepsilon_{t-1}^2, (26)$ where $\eta_t = 1$ if $\varepsilon_{t-1} < 0$ and 0 otherwise.
The regression estimates from (26) are used to generate h_{t+1}, volatility forecast for the next day. h_{t+1} is then substituted back into the equation to generate a volatility forecast for the following day, h_{t+2}. This substitution continues for each day through the life of the option.

Fleming (1998), Blair et al. (2001), Szakmary et al. (2003), Corrado and Miller (2003) and Ederington and Guan (2005).

8. Summary

This paper explores the structure, characteristics, and determinants of crude oil and natural gas implied volatilities. Using the IVs calculated from crude oil and natural gas futures and futures' call options prices from September 1999 through June 2006, I find that the behavior of IV in these two markets is much different from that in most financial options markets that we are more familiar with. In both markets, IVs tend to increase as the options approach expiration, yielding lower IVs on options at longer terms to maturity. This term structure pattern is opposite to that in the stock, stock index, currency and T-bond futures options markets. While inconsistent with the pattern for IV in those financial options markets, the oil and gas IV term structure pattern is consistent with the actual volatility pattern for different maturity futures contracts.

The cross-sectional pattern in crude oil options varies by term to maturity. For the nearby group, IVs are lowest when options are near the money and increase as call options become increasingly in or out of the money. For the second-month group, IVs are lowest for moderately low strike options and increase for out-of-the-money and deep in-the-money call options. The IVs in the third- and fourth-month groups exhibit a positive "skew" pattern where IVs are lowest for deep ITM calls and increase as the option strikes increase. The "smile" pattern in natural gas options is consistent across all maturity groups in that IVs are lowest when strikes are low and increase monotonically with strikes. This "smile" or positive "skew" pattern is opposite to the “sneer”, or “smirk” pattern in the stock and stock index options markets where IVs monotonically decrease with strikes. The hedging pressure hypothesis – in particular, hedgers buying out-of-the-money call options to protect against a sharp price increase, could partially explain the positive “skew” pattern in natural gas IVs. However, there is no evidence that the cross-sectional IV pattern in crude oil options is caused by hedging pressures in that market.

There is evidence of a winter effect in natural gas IVs in that IVs are significantly higher on options expiring in the winter months than on those expiring in other months. This seasonality effect is consistent with the high actual volatility in winter during which demand for natural gas may increase dramatically while supply of natural gas is essentially fixed. To a lesser extent, crude oil IVs are significantly lower on options expiring in the summer months than on those expiring in other months.

Oil and gas IVs tend to decrease from Friday close to Monday close, implying that volatility tends to be high over the three-day weekend in both markets. This is consistent with the findings for oil and gas actual volatilities. There is evidence that the Weekly Natural Gas Storage Report has significant impact on gas IV after May 2002. Contrary to earlier findings for actual volatilities, there is no significant evidence that crude oil IV declines following the release of the Petroleum Status Report and that natural gas IV declines following the release of the Storage Report prior to May 2002.

There is evidence that oil and gas IVs have an asymmetric response to positive and negative futures returns. Crude oil IV tends to increase more following an unexpected negative return than a positive return of equal magnitude while natural gas

IV tends to increase more following an unexpected positive return than an equal negative return. While it is left unexplained why crude oil IV increases more following a negative return shock, the finding that natural gas IV increases more following a positive return shock is likely attributable to the hypothesized shape of the supply and demand curves which are likely to be inelastic at high volumes and prices.

Oil and gas IVs are efficient forecast of future volatility across terms to maturity. For crude oil options, the most informative in terms of predicting future volatility are IVs on nearby group, except for deep ITM options. For natural gas options, the most informative are IVs calculated from the near-the-money options in the nearby group and in the second-month group.

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Table I. Summary Statistics: Crude oil returns

This table presents summary statistics for crude oil returns where r_t=ln(P_t/P_{t-1}); P_t is the price of the futures contract on day t and P_{t-1} is the price of the same futures contract on the previous day. The third, fifth and seventh columns present summary statistics for absolute values of daily returns. (**) and (*) on Rho designate estimates significantly different from zero at the 0.01 and 0.05 levels, respectively. The sample extends from January 1, 1997 to November 28, 2008.

	Nearby		Second-month		Third-month	
	Returns	Absolute Returns	Returns	Absolute Returns	Returns	Absolute Returns
Mean (x10^2)	0.0249	1.8033	0.0243	1.6534	0.0283	1.5486
Maximum	0.1454	0.1654	0.1379	0.1572	0.1166	0.1216
Minimum	-0.1654	0.0000	-0.1572	0.0000	-0.1216	0.0000
Std Dev	0.0242	0.0162	0.0220	0.0145	0.0206	0.0136
Annualized Std Dev	0.3826	0.2561	0.3479	0.2293	0.3257	0.2150
Skewness	-0.2598	0.2283	-0.2512	0.2104	-0.2398	0.1972
Kurtosis	6.3969	12.9479	5.8826	11.9163	5.4104	10.0491
Rho (First order Autocorrelation coefficient)	-0.0114	0.0529^{**}	-0.0279	0.0340^{*}	0.0043	0.0492^{*}

Table II. The multiplicative GARCH-type model of volatility determinants

Estimates of the model:

$$r_t = \mu + \varphi_1 r_{t-1} + \varepsilon_t \quad (1)$$

where:

$$\varepsilon_t \sim N(0, \sigma_t^2) \text{ and } \sigma_t^2 = h_t \cdot s_t \quad (2)$$

$$h_t = \mathrm{Var}(\zeta_t) = \omega + \alpha\zeta_{t-1}^2 + \beta h_{t-1} + \gamma\zeta_{t-1}^2 I_{t-1}, \text{ where } \zeta_t = \varepsilon_t / s_t^{.5} \quad (3)$$

$$s_t = \prod_{i=1}^{4} s_{i,t} \quad (4)$$

$$s_{1,t} = [AP_t/\overline{AP}]^{\kappa} \quad (4.a)$$

$$s_{2,t} = (1+\delta_{-1}DA_{t-1})(1+\delta_0 DA_t)(1+\delta_1 DA_{t+1}) \quad (4.b)$$

$$s_{3,t} = \prod_{i=1}^{4}(1+\lambda_i DW_{i,t}) \quad (4.c)$$

$$s_{4,t} = (1+\theta_1 DSUM_{i,t})(1+\theta_2 DWIN_{i,t}) \quad (4.d)$$

are presented where r_t is the log percentage change in price of the futures contract on day t, ε_t is a normally distributed random variable with conditional mean zero and conditional variance h_t. I_{t-1}=1 if ε_{t-1} >0 and 0 otherwise. AP_t is the inflation-adjusted price, $\overline{AP}$ represents the average inflation-adjusted price over the sample period. DA_t is 1 on OPEC meeting days and 0 otherwise. DA_{t-1} (DA_{t+1}) is 1 on the day before (after) the OPEC meeting days. $DW_{i,t}$ are zero-one dummies for Monday (including weekend), Wednesday, Thursday and Friday. SUM_t =1 if the contract expires in summer months (from May through August) and 0 otherwise; WIN_t =1 if the contract expires in winter months (from November through February) and 0 otherwise. Standard errors are shown in parentheses. (***), (**), (*) designate estimates significantly different from zero at the 0.001, 0.01 and 0.05 levels, respectively. The sample extends from January 01, 1997 to November 28, 2008.

	GJR model	Full model		
		Nearby futures contract	Second-month futures contract	Third-month futures contracts
ω	0.1847***	0.2114***	0.2639***	0.2361***
	(0.0387)	(0.0629)	(0.0791)	(0.0719)
α	0.0829***	0.0586***	0.0700***	0.0656***
	(0.0089)	(0.0123)	(0.0136)	(0.0129)
β	0.9066***	0.8974***	0.8681***	0.8636***
	(0.0111)	(0.0220)	(0.0296)	(0.0306)
γ	-0.0413***	-0.0179*	-0.0318*	-0.0182
	(0.0107)	(0.0089)	(0.0137)	(0.0148)

Level		-0.5354***	-0.3960***	-0.3095**
		(0.1134)	(0.1035)	(0.1040)
OPEC meetings		0.0605	0.1132	0.1251
		(0.2014)	(0.2145)	(0.2143)
OPEC meetings (+1)		0.5447*	0.7101*	0.6772*
		(0.2619)	(0.2858)	(0.3023)
OPEC meetings (-1)		0.4663	0.4471	0.4513
		(0.2919)	(0.2930)	(0.2845)
Monday		0.4040***	0.3902***	0.3293***
		(0.0936)	(0.0968)	(0.0981)
Wednesday		0.3260***	0.3282**	0.3169**
		(0.0902)	(0.0982)	(0.0964)
Thursday		0.0474	0.1084	0.1042
		(0.0774)	(0.0899)	(0.0893)
Friday		-0.0525	0.0370	0.0555
		(0.0681)	(0.0815)	(0.0831)
Summer		-0.0467	-0.1226	-0.1148
		(0.0885)	(0.0816)	(0.0815)
Winter		0.0629	0.0684	0.1259
		(0.0931)	(0.0933)	(0.0979)
Log-likelihood	-6716.549	-6687.190	-6423.765	-6219.350

Table III. The Diagonal VECH model of the crude oil and exchange index covariance matrix

Estimates of the model

$$\mathbf{r}_t = \boldsymbol{\mu} + \boldsymbol{\varepsilon}_t$$

$$\boldsymbol{\varepsilon}_t \sim N(0, H_t)$$

$$(H_t)_{ij} = (\Omega)_{ij} + (A_{ij})\varepsilon_{j,t-1}\varepsilon_{i,t-1} + (B)_{i,j}(H_{t-1})_{ij} \qquad (7)$$

are presented where $\mathbf{r}_t = (r_{1,t}, r_{2,t})'$ is a (2x1) vector where r_1 and r_2 are crude oil and exchange index returns, respectively and H_t is a (2x2) conditional covariance matrix. H_t is presumed to follow the most unrestricted Diagonal VECH process where the parameters in the matrices Ω, A, and B are allowed to vary without any restriction. Ω is a (3x1) parameter vector; A and B are (3x3) diagonal parameter matrices. For comparison, the estimates from univariate GARCH(1,1) model are presented in the first column. Returns are expressed in log percent. Standard errors are shown in parentheses. (***), (**) and (*) designate estimates significantly different from zero at the 0.001, 0.01 and 0.05 levels, respectively. The sample extends from January 01, 1997 through November 28, 2008.

	Univariate GARCH (1,1)		Diagonal VECH
	Exchange index	Crude oil	
$\Omega(1,1)$	0.0015**		0.0015**
	(0.0005)		(0.0005)
$\Omega(1,2)$			-0.0035*
			(0.0020)
$\Omega(2,2)$		0.2051***	0.1935***
		(0.0437)	(0.0421)
$A(1,1)$	0.0376***		0.0362***
	(0.0053)		(0.0050)
$A(1,2)$			0.0268***
			(0.0074)
$A(2,2)$		0.0693***	0.0651***
		(0.0067)	(0.0064)
$B(1,1)$	0.9549***		0.9563***
	(0.0074)		(0.0071)
$B(1,2)$			0.9290***
			(0.0275)
$B(2,2)$		0.8968***	0.9026***
		(0.0123)	(0.0118)

Table IV. Summary Statistics: Natural gas returns and extreme value estimators

This table presents summary statistics for natural gas returns, absolute returns and extreme value estimators of volatility. The second column presents summary statistics for daily returns, r_t, where $r_t=\ln(P_t/P_{t-1})$; P_t is the price of the nearby futures contract on day t and P_{t-1} is the price of the same futures contract on the previous day. The third column presents summary statistics for absolute values of daily returns. The fourth column presents summary statistics for extreme value estimators of volatility, Std_t, where $Std_t = \frac{|\ln(High_t) - \ln(Low_t)|}{2\sqrt{\ln(2)}}$, $High_t$ and Low_t denote the highest and the lowest prices of the nearby natural gas futures contract on day t, respectively. (**) on Rho designates estimates significantly different from zero at the 0.01 level. The sample extends from January 02, 1997 to December 31, 2008.

	Returns	Absolute Returns	Extreme value estimator
Mean (x10^2)	0.0340	2.7597	2.8610
Maximum	0.3244	0.3244	0.1950
Minimum	-0.1990	0.0000	0.0012
Std Dev	0.0382	0.0264	0.0148
Annualized Std Dev	0.6219	0.4298	
Skewness	0.4570	2.6122	2.7047
Kurtosis	8.0764	16.6902	21.9202
Rho (First order autocorrelation coefficient)	-0.0614	0.1151**	0.3941**

Table V. The multiplicative GARCH-type model of volatility determinants

Table V presents the estimates of the following model:

$$r_t = \mu + a_1 Oilret_t + a_2 CddDif_t + a_3 HddDif_t^{\{+\}} + a_4\ HddDif_t^{\{-\}} + a_5 SRFE_t + \sum_{i=1}^{4} \vartheta_i DW_{i,t} + \varepsilon_t \quad (10)$$

$$\varepsilon_t \sim N(0, \sigma_t^2) \text{ and } \sigma_t^2 = h_t \cdot s_t \quad (11)$$

$$h_t = Var(\zeta_t) = \omega + \alpha\zeta_{t-1}^2 + \beta h_{t-1} + \gamma\zeta_{t-1}^2 I_{t-1}, \text{ where } \zeta_t = \varepsilon_t / s_t^{.5} \quad (12)$$

$$s_t = \prod_{i=1}^{5} s_{i,t} \quad (13)$$

$$s_{1,t} = \prod_{i=1}^{4}(1+\lambda_i DW_{i,t}) \quad (13.a)$$

$$s_{2,t} = (SR_t)^{\kappa} \quad (13.b)$$

$$s_{3,t} = \prod_{i=1}^{11}(1+\theta_i DM_{i,t}) \quad (13.c)$$

$$s_{4,t} = (1+\psi W_t) \quad (13.d)$$

$$s_{5,t} = (1+\delta_0 BW_t)(1+\delta_1 ABW_t) \quad (13.e)$$

r_t is the log percentage change in price of the nearby natural gas futures contract on day t, ε_t is a normally distributed random variable with conditional mean zero and conditional variance σ_t^2. $Oilret_t$ is the log percentage change in price of the nearby crude oil futures contract on day t. $CddDif_t$ is the difference between the actual Cooling Degree Day measure and the 30-year average CDD measure for day t; $HddDif_t$ is the difference between the actual Heating Degree Day measure and the 30-year normal HDD measure for day t, $HddDif_t^{\{+\}} = HddDif_t$ if $HddDif_t > 0$ and 0 otherwise, $HddDif_t^{\{-\}} = HddDif_t$ if $HddDif_t < 0$ and 0 otherwise; $SRFE_t$ is the surprise in the change in storage = the actual storage change as reported in the EIA storage survey - the consensus expected storage change as reported by Bloomberg prior to the EIA report release; $DW_{i,t}$ are zero-one dummies for Monday (which includes the weekend), Wednesday, Thursday and Friday with Tuesday being the left-out day. I_{t-1}=1 if $\varepsilon_{t-1} < 0$ and 0 otherwise. $SR_t = \frac{|SRFE_t|}{s_{SR}}$ on days the storage report announcement is released and 1 otherwise where s_{SR} is the sample standard deviation of $|SRFE_t|$. $DM_{i,t}$=1 if the futures contract observed on day t expires in month i. W_t= 1 if the difference between the actual Heating Degree Day measure and the 30-year normal HDD measure for day t ($HddDif_t$) is < 0 and W_t= 0 otherwise. BW_t is 1 if day t is one of the last five trading days in a month and 0 otherwise. ABW_t is 1 if day t is the first trading day in a month and 0 otherwise. Standard errors are shown in parentheses. (***), (**), (*) designate estimates significantly different from zero at the 0.001, 0.01 and 0.05 levels, respectively. The sample extends from January 02, 1997 to December 31, 2008.

Panel A. Mean equation

	1997-2008	1997-2002	2002-2008
μ	0.1580	-0.003	0.2398
	(0.1565)	(0.2324)	(0.1648)
Oilret	0.4632***	0.3320***	0.5329***
	(0.0304)	(0.0416)	(0.0502)
CddDif	0.0443	0.0145	0.0870
	(0.0435)	(0.0307)	(0.0715)
$HddDif^{\{+\}}$	0.0016	-0.0023	0.0060
	(0.0221)	(0.0309)	(0.0304)
$HddDif^{\{-\}}$	-0.0362*	0.0216	-0.0559*
	(0.0188)	(0.0269)	(0.0230)
Monday	-0.1523	0.06262	-0.3291
	(0.2269)	(0.3369)	(0.2803)
Wednesday	-0.2572	-0.4183	-0.0500
	(0.2214)	(0.3284)	(0.2261)
Thursday	-0.2759	0.17503	-0.6216**
	(0.2225)	(0.3299)	(0.2453)
Friday	-0.0356	0.34631	-0.4796**
	(0.2248)	(0.3336)	(0.2037)
SRFE			-0.0636***
			(0.0148)

Panel B. Variance Equation

	GJR model	Full model		
		1997-2008	1997-2002	2002-2008
ω	0.3673**	0.1668***	0.1677*	0.1677*
	(0.0652)	(0.0483)	(0.0742)	(0.0660)
α	0.0995**	0.0691***	0.0681***	0.0714**
	(0.0077)	(0.009)	(0.0159)	(0.0137)
β	0.8869***	0.9235***	0.9244***	0.9007**
	(0.0104)	(0.0119)	(0.0193)	(0.0235)
γ	-0.0158*	-0.0359**	-0.0239	-0.0396*
	(0.0088)	(0.0125)	(0.0214)	(0.0174)
Monday		0.8772***	0.7047***	0.8201***
		(0.1434)	(0.1914)	(0.1839)
Wednesday		0.1080	0.1678	-0.0422
		(0.0843)	(0.1288)	(0.0967)
Thursday		0.4752***	0.2848*	0.6760***
		(0.1187)	(0.1462)	(0.2016)
Friday		-0.2575***	-0.2640**	-0.2740*
		(0.0576)	(0.0849)	(0.0742)
January		1.2836**	1.2888*	1.5620**
		(0.3979)	(0.5925)	(0.5736)
February		1.0768**	0.8148*	1.5867**
		(0.3663)	(0.4635)	(0.5825)
March		0.4082*	0.1985	1.7769**
		(0.2371)	(0.3270)	(0.6602)
April		-0.1847	-0.1062	0.9597*
		(0.1277)	(0.2351)	(0.4115)
May		-0.3292	-0.3109*	0.0804
		(0.1031)	(0.1758)	(0.2203)

July		-0.2519**	-0.1702	-0.0954
		(0.0946)	(0.1779)	(0.1753)
August		0.0157	-0.1635	0.3141
		(0.1455)	(0.1705)	(0.2302)
September		0.3961*	0.1688	0.9475*
		(0.2178)	(0.2564)	(0.4355)
October		1.5795***	1.3393*	1.8148**
		(0.3985)	(0.5977)	(0.6055)
November		1.2622***	1.2646*	3.4377***
		(0.3626)	(0.5809)	(0.8879)
December		0.6336*	0.7675	2.0524**
		(0.2926)	(0.5106)	(0.6494)
W		0.3158**	0.1051	0.3032**
		(0.1093)	(0.1629)	(0.1067)
BW		0.6592***	0.3065**	0.8004***
		(0.0925)	(0.1190)	(0.1292)
ABW		0.4802**	0.6451*	0.4595*
		(0.1829)	(0.2789)	(0.2525)
SR_t				0.2167**
				(0.0774)
Log-Likelihood	-7116.32	-6947.23	-3560.01	-4277.48

Table VI. Robustness check

Table VI presents the estimates of the following model:

$$Std_t = \omega^{'} + \sum_{i=1}^{5}\alpha_i Std_{t-i} + \gamma_1\varepsilon_{t-1}^{\{+\}} + \gamma_2\varepsilon_{t-1}^{\{-\}} + \sum_{j=1}^{4}\lambda_j^{'} DW_{j,t} + \kappa^{'} SR_t + \sum_{k=1}^{11}\theta_k^{'} DM_{k,t} + \psi^{'} W_t + \delta_0^{'} BW_t$$

$$+\delta_1^{'} ABW_t + \rho OilStd_t + e_t \quad (16)$$

$Std_t = \frac{|\ln(High_t) - \ln(Low_t)|}{2\sqrt{\ln(2)}}$, $High_t$ and Low_t denote the highest and the lowest prices of the nearby natural gas futures contract on day t, respectively. $r_t = \ln(P_t/P_{t-1})$ where P_t is the price of the nearby futures contract on day t and P_{t-1} is the price of the same contract the previous day. $\varepsilon_{t-1}^{\{+\}} = \varepsilon_{t-1}$ if $\varepsilon_{t-1} \geq 0$ and 0 otherwise; $\varepsilon_{t-1}^{\{-\}} = \varepsilon_{t-1}$ if $\varepsilon_{t-1} < 0$ and 0 otherwise and ε_t is the residual from the mean equation:

$$r_t = \mu + a_1 Oilret_t + a_2 CddDif_t + a_3 HddDif_t^{\{+\}} + a_4\ HddDif_t^{\{-\}} + a_5 SRFE_t + \sum_{i=1}^{4}\vartheta_i DW_{i,t}$$

$$+ \varepsilon_t \qquad (10)$$

$DW_{j,t}$ are zero-one dummies for Monday, Wednesday, Thursday and Friday.

$SR_t = \frac{|SRFE_t|}{s_{SR}}$ on days the storage report announcement is released and 0 otherwise where $SRFE_t$ is the surprise in the change in storage = the actual storage change (reported in the EIA report) - the consensus expected storage change (reported by Bloomberg prior to the EIA report release) and s_{SR} is the sample standard deviation of $|SRFE_t|$. $DM_{k,t}$ =1 if the futures contract observed on day t expires in month k. W_t = 1 if the difference between the actual Heating Degree Day measure and the 30-year normal HDD measure for day t ($HddDif_t$) is < 0 and W_t= 0 otherwise. BW_t is 1 if day t is one of the last five trading days in a month and 0 otherwise. ABW_t =1 if day t is the first trading day in a month. $OilStd_t = \frac{|\ln(OilHigh_t) - \ln(OilLow_t)|}{2\sqrt{\ln(2)}}$, $OilHigh_t$ and $OilLow_t$ denote the highest and the lowest prices of the nearby crude oil futures contract on day t, respectively. (**) and (*) designate estimates significantly different from zero at the 0.01 and 0.05 levels, respectively. The sample extends from January 02, 1997 to December 31, 2008.

	1997-2008		1997-2002		2002-2008	
	Estimate	Std. error	Estimate	Std. error	Estimate	Std. error
ω' (x10^2)	0.2922*	0.1331	-0.0442	0.2326	0.4472*	0.1803
Std(-1)	0.1828**	0.0546	0.1929**	0.0637	0.1083**	0.0417
Std (-2)	0.1379**	0.0324	0.0937*	0.0411	0.1724**	0.0325
Std (-3)	0.0604*	0.0291	0.0732*	0.0349	0.0588*	0.0329
Std (-4)	0.1119**	0.0265	0.0929*	0.0387	0.1148**	0.0323
Std (-5)	0.0805**	0.0299	0.0830*	0.0345	0.0599*	0.0319
$\varepsilon_t^{\{+\}}$	0.0862*	0.0428	0.0913	0.0715	0.0874**	0.0223
$\varepsilon_t^{\{-\}}$	-0.0009	0.0222	0.0084	0.0371	-0.0261	0.0247
Monday (x10^2)	0.3482**	0.1172	0.4871**	0.1768	0.2512*	0.1161
Wednesday (x10^2)	0.1761*	0.0877	0.1845	0.1195	0.1945*	0.1122
Thursday (x10^2)	0.5971**	0.0924	0.7274**	0.1298	0.2243*	0.1335
Friday (x10^2)	-0.2200*	0.0863	-0.2812*	0.1136	-0.1311	0.1134
W (x10^2)	0.1227*	0.0721	0.1512	0.1133	0.1057	0.0923
January (x10^2)	0.2617*	0.1375	0.5075*	0.2221	0.3099*	0.1738
February (x10^2)	0.4132**	0.1322	0.5651**	0.2062	0.1803	0.1875
March (x10^2)	0.4182*	0.2471	0.6282	0.4563	0.3499*	0.1885
April (x10^2)	-0.0693	0.0929	-0.0672	0.1382	0.0287	0.1786
May (x10^2)	0.0918	0.0866	-0.0253	0.1166	0.0654	0.1696
July (x10^2)	0.1477	0.0954	0.2673*	0.1288	0.1178	0.1719
August (x10^2)	0.2414*	0.1132	0.1937	0.1496	0.3945*	0.1767
September (x10^2)	0.4985**	0.1201	0.3825**	0.1312	0.8041**	0.1797
October (x10^2)	0.6022**	0.1352	0.5978**	0.1667	0.8272**	0.1947
November (x10^2)	0.2732*	0.1261	0.4056**	0.1571	0.2815	0.1738
December (x10^2)	0.3724**	0.1219	0.6243**	0.1862	0.3424*	0.1766
BW (x10^2)	0.1658*	0.0736	0.2661*	0.1116	0.1177	0.0848
ABW (x10^2)	0.2039	0.1363	0.0482	0.1669	0.2653	0.1739
OilStd	0.1431**	0.0337	0.2943**	0.0591	0.1265**	0.0298
SR_t (x10^2)					0.4746**	0.1542
Adjusted R^2	0.3221		0.3334		0.3562	

Table VII. Summary Statistics

This table presents the summary statistics of crude oil and natural gas implied standard deviations calculated from daily closing prices of nearby, second-, third-, and fourth-month futures and call options on futures from September 01, 1999 to June 30, 2006.

Crude Oil	1999-2006	1999	2000	2001	2002	2003	2004	2005	2006
Mean	0.329	0.351	0.315	0.350	0.370	0.359	0.341	0.320	0.247
Median	0.323	0.357	0.311	0.315	0.361	0.329	0.344	0.320	0.252
Maximum	1.222	0.545	0.579	0.983	0.858	0.796	1.222	1.184	0.344
Minimum	0.063	0.109	0.121	0.084	0.191	0.192	0.063	0.085	0.085
Std. Dev.	0.065	0.042	0.050	0.098	0.049	0.079	0.049	0.032	0.028
Skewness	1.297	-.692	0.334	1.097	0.627	1.605	2.719	0.541	-1.078
Kurtosis	8.58	4.15	3.73	3.50	4.04	5.49	4.01	6.50	5.12
Number of Obs	74604	1756	7050	6989	8647	10085	13195	18143	8739
2nd decile	0.281	0.318	0.275	0.275	0.328	0.301	0.303	0.298	0.228
4th decile	0.312	0.346	0.301	0.302	0.350	0.320	0.332	0.314	0.246
6th decile	0.335	0.367	0.322	0.329	0.375	0.343	0.357	0.327	0.258
8th decile	0.370	0.387	0.354	0.453	0.417	0.418	0.379	0.343	0.270
Natural Gas									
Mean	0.515	0.551	0.555	0.603	0.540	0.536	0.470	0.402	0.561
Median	0.510	0.564	0.551	0.596	0.540	0.526	0.433	0.386	0.552
Maximum	1.480	0.727	1.480	1.429	1.026	1.202	0.973	0.937	0.888
Minimum	0.112	0.238	0.112	0.182	0.262	0.203	0.150	0.129	0.203
Std. Dev.	0.131	0.077	0.169	0.133	0.062	0.107	0.137	0.088	0.103
Skewness	0.710	-0.704	1.204	0.524	0.046	0.961	0.821	0.988	0.091
Kurtosis	4.63	3.48	6.21	3.16	3.55	5.52	2.81	4.13	2.36
Number of Obs	79162	1425	8111	8481	10883	15615	15384	11938	7324
2nd decile	0.422	0.486	0.423	0.486	0.490	0.451	0.351	0.332	0.467
4th decile	0.475	0.542	0.521	0.562	0.525	0.502	0.398	0.368	0.516
6th decile	0.530	0.582	0.581	0.623	0.556	0.552	0.471	0.405	0.597
8th decile	0.602	0.617	0.647	0.703	0.592	0.613	0.599	0.460	0.660

Table VIII. The implied volatility term structure

Panel A. The term structure pattern

The "All-strike ISD Mean" and the "ATM ISD Mean" columns report the average implied standard deviations (ISDs) over all options with $-.2 \leq (X/F-1) \leq .2$ where X is the option's strike price and F is the underlying futures price and the average ISDs on ATM options when the sample is stratified by time to expiration. ISDs are calculated from daily closing prices of futures and call options on futures.

The "Forward ISD" column reports the average forward ISDs calculated from ISDs on nearby, second-, third- and fourth-month options with $-.2 \leq (X/F-1) \leq .2$. The forward ISDs are calculated as follow. If on a given day, the ISD of an option expiring in t_1 days is x, and that of an option in the same "moneyness" group maturing in t_2 days is y, the forward ISD over the period from day t_1+1through day t_2 is calculated as $\left(y - \frac{t_1}{t_2}x\right) \Big/ \left(\frac{t_2 - t_1}{t_2}\right)$. Thus, the second-month forward group contains forward ISDs calculated from ISDs on nearby and second-month options, the third-month forward group contains forward ISDs calculated from ISDs on second- and third-month options and so on.

The "Different futures contracts volatility" column presents the annualized standard deviation of nearby, second-, third- and fourth-month futures contracts over the next month which are calculated according to the following formula: $\overline{\sigma_j} = \left(\frac{1}{82}\sum_{j=1}^{82}\sigma_j\right) \cdot \sqrt{252}$ where $\sigma_j = \sqrt{\frac{1}{k-1}\sum_{t=1}^{k}(r_t - \bar{r})^2}$; $r_t = \ln(F_t / F_{t-1})$; F_t is the closing futures price on day t; k is the next month's number of days; F_k is the futures price on the day the nearby futures expires, F_1 is the price of the same contract on the day the contract switches from second-month to nearby contract (for nearby futures), from third- to second-month (for second-month futures), from fourth- to third-month (for third-month futures) and from fifth- to fourth-month (for fourth-month futures). F_0 is the price of the same contract on the previous day. Therefore, 0.3645 is the average of annualized standard deviations of nearby futures returns over next month, 0.3353 is the average of annualized standard deviation of second-month futures returns over next month and so on. 82 is the number of months in the sample from September 1999 through June 2006.

Crude Oil

Time to expiration	All-strike ISD Mean	ATM ISD Mean		Forward ISD		Different futures contracts volatility
Near-month	0.3556	0.3442	Nearby	0.3556	Nearby	0.3645
Second-month	0.3468	0.3406	Second-month forward	0.3477	Second-month	0.3353
Third-month	0.3333	0.3308	Third-month forward	0.3180	Third-month	0.3125
Fourth-month	0.3212	0.3194	Fourth-month forward	0.2915	Fourth-month	0.3005

Natural Gas

Time to expiration	All strike ISD Mean	ATM ISD Mean		Forward ISD		Different futures contracts volatility
Near-month	0.5720	0.5614	Nearby	0.5720	Nearby	0.6010
Second-month	0.5432	0.5369	Second-month forward	0.5150	Second-month	0.5520
Third-month	0.5088	0.5072	Third-month forward	0.4625	Third-month	0.4978
Fourth-month	0.4757	0.4750	Fourth-month forward	0.4180	Fourth-month	0.4462

Panel B. ISDs by time to expiration and option's strike price

This panel reports the average implied standard deviations (ISDs) when the sample is stratified by time to expiration and by the option's strike price. In the "Group" column, the second letter (I or O) refers to In-the-money (low-strike calls) or Out-of-the-money (high-strike calls); and the last digit indicates the "moneyness" of that group where 1 indicates that the group is the nearest-to-the-money and 2 indicates that the group is 4% in or out of the money, etc. The "moneyness" of a group is measured by (X/F – 1) where X is the strike price and F is the underlying futures price.

		Crude Oil Mean ISD			
Group	Moneyness (X/F – 1)	Nearby	Second month	Third month	Fourth month
GI7	(0.28)-(0.24)	0.4579	0.3792	0.3297	0.3094
GI6	(0.24)-(0.20)	0.4031	0.3508	0.3242	0.3026
GI5	(0.20)-(0.16)	0.3788	0.3488	0.3321	0.3147
GI4	(0.16)-(0.12)	0.3575	0.3372	0.3218	0.3044
GI3	(0.12)-(0.08)	0.3442	0.3381	0.3254	0.3111
GI2	(0.08)-(0.04)	0.3451	0.3401	0.3288	0.3175
GI1	(0.04)-0.00	0.3429	0.3404	0.3298	0.318
GO1	0.00-0.04	0.3456	0.3429	0.3318	0.3207
GO2	0.04-0.08	0.3513	0.3467	0.3346	0.3233
GO3	0.08-0.12	0.3619	0.3509	0.3378	0.3269
GO4	0.12-0.16	0.3796	0.3565	0.3415	0.3315
GO5	0.16-0.20	0.404	0.366	0.3475	0.3365
GO6	0.20-0.24	0.4342	0.3777	0.356	0.3403
GO7	0.24-0.28	0.4818	0.3959	0.3705	0.3463
GO8	0.28-0.32	0.5302	0.4179	0.3912	0.3567

		Natural Gas Mean ISD			
Group	Moneyness (X/F – 1)	Nearby	Second month	Third month	Fourth month
GI6	(0.24)-(0.20)	0.481	0.496	0.4597	0.4293
GI5	(0.20)-(0.16)	0.5115	0.4954	0.4642	0.433
GI4	(0.16)-(0.12)	0.5148	0.4975	0.4677	0.4393
GI3	(0.12)-(0.08)	0.5339	0.514	0.4822	0.45
GI2	(0.08)-(0.04)	0.5433	0.5219	0.4935	0.462
GI1	(0.04)-0.00	0.5548	0.5308	0.5024	0.4704
GO1	0.00-0.04	0.5679	0.5429	0.5119	0.4796
GO2	0.04-0.08	0.5826	0.5569	0.5201	0.4882
GO3	0.08-0.12	0.612	0.5652	0.5282	0.4954
GO4	0.12-0.16	0.6546	0.5783	0.5391	0.5014
GO5	0.16-0.20	0.6938	0.5962	0.5493	0.5106
GO6	0.20-0.24	0.6968	0.6159	0.5626	0.5219

Panel C

Correlation in monthly returns

This panel presents the results from the following specification:

$$Returns_t = \mu + a_1 Returns_{t-1} + a_2 Returns_{t-2} + a_3 Returns_{t-3} + e_t \qquad (18)$$

where $Returns_t$ represents the monthly returns in month t.

	Crude oil returns		Natural gas returns	
	Estimate	Std. Error	Estimate	Std. Error
μ	0.0106	0.0076	0.0100	0.0118
a_1	0.0796	0.0964	0.1300	0.0893
a_2	-0.0355	0.0954	-0.1227	0.0870
a_3	-0.0240	0.0958	-0.0539	0.0865

Panel D

Volatility of nearby futures returns over different periods

This Panel presents the annualized standard deviations of monthly, two-, three- and four-month nearby futures returns which are calculated according to the following formula: $\sigma_{i-month\ returns} = \sqrt{\frac{1}{83-i-1}\sum_{T=1}^{83-i}(R_{T,i-month\,returns} - \bar{R})^2} \cdot \sqrt{12/i}$ where $R_{T,i-month\,returns} = \ln(F_\tau / F_{\tau-i})$; F_τ is the nearby futures price on the expiration date and $F_{\tau-i}$ is the price of the same contract on the day it switches from second-month to nearby contract (i=1), from third- to second-month (i=2), from fourth- to third-month (i=3) and from fifth- to fourth-month (i=4).

	Annualized Standard Deviation	
	Crude oil	Natural gas
1-month returns	0.2763	0.5042
2-month returns	0.3083	0.5507
3-month returns	0.3149	0.5531
4-month returns	0.3167	0.5523

Table IX. The implied volatility smile

This table presents the implied standard deviation (ISD) pattern when the sample is stratified by maturity and by the options' strike price. ISDs are calculated from daily closing prices of futures and call options on futures. The sample ranges from September 01, 1999 to June 30, 2006. In the "Group" column, the second letter (I or O) refers to In-the-money (low-strike calls) or Out-of-the-money (high-strike calls); and the last digit indicates the "moneyness" of that group where 1 indicates that the group is the nearest-to-the-money and 2 indicates that the group is 4% in or out of the money, etc. The "moneyness" of a group is measured by (X/F – 1) where X is the strike price and F is the underlying futures price. The "Mean ISD ratio" measures the ratio of the mean ISD on the options in the "Group" column to the average ISD of the two nearest-the-money groups: GI1 and GO1.

Panel A. The smile

Crude Oil

		Nearby			Second		
	X/F – 1	Mean ISD	Mean ISD ratio	Obs	Mean ISD	Mean ISD ratio	Obs
GI7	(0.28)-(0.24)	0.4579	1.0974	104	0.3792	1.0273	265
GI6	(0.24)-(0.20)	0.4031	1.0988	316	0.3508	1.0158	625
GI5	(0.20)-(0.16)	0.3788	1.0700	668	0.3488	0.9997	931
GI4	(0.16)-(0.12)	0.3575	1.0252	1102	0.3372	0.9820	1290
GI3	(0.12)-(0.08)	0.3442	1.0026	1432	0.3381	0.9936	1505
GI2	(0.08)-(0.04)	0.3451	1.0052	1532	0.3401	0.9966	1565
GI1	(0.04)-0.00	0.3429	0.9962	1569	0.3404	0.9968	1594
GO1	0.00-0.04	0.3456	1.0038	1599	0.3429	1.0032	1618
GO2	0.04-0.08	0.3513	1.0176	1585	0.3467	1.0149	1624
GO3	0.08-0.12	0.3619	1.0351	1372	0.3509	1.0275	1628
GO4	0.12-0.16	0.3796	1.0554	955	0.3565	1.0435	1605
GO5	0.16-0.20	0.4040	1.0719	552	0.3660	1.0603	1449
GO6	0.20-0.24	0.4342	1.0784	290	0.3777	1.0697	1183
GO7	0.24-0.28	0.4818	1.0906	132	0.3959	1.0866	867
GO8	0.28-0.32	0.5302	1.1100	71	0.4179	1.1016	543
GO9	0.32-0.36				0.4447	1.1189	300
GO10	0.36-0.40				0.4838	1.1333	151

				Third			Fourth
	X/F – 1	Mean ISD	Mean ISD ratio	Obs	Mean ISD	Mean ISD ratio	Obs
GI7	(0.28)-(0.24)	0.3242	0.9771	632	0.3026	0.9501	572
GI6	(0.24)-(0.20)	0.3321	0.9786	917	0.3147	0.9683	800
GI5	(0.20)-(0.16)	0.3218	0.9686	1285	0.3044	0.9595	1218
GI4	(0.16)-(0.12)	0.3254	0.9886	1499	0.3111	0.9830	1452
GI3	(0.12)-(0.08)	0.3288	0.9956	1592	0.3175	0.9982	1577
GI2	(0.08)-(0.04)	0.3298	0.9965	1636	0.3180	0.9961	1628
GI1	(0.04)-0.00	0.3318	1.0035	1648	0.3207	1.0039	1645
GO1	0.00-0.04	0.3346	1.0130	1640	0.3233	1.0130	1641
GO2	0.04-0.08	0.3378	1.0227	1621	0.3269	1.0233	1636
GO3	0.08-0.12	0.3415	1.0334	1550	0.3315	1.0341	1592
GO4	0.12-0.16	0.3475	1.0487	1440	0.3365	1.0475	1535
GO5	0.16-0.20	0.3560	1.0550	1267	0.3403	1.0578	1471
GO6	0.20-0.24	0.3705	1.0709	1017	0.3463	1.0708	1361
GO7	0.24-0.28	0.3912	1.0833	723	0.3567	1.0841	1073
GO8	0.28-0.32	0.4086	1.0869	466	0.3687	1.0949	855
GO9	0.32-0.36	0.4274	1.0918	308	0.3828	1.1053	611
GO10	0.36-0.40	0.4522	1.0919	188	0.3946	1.1100	440

Natural Gas

	X/F – 1	Nearby Mean ISD	Nearby Mean ISD ratio	Nearby Obs	Second Mean ISD	Second Mean ISD ratio	Second Obs
GI8	(0.32)-(0.28)				0.4465	0.7702	220
GI7	(0.28)-(0.24)				0.4830	0.8445	563
GI6	(0.24)-(0.20)	0.4810	0.8287	206	0.4960	0.8758	946
GI5	(0.20)-(0.16)	0.5115	0.8855	543	0.4954	0.9097	1235
GI4	(0.16)-(0.12)	0.5148	0.9206	867	0.4975	0.9345	1386
GI3	(0.12)-(0.08)	0.5339	0.9566	997	0.5140	0.9611	1434
GI2	(0.08)-(0.04)	0.5433	0.9784	1016	0.5219	0.9774	1472
GI1	(0.04)-0.00	0.5548	0.9888	1049	0.5308	0.9903	1508
GO1	0.00-0.04	0.5679	1.0113	1040	0.5429	1.0095	1533
GO2	0.04-0.08	0.5826	1.0331	1000	0.5569	1.0307	1507
GO3	0.08-0.12	0.6120	1.0546	834	0.5652	1.0479	1479
GO4	0.12-0.16	0.6546	1.0692	586	0.5783	1.0664	1435
GO5	0.16-0.20	0.6938	1.0819	312	0.5962	1.0819	1321
GO6	0.20-0.24	0.6968	1.0922	155	0.6159	1.0961	1162
GO7	0.24-0.28				0.6411	1.1101	934
GO8	0.28-0.32				0.6431	1.1252	613
GO9	0.32-0.36				0.6475	1.1340	334
GO10	0.36-0.40				0.6416	1.1526	117

			Third			Fourth	
	X/F – 1	Mean ISD	Mean ISD ratio	Obs	Mean ISD	Mean ISD ratio	Obs
GI8	(0.32)-(0.28)	0.4655	0.8227	553	0.4307	0.8147	683
GI7	(0.28)-(0.24)	0.4618	0.8515	849	0.4245	0.8471	1008
GI6	(0.24)-(0.20)	0.4597	0.8831	1154	0.4293	0.8813	1203
GI5	(0.20)-(0.16)	0.4642	0.9123	1305	0.4330	0.9085	1347
GI4	(0.16)-(0.12)	0.4677	0.9363	1406	0.4393	0.9335	1431
GI3	(0.12)-(0.08)	0.4822	0.9622	1458	0.4500	0.9577	1442
GI2	(0.08)-(0.04)	0.4935	0.9797	1504	0.4620	0.9770	1488
GI1	(0.04)-0.00	0.5024	0.9908	1551	0.4704	0.9911	1540
GO1	0.00-0.04	0.5119	1.0091	1563	0.4796	1.0087	1561
GO2	0.04-0.08	0.5201	1.0277	1565	0.4882	1.0268	1562
GO3	0.08-0.12	0.5282	1.0452	1543	0.4954	1.0446	1557
GO4	0.12-0.16	0.5391	1.0613	1508	0.5014	1.0607	1510
GO5	0.16-0.20	0.5493	1.0783	1456	0.5106	1.0765	1461
GO6	0.20-0.24	0.5626	1.0932	1390	0.5219	1.0916	1415
GO7	0.24-0.28	0.5747	1.1121	1304	0.5322	1.1063	1331
GO8	0.28-0.32	0.5927	1.1220	1148	0.5440	1.1208	1241
GO9	0.32-0.36	0.6097	1.1371	1018	0.5598	1.1368	1110
GO10	0.36-0.40	0.6236	1.1526	810	0.5722	1.1488	951

Panel B. Sample Statistics for crude oil and natural gas daily returns

This Panel reports some descriptive statistics for crude oil and natural gas daily return series from September 01, 1999 to June 30, 2006. ** on *D*-statistic indicates rejection at the 0.01 level. For a .01 significance level, the critical value of the *D*-statistic is given by 0.026. Under the assumption of normality, the asymptotic standard errors for kurtosis and skewness are respectively given by $(24/N)^{.5}$ and $(6/N)^{.5}$ where N denotes the number of observations. For $N = 1702$, these standard errors are calculated as 0.1187 and 0.0594, respectively.

	Crude oil			
	Nearby	Second-month	Third-month	Fourth-month
Observations	1702	1702	1702	1702
Mean return	0.0654	0.0681	0.0706	0.0730
Standard Deviation	0.0239	0.0219	0.0204	0.0197
Skewness	-0.6059	-0.4715	-0.3768	-0.4674
Kurtosis	6.0133	5.6260	4.8176	6.0415
D-Statistic	0.0380**	0.0265**	0.0294**	0.0313**
Skewness/s.e	-10.20	-7.94	-6.34	-7.87
Excess kurtosis / s.e	25.39	22.12	15.31	25.62

	Natural gas			
	Nearby	Second-month	Third-month	Fourth-month
Observations	1702	1702	1702	1702
Mean return	0.0595	0.0621	0.0656	0.0770
Standard Deviation	0.0390	0.0355	0.0326	0.0291
Skewness	0.4528	0.1316	-0.5064	-0.1606
Kurtosis	8.4198	6.1718	9.6408	7.0398
D-Statistic	0.0536**	0.0506**	0.0510**	0.0497**
Skewness/s.e	7.62	2.21	-8.53	-2.70
Excess kurtosis / s.e	45.66	26.72	55.95	34.03

Panel C: Average trading volume

This panel reports the average number of crude oil and natural gas call and put options traded per day during the period from September 1999 through June 2006. The options are stratified by term-to-maturity and the options' moneyness. Deep ITM calls and deep OTM puts are options with (X/F)-1 ≤ -.10; ITM calls and OTM puts are options with -.10<(X/F)-1 < -.02. ATM calls and puts are options with -.02 ≤ (X/F) -1 ≤ .02. OTM calls and ITM puts are options with .02 < (X/F)-1 < .10. Deep OTM calls and deep ITM puts are options with (X/F)-1 ≥ .10.

	Call options					Put options				
	Deep				Deep	Deep				Deep
Crude Oil	ITM	ITM	ATM	OTM	OTM	OTM	OTM	ATM	ITM	ITM
Nearby	7,009	899	4,169	6,865	1,823	4,275	11,643	8,367	265	112
Second-month	1,301	777	2,974	2,604	5,289	7,148	4,645	2,997	176	86
Third-month	4	16	2,892	2,227	3,068	4,232	3,572	813	28	5
Fourth-month	2	7	545	469	698	1,693	1,358	366	17	2
Natural Gas										
Nearby	7	37	131	674	1,026	295	834	410	236	82
Second-month	48	39	19	814	485	260	437	46	27	3
Third-month	14	68	273	27	387	288	55	22	4	2
Fourth-month	6	4	15	17	225	196	23	11	3	1

Table X. Month-of-the-year pattern

This table reports mean values of the forward implied standard deviations where the sample is stratified by month-of-the-year. ISDs are calculated from daily closing prices of futures and call options on futures. The second-, third- and fourth-month forward columns represent the average forward ISDs over all options with $-.2 \le (X/F\text{-}1) \le .2$ (where X is the option's strike price and F is the underlying futures price) for the expiration month in the first column. For example, the figure of .3133 in the first row is the average forward ISD over all options with $-.2 \le (X/F\text{-}1) \le .2$ for January expiration month calculated from the ISDs observed in October of fourth-month options expiring in January and of third-month options expiring in December. Winter is from November to February. Summer is from May to September. The sample ranges from September 01, 1999 to June 30, 2006. ** on F- and t-test statistics denote rejection at the 0.01 level.

Expiration month of the option	Nearby	Second-month forward	Third-month forward	Fourth-month forward
Panel A. Crude oil				
January (F)	0.3768	0.3825	0.3785	0.3133
February (G)	0.3841	0.3754	0.3756	0.3251
March (H)	0.3612	0.3325	0.3282	0.3443
April (J)	0.3835	0.3543	0.2996	0.3008
May (K)	0.3734	0.3258	0.2995	0.2549
June (M)	0.3372	0.3063	0.2916	0.2647
July (N)	0.3249	0.3139	0.2758	0.2708
August (Q)	0.3232	0.3189	0.2841	0.2573
September (U)	0.3222	0.3138	0.3004	0.2716
October (V)	0.3362	0.3369	0.3031	0.2898
November (X)	0.3712	0.3673	0.3132	0.2893
December (Z)	0.3758	0.3839	0.3443	0.2892
F-Statistic (H_0: $\mu_F=\mu_G=\mu_H=\mu_J=\mu_K=\mu_M=\mu_N=\mu_Q=\mu_U=\mu_V=\mu_X=\mu_Z$)	14.70**	26.63**	32.49**	22.87**
t-statistic (H_0: $\mu_{Summer}=\mu_{Non\text{-}Summer}$)	11.71**	13.95**	12.27**	11.16**

Panel B. Natural Gas

January (F)	0.7292	0.6909	0.5928	0.5017
February (G)	0.7085	0.5778	0.5305	0.4177
March (H)	0.6153	0.4263	0.2825	0.2749
April (J)	0.5250	0.3905	0.3459	0.2672
May (K)	0.4453	0.4117	0.3737	0.3492
June (M)	0.4741	0.4552	0.4154	0.3668
July (N)	0.5116	0.4934	0.4686	0.4282
August (Q)	0.4898	0.4991	0.5173	0.4791
September (U)	0.4877	0.5105	0.5074	0.5040
October (V)	0.5351	0.5067	0.4828	0.4762
November (X)	0.5721	0.5648	0.5126	0.4896
December (Z)	0.6422	0.6448	0.5898	0.5351
F-Statistic (H_0: $\mu_F=\mu_G=\mu_H=\mu_J=\mu_K=\mu_M=\mu_N=\mu_Q=\mu_U=\mu_V=\mu_X=\mu_Z$)	184.09**	56.72**	106.50**	697.94**
t-statistic (H_0: $\mu_{Winter}=\mu_{Non\text{-}winter}$)	33.40**	19.33**	19.05**	12.88**

Table XI. Day-of-the-week pattern

This table reports mean values of the log percentage change in the implied standard deviations, $\ln(ISD_{a,t}/ISD_{a,t\text{-}1})$, calculated from nearby near-the-money options where the sample is stratified by day-of-the-week. ISDs, based on trading days, are calculated from daily closing prices of futures and call options on futures. $ISD_{a,t}$ is the average ISD of the two nearest-the-money options (GO1 and GI1) in the nearby group on day *t*. The sample ranges from September 01, 1999 to June 30, 2006. * and ** on *t*-statistics denote rejection, at the 0.05 and 0.01 levels.

			Natural Gas	
	Crude Oil	Natural Gas	Before May 2002	After May 2002
Monday (M)	-0.0381	-0.0198	-0.0157	-0.0217
Tuesday (T)	0.0145	0.0197	0.0257	0.0171
Wednesday (W)	-0.0035	0.0139	0.0021	0.0197
Thursday (R)	-0.0136	-0.0107	-0.0021	-0.0149
Friday (F)	-0.0113	0.0107	0.0111	0.0105
F-Statistic (H_0: $\mu_M = \mu_T = \mu_W = \mu_R = \mu_F$)	7.5592**	17.9749**	4.1975**	16.0246**
t-Statistic (H_0: $\mu_M = \mu_{T,W,R,F}$)	-4.3319**	-5.9401**	-2.8356**	-5.2422**
t-Statistic (H_0: $\mu_T = \mu_{M,W,R,F}$)	4.0631**	4.4274**	3.0965**	3.2735**
t-Statistic (H_0: $\mu_W = \mu_{M,T,R,F}$)	0.9679	3.1093**	-0.2944	4.0247**
t-Statistic (H_0: $\mu_R = \mu_{M,T,W,F}$)	-0.7466	-3.9286**	-1.0201	-4.0970**
t-Statistic (H_0: $\mu_F = {}_{M,T,W,R}$)	-0.3306	2.2362*	1.0791	2.0076*

Table XII. Impact of unexpected positive and negative returns on implied volatility

Estimates from specification:

$$\Delta ISD_{a,t} = \alpha_0 + \sum_{i=1}^{4} \alpha_i D_i + \sum_{j=-1}^{0} \delta_j \left[R_{t+j}^{\{+\}} \Big/ \left(ISD_{a,t+j-1} / \sqrt{252} \right) \right] + \sum_{j=-1}^{0} \kappa_j \left[R_{t+j}^{\{-\}} \Big/ \left(ISD_{a,t+j-1} / \sqrt{252} \right) \right] + u_t \quad (19)$$

are reported where $\Delta ISD_{a,t}$ is the change in average implied standard deviations of the two nearby nearest-the-money options, GI1 and GO1; D_i's are dummy variables to control for day-of-the-week effects; $R_t = \ln(F_t/F_{t-1})$ where F_t is the price of the nearby futures contract on day t and F_{t-1} is the price of the same contract on day t-1. $^{\{+\}}$ and $^{\{-\}}$ denote positive and negative returns, and u_t is an error term. The model is estimated using an ARMA (2,1) model. Standard errors are in parentheses. The coefficient estimates and standard errors are multiplied by 100. * and ** denote rejection at the 0.05 and 0.01 levels.

	Crude oil	Natural gas
α_0	-0.7211	-1.1271
	(0.5358)	(0.9446)
Monday	-0.4344**	-2.1067**
	(0.1609)	(0.4415)
Tuesday	0.1790	-0.3746
	(0.1478)	(0.4498)
Wednesday	-0.1385	
	(0.1314)	
Thursday		-1.4905**
		(0.4417)
Friday	-0.2120	0.0120
	(0.1373)	(0.4332)
δ_0	0.2692*	2.7033**
	(0.1491)	(0.2241)
δ_1	0.4427**	0.4960*
	(0.0841)	(0.2235)
κ_0	-0.8050**	-0.7480**
	(0.1363)	(0.2636)
κ_1	-0.1981*	-0.7066**
	(0.0813)	(0.2624)

Table XIII. Realized volatility regressed on implied volatility

The table reports regression results from Equation 21: $\sigma_t(\tau) = \alpha + \beta_1 \cdot ISD_{i,j,t} + u_{i,j,t}$, for each of the subsample defined by maturity and "moneyness" of oil and gas options between September 01, 1999, and June 30, 2006. The coefficients are fitted by OLS, but the standard errors (labeled s.e) are corrected for intercorrelation. $ISD_{i,j,t}$ is the implied standard deviation computed from the price of the call option from maturity group *i* (expiring at $t+\tau$) and "moneyness" group *j* on date *t*. $\sigma_t(\tau)$ is the realized standard deviation of the underling futures log returns from date t to $t+\tau$. $u_{t,i,j}$ is the regression error. * and ** designate parameters which are significantly different from zero at the 0.05 and 0.01 levels, respectively and † and †† designate coefficients of $ISD_{i,j,t}$ which are significantly different from 1.0 at the 0.05 and 0.01 levels, respectively. Tests are two-tailed for intercept and one-tailed for slope coefficient. *Y* is the reciprocal of the ratio of the sum of squared errors (SSE) from the regression for strike *j* to the SSE from a regression with the average ISD for ATM options as the independent variable over observations common to both regressions.

Crude Oil

Nearby	GI4	GI3	GI2	GI1	GO1	GO2	GO3
α	0.1561**	0.0928*	0.0497	0.0342	0.0283	0.0314	0.0285
s.e	0.0430	0.0448	0.0456	0.0462	0.0473	0.0481	0.0522
β_1	0.4930**	0.6917**	0.8179**	0.8717**	0.8851**	0.8614**	0.8486**
s.e	0.1321	0.1418	0.1439	0.1473	0.1498	0.1497	0.1581
Adj.R^2	0.1085	0.1727	0.2158	0.2287	0.2304	0.2303	0.2257
Y ratio	0.9212	0.9379	0.9662	0.9993	1.0002	0.9990	0.9890
Second							
α	0.2059**	0.1442**	0.1214*	0.1075*	0.1066*	0.0981*	0.0924
s.e	0.0532	0.0514	0.052	0.0504	0.0492	0.048	0.0481
β_1	0.4144**	0.5924**	0.6584**	0.7024**	0.7031**	0.7211**	0.7283**
s.e	0.1599	0.1509	0.1539	0.1493	0.1438	0.1388	0.1376
Adj.R^2	0.1362	0.2285	0.2541	0.2780	0.2774	0.2908	0.2972
Y ratio	0.9020	0.9434	0.9734	1.0011	1.0012	1.0213	1.0259
Third							
α	0.2474**	0.2113**	0.1826**	0.1642*	0.1513*	0.1471*	0.1371
s.e	0.0525	0.0612	0.0635	0.0689	0.0706	0.0715	0.0717
β_1	0.2723*,	0.3803*,	0.4732**	0.5341**	0.5711**	0.5787**	0.6023**
s.e	0.1648	0.1774	0.1868	0.2076	0.212	0.2135	0.2117
Adj.R^2	0.082	0.1222	0.1646	0.1927	0.2114	0.2158	0.229
Y ratio	0.9152	0.9638	0.9798	0.9859	1.0103	1.0134	1.0240

Fourth							
α	0.2797**	0.2627**	0.2410**	0.2257**	0.2143**	0.2029*	0.1973*
s.e	0.0659	0.065	0.0706	0.0804	0.0832	0.0825	0.0816
β_1	0.1393	0.2044	0.2858	0.3390	0.3738	0.4062	0.4199*,
s.e	0.2098	0.1969	0.2092	0.2453	0.2542	0.2506	0.2445
Adj.R^2	0.0269	0.0428	0.0706	0.0855	0.1001	0.1161	0.1258
Y ratio	0.9796	0.9819	0.9886	0.9914	1.0009	1.0153	1.0239

<u>Natural Gas</u>

Nearby	GI4	GI3	GI2	GI1	GO1	GO2	GO3
α	0.1180*	0.0752	0.0622	0.0587	0.0488	0.0693	0.1065
s.e	0.0578	0.0463	0.0509	0.0514	0.0559	0.0640	0.0747
β_1	0.8193**	0.8581**	0.8709**	0.8685**	0.8684**	0.8092**	0.7458**
s.e	0.0955	0.0712	0.0829	0.0775	0.0851	0.0953	0.1106
Adj. R^2	0.2613	0.3465	0.3188	0.3276	0.3174	0.2676	0.2255
Y ratio	0.9991	1.0116	1.0072	1.0030	0.9993	0.9947	0.9878
Second							
α	0.1136	0.0892	0.0810	0.0824	0.0760	0.0841	0.0742
s.e	0.0588	0.0606	0.0622	0.0598	0.0638	0.0644	0.0700
β_1	0.8084**	0.8412**	0.8436**	0.8276**	0.8279**	0.7935**	0.7982**
s.e	0.1234	0.1252	0.1274	0.1211	0.1275	0.1252	0.1348
Adj. R^2	0.4485	0.4554	0.4516	0.4487	0.4347	0.4201	0.4036
Y ratio	0.9921	0.9868	0.9950	1.0113	0.9961	0.9771	0.9740
Third							
α	0.2084**	0.1908**	0.1843**	0.1715*	0.1668*	0.1546*	0.1533*
s.e	0.0614	0.0645	0.0644	0.0702	0.0717	0.0759	0.0748
β_1	0.5277**	0.5613**	0.5671**	0.5937**	0.5928**	0.6081**	0.5985**
s.e	0.1319	0.1381	0.1358	0.1484	0.1487	0.1572	0.1526
Adj. R^2	0.3125	0.3199	0.3236	0.3239	0.3209	0.3160	0.3099
Y ratio	0.9861	0.9896	0.9948	1.0027	0.9983	0.9921	0.9819
Fourth							
α	0.2145*	0.1842*	0.1778*	0.1605	0.1454	0.1345	0.1278
s.e	0.0865	0.0863	0.0859	0.0850	0.0856	0.0860	0.0869
β_1	0.5180**	0.5790**	0.5788**	0.6145**	0.6367**	0.6473**	0.6482**

s.e	0.2049	0.1998	0.1949	0.1904	0.1887	0.1871	0.1863
Adj. R^2	0.2245	0.2648	0.2679	0.2898	0.3076	0.3171	0.3202
Y ratio	0.9407	0.9609	0.9815	0.9890	1.0057	0.9981	0.9946

Table XIV. Realized volatility regressed on implied volatility and historical volatility

The table reports regression results from Equation 22:

$\sigma_t(\tau) = \alpha + \beta_1 \cdot ISD_{i,j,t} + \beta_2 \cdot HIS_{i,j,t} + u_{i,j,t}$. $ISD_{i,j,t}$ is the implied standard deviation computed from the price of the call option from maturity group *i* (expiring at $t+\tau$), and "moneyness" group *j* on date t. $HIS_{i,j,t}$ is the volatility forecast over the life of the option generated by the Glosten et al. (1993) model. The coefficients are fitted by OLS, but the standard errors (labeled s.e) are corrected for intercorrelation. $\sigma_t(\tau)$ is the realized standard deviation of the underlying futures log returns from date t to $t+\tau$. $u_{i,j,t}$ is the regression error. * and ** designate parameters which are significantly different from zero at the 0.05 and 0.01 levels, respectively and † and †† designate coefficients of $ISD_{i,j,t}$ which are significantly different from 1.0 at the 0.05 and 0.01 levels, respectively. Tests are two-tailed for intercept and one-tailed for slope coefficient.

Crude Oil

Nearby	GI4	GI3	GI2	GI1	GO1	GO2	GO3
α	0.0202	0.0069	-0.0107	-0.0107	-0.0049	-0.0011	-0.0143
s.e	0.0607	0.0582	0.0527	0.0538	0.0600	0.0642	0.0652
β_1	0.4343**,	0.5678**,	0.7045**,	0.7774**	0.8040**	0.7820**	0.7455**
s.e	0.1263	0.1509	0.1699	0.1793	0.1865	0.1857	0.1939
β_2	0.4178**,	0.3428*,†	0.2643	0.2039	0.1609	0.1581	0.2086
s.e	0.1597	0.1709	0.1774	0.1802	0.2035	0.2187	0.2244
Adj.R^2	0.1419	0.1861	0.2235	0.2336	0.2336	0.2335	0.2313
Second							
α	0.1569*	0.1242*	0.1221*	0.1098*	0.1062*	0.1001*	0.0964*
s.e	0.0613	0.0548	0.0505	0.0461	0.0436	0.0437	0.0441
β_1	0.3638*,†	0.5633**,	0.6418**,	0.7079**	0.7018**	0.7266**	0.7395**
s.e	0.1843	0.1797	0.1923	0.1888	0.1869	0.1781	0.1737
β_2	0.1941	0.0869	0.0146	-0.0122	0.0026	-0.0113	-0.0228
s.e	0.2046	0.1751	0.1654	0.1422	0.1359	0.1296	0.1213
Adj.R^2	0.1428	0.2299	0.2500	0.2781	0.2774	0.2908	0.2974

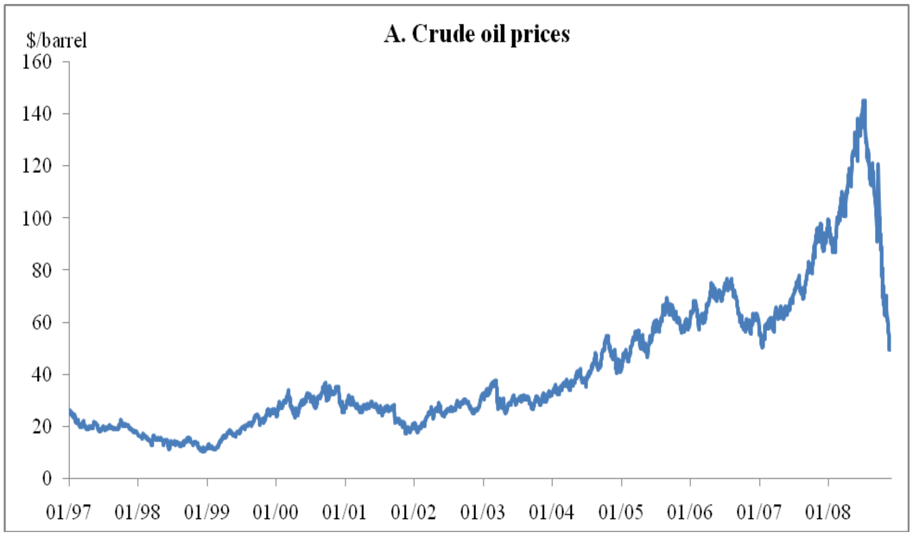
Third							
α	0.2132^{**}	0.1917^{**}	0.1689^{*}	0.1541^{*}	0.1463^{*}	0.1452	0.1341
s.e	0.0772	0.0721	0.0730	0.0747	0.0739	0.0766	0.0766
β_1	0.2399	$0.3537^{*,\dagger}$	$0.4473^{*,\dagger}$	$0.5134^{*,\dagger}$	$0.5595^{*,\dagger}$	$0.5744^{**,}$	$0.5949^{**,}$
s.e	0.1829	0.2036	0.2092	0.2360	0.2468	0.2419	0.2399
β_2	0.1406	0.0881	0.0686	0.0522	0.0271	0.0103	0.0170
s.e	0.2536	0.2278	0.2072	0.2072	0.2077	0.2043	0.1999
Adj.R^2	0.0870	0.1242	0.1659	0.1934	0.2116	0.2158	0.2291
Fourth							
α	0.2741^{**}	0.2514^{**}	0.2350^{**}	0.2172^{**}	0.2037^{*}	0.1946^{*}	0.1857^{*}
s.e	0.0626	0.0643	0.0758	0.0821	0.0852	0.0867	0.0854
β_1	0.1371	0.2003	0.2832	0.3338	0.3659	0.4006	$0.4101^{*,\dagger}$
s.e	0.2132	0.1990	0.2096	0.2469	0.2556	0.2505	0.2437
β_2	0.0203	0.0405	0.0217	0.0324	0.0421	0.0325	0.0472
s.e	0.0785	0.0809	0.0834	0.0757	0.0781	0.0813	0.0795
Adj.R^2	0.0271	0.0436	0.0707	0.0859	0.1008	0.1165	0.1269

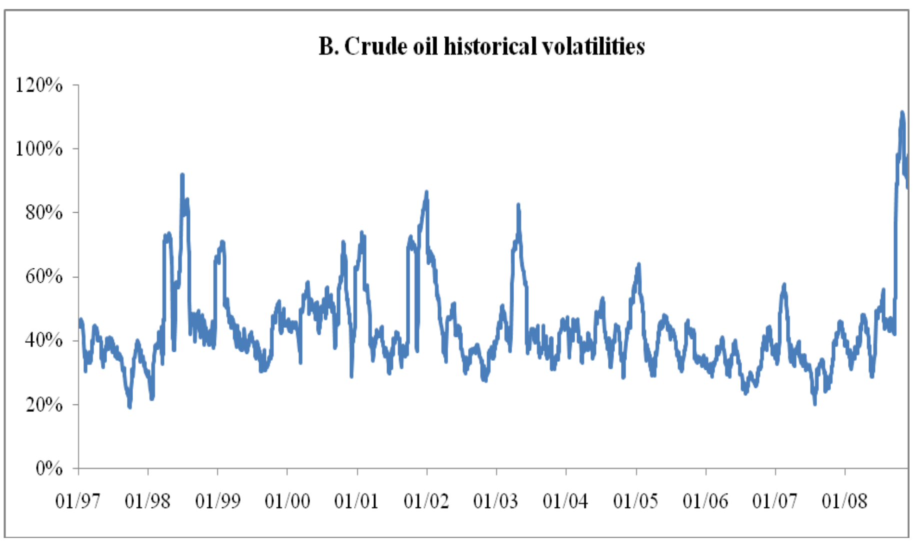
<u>Natural Gas</u>

Nearby	GI4	GI3	GI2	GI1	GO1	GO2	GO3
α	0.1022	0.0618	0.0507	0.0505	0.0420	0.0627	0.1044
s.e	0.0584	0.0483	0.0542	0.0524	0.0571	0.0655	0.0772
β_1	$0.6940^{**,}$	0.7492^{**}	0.7593^{**}	0.7579^{**}	0.7694^{**}	0.7097^{**}	$0.6326^{**,}$
s.e	0.1813	0.1587	0.1501	0.1631	0.1723	0.1792	0.1893
β_2	0.1303	0.1173	0.1187	0.1132	0.1029	0.1050	0.1126
s.e	0.1553	0.1559	0.1472	0.1492	0.1569	0.1554	0.1493
Adj. R^2	0.2647	0.3511	0.3236	0.3316	0.3208	0.2715	0.2302
Second							
α	0.1395^{*}	0.1174	0.1076	0.1086	0.0927	0.0987	0.0899
s.e	0.0694	0.0682	0.0680	0.0657	0.0717	0.0719	0.0757
β_1	0.8792^{**}	0.9287^{**}	0.9296^{**}	0.9094^{**}	0.8798^{**}	0.8364^{**}	0.8492^{**}
s.e	0.1578	0.1638	0.1685	0.1607	0.1724	0.1712	0.1865
β_2	-0.1111	-0.1323	-0.1292	-0.1258	-0.0809	-0.0694	-0.0803
s.e	0.1548	0.1506	0.1487	0.1460	0.1693	0.1708	0.1788
Adj. R^2	0.4513	0.4597	0.4558	0.4527	0.4360	0.4210	0.4049

Third							
α	0.1984**	0.1803*	0.1715*	0.1592*	0.1596*	0.1433	0.1436
s.e	0.0693	0.0742	0.0748	0.0763	0.0806	0.0832	0.0833
β_1	0.5062**,	0.5382**,	0.5393**,	0.5631**,	0.5759**,	0.5777**,	0.5714**,
s.e	0.1732	0.1783	0.1747	0.1987	0.1922	0.2105	0.2088
β_2	0.0400	0.0431	0.0527	0.0548	0.0315	0.0537	0.0478
s.e	0.1641	0.1759	0.1791	0.1906	0.1935	0.2103	0.2199
Adj. R^2	0.3130	0.3204	0.3247	0.3243	0.3210	0.3163	0.3099
Fourth							
α	0.2228**	0.1999*	0.1894*	0.1716*	0.1591	0.1478	0.1415
s.e	0.0854	0.0849	0.0831	0.0837	0.0837	0.0833	0.0839
β_1	0.5365*,†	0.6190**	0.6065**	0.6410**	0.6707**	0.6815**	0.6846**
s.e	0.2670	0.2633	0.2571	0.2483	0.2491	0.2486	0.2490
β_2	-0.0363	-0.0744	-0.0538	-0.0519	-0.0660	-0.0659	-0.0701
s.e	0.2083	0.2073	0.2047	0.2018	0.2040	0.2055	0.2085
Adj. R^2	0.2247	0.2673	0.2690	0.2908	0.3094	0.3188	0.3222

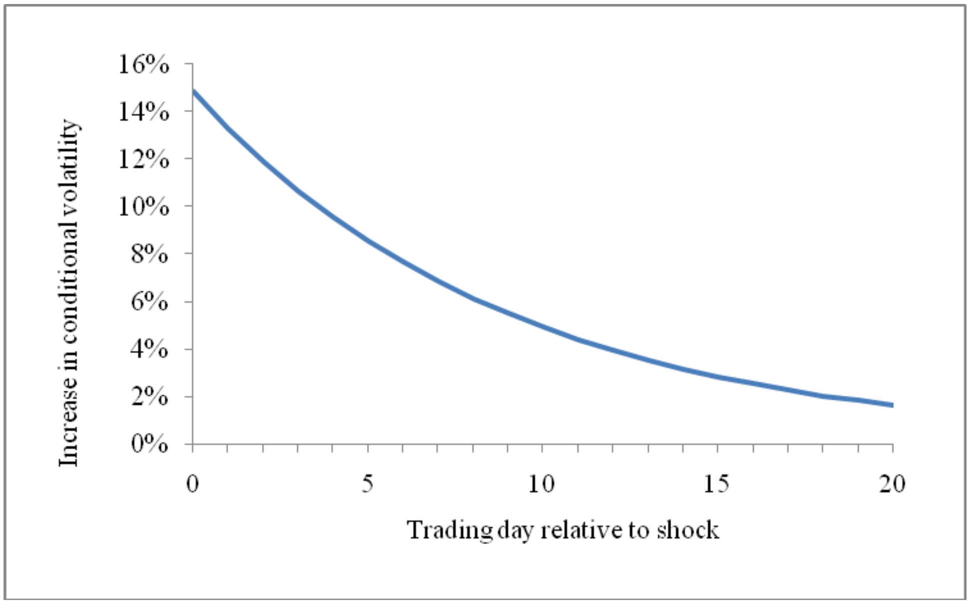
Figure 1. Crude oil prices and historical volatilities from January 1997 to November 2008





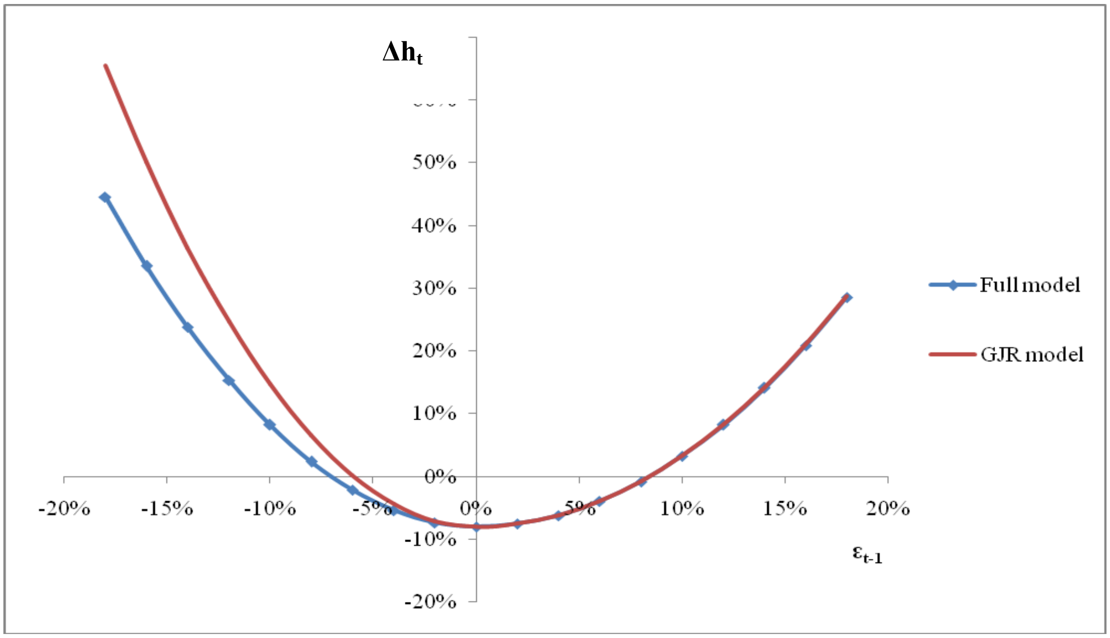
This figure presents crude oil prices and historical volatilities from January 1997 through November 2008. The vertical axes depict nearby futures prices and annualized rolling 30-day standard deviations of returns.

Figure 2. The change in conditional volatility following an oil return shock



This figure presents the impact of a two-standard deviation oil return shock on the predicted volatility. Suppose the conditional variance, h_{t-1}=Var(ζ_{t-1}) is at its steady-state level and suppose there is a shock such that ζ_{t-1}^2= 4Var(ζ_{t-1}). This figure demonstrates the percentage difference in expected volatility on day t+x and on day *t*-1, $\left[\frac{\mathrm{Var}(\zeta_{t+x})}{\mathrm{Var}(\zeta_{t-1})}\text{-1}\right]$, assuming E($\zeta_{t+x}^2$) = Var($\zeta_{t+x}$) for x > -1 and that negative and positive return shocks are equally likely.

Figure 3. Estimated News Impact Curves



This figure depicts how equal positive and negative return shocks at time t-1 impact predicted volatility in the crude oil market according to the estimates of the GJR model and those of the full model. These curves demonstrate how a return shock in time t-1, ε_{t-1}, is incorporated into volatility estimates (as measured by Δh_t, the percentage change in conditional variance from day t-1 to day t). h_{t-1} is assumed to be equal the unconditional variance.

Figure 4. Conditional covariance between crude oil prices and the value of the dollar

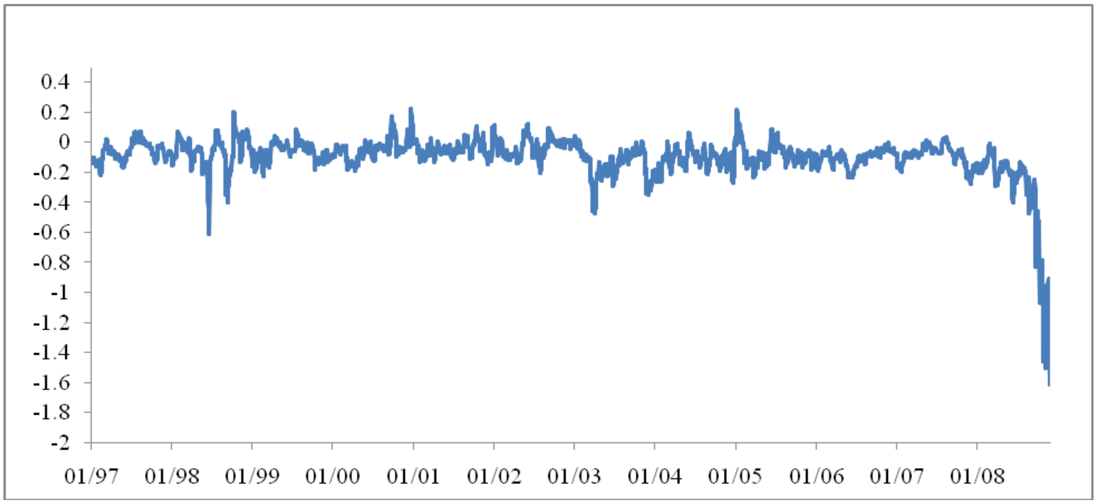


Figure 5. Conditional correlation between crude oil prices and the value of the dollar

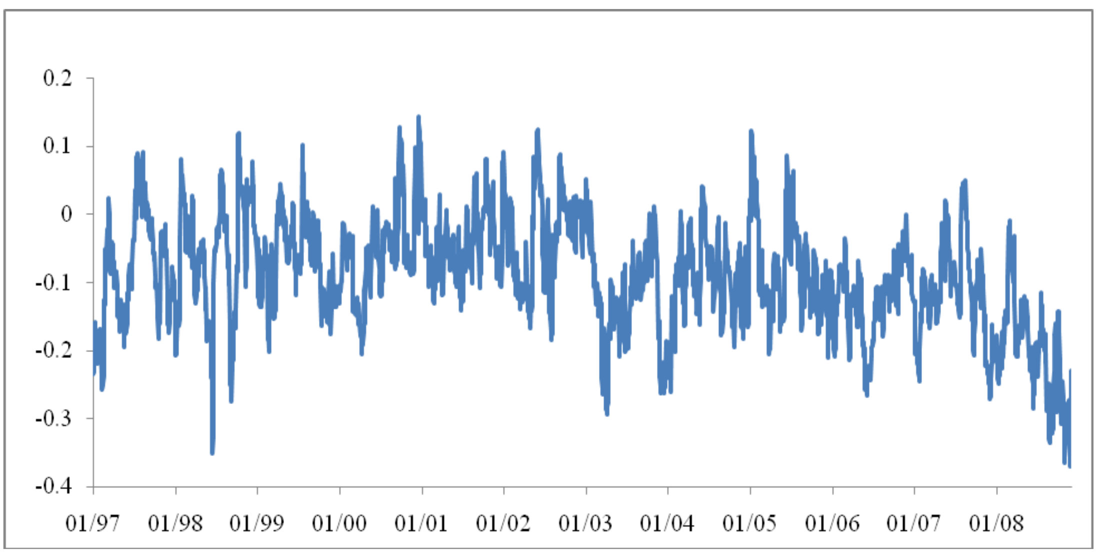
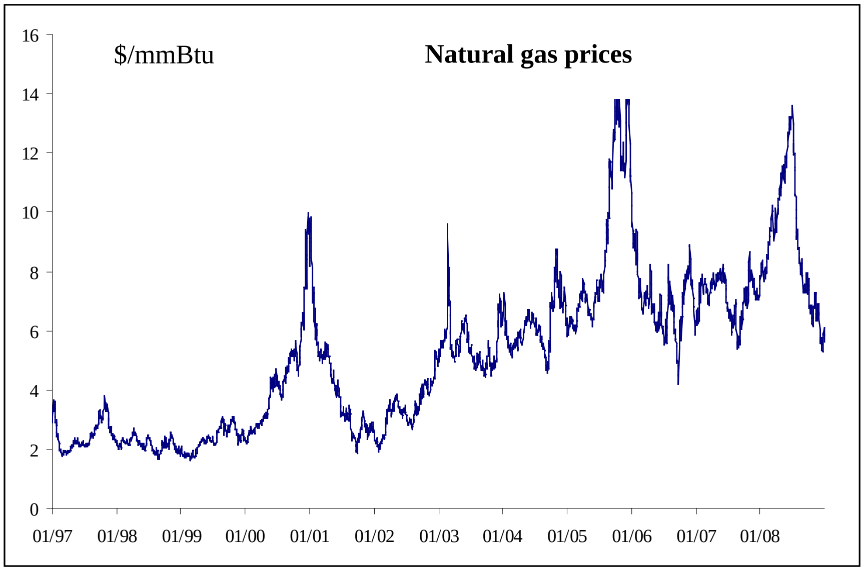
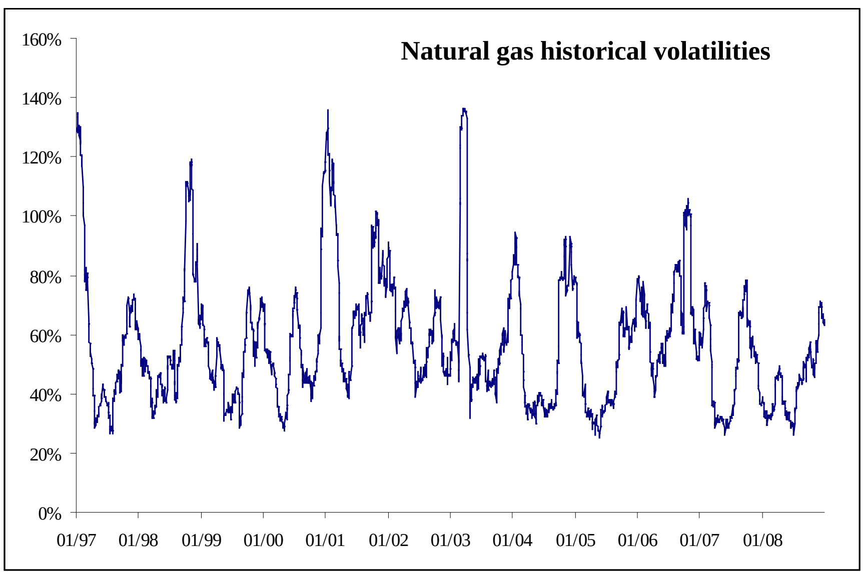


Figure 6. Natural gas prices and historical volatilities from January 1997 to December 2008

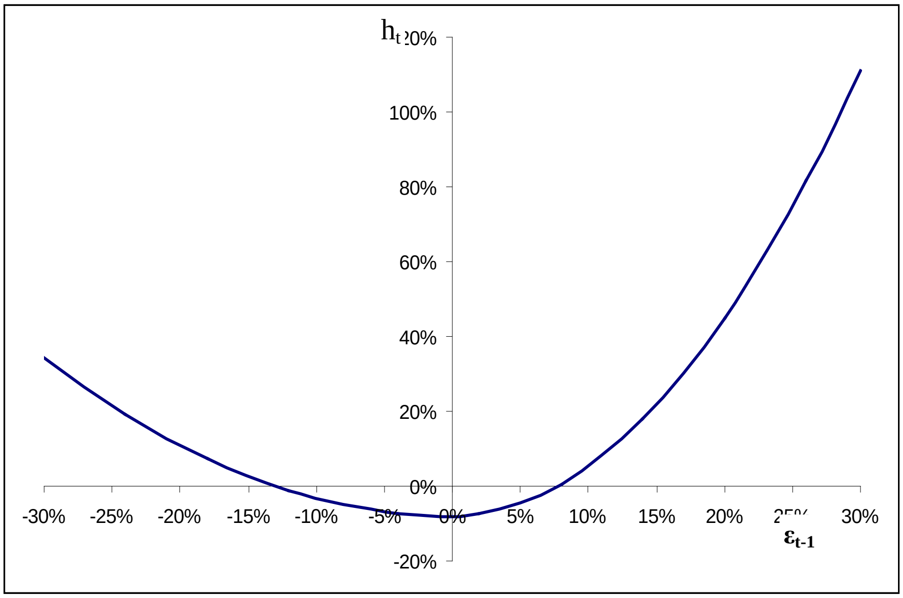




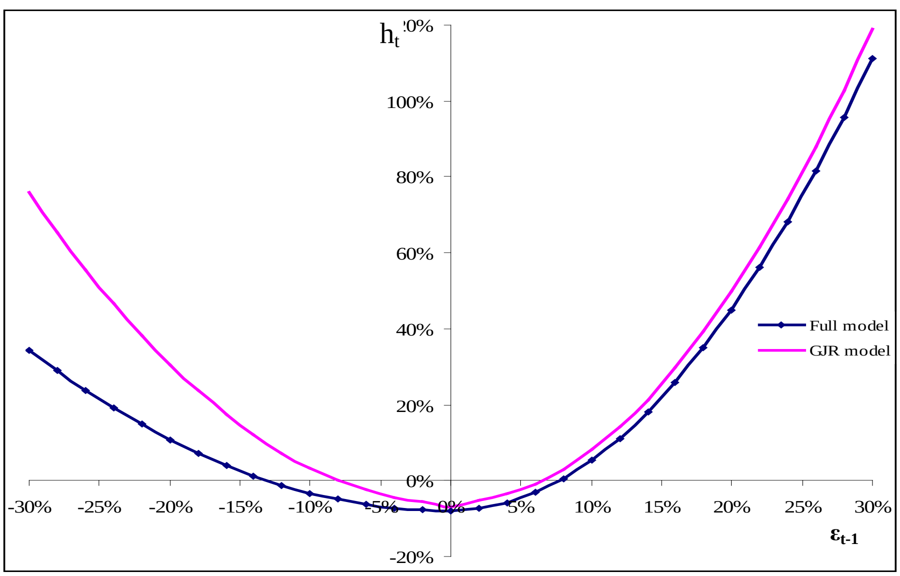
This figure presents natural gas prices and historical volatilities from January 1997 through December 2008. The vertical axes depict nearby futures prices and annualized rolling 30-day standard deviations of returns.

Figure 7. Estimated News Impact Curves

7.a

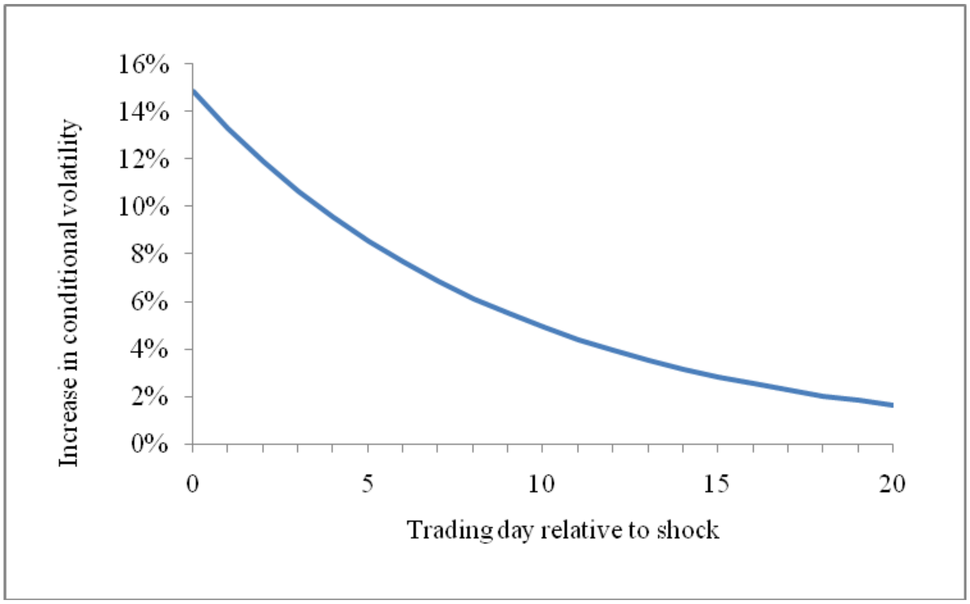


7.b



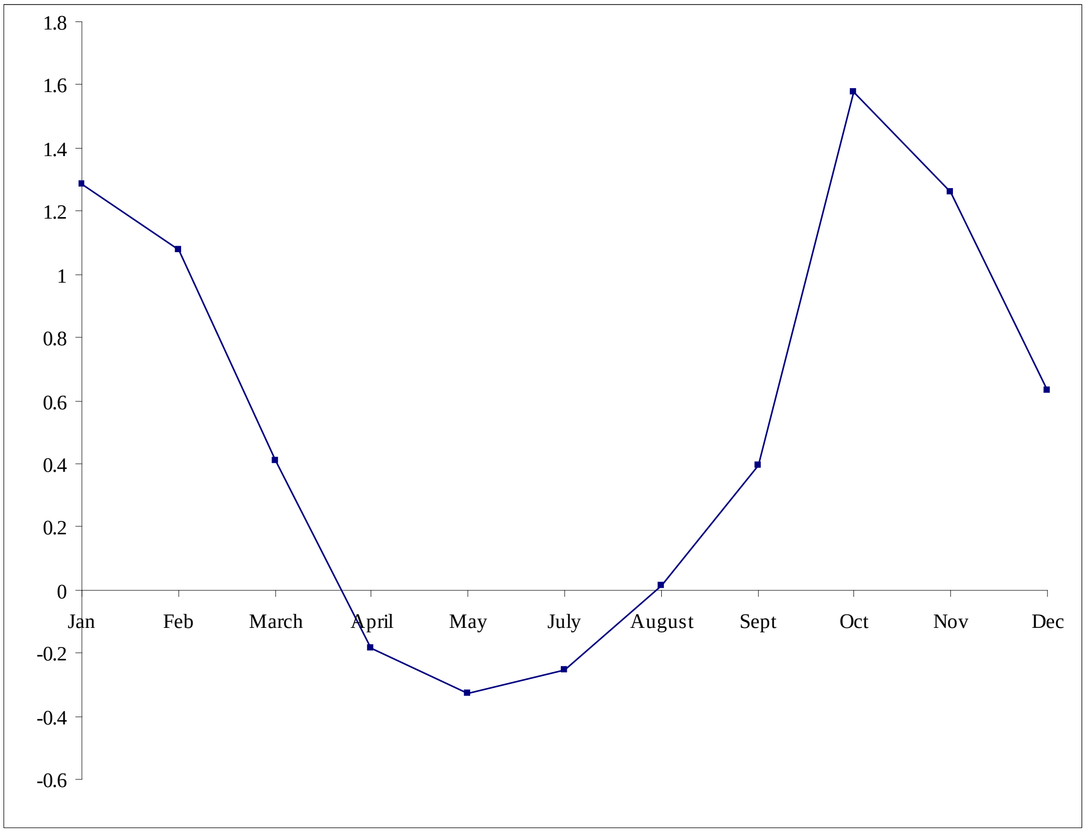
This figure depicts how equal positive and negative return shocks at time *t-1* impact predicted volatility in the natural gas market according to the estimates of the GJR model and those of the full model (in the second and third columns of Panel B in Table 2). These curves demonstrate how a return shock in time *t-1*, ε_{t-1}, is incorporated into volatility estimates (as measured by Δh_t), the percentage change in conditional variance from day *t-1* to day *t*). h_{t-1} is assumed to be equal the unconditional variance.

Figure 8. The change in conditional volatility following a return shock



This figure presents the impact of a two-standard deviation natural gas return shock on the predicted volatility. Suppose the conditional variance, h_{t-1}=Var(ζ_{t-1}) is at its steady-state level and suppose there is a shock such that ζ^2_{t-1} = 4Var(ζ_{t-1}). This figure demonstrates the percentage difference in expected volatility on day *t+x* and on day *t*-1, $\left[\frac{\mathrm{Var}(\zeta_{t+x})}{\mathrm{Var}(\zeta_{t-1})}\text{-}1\right]$, assuming E($\zeta^2_{t+x}$) = Var($\zeta_{t+x}$) for x > -1 and that negative and positive return shocks are equally likely.

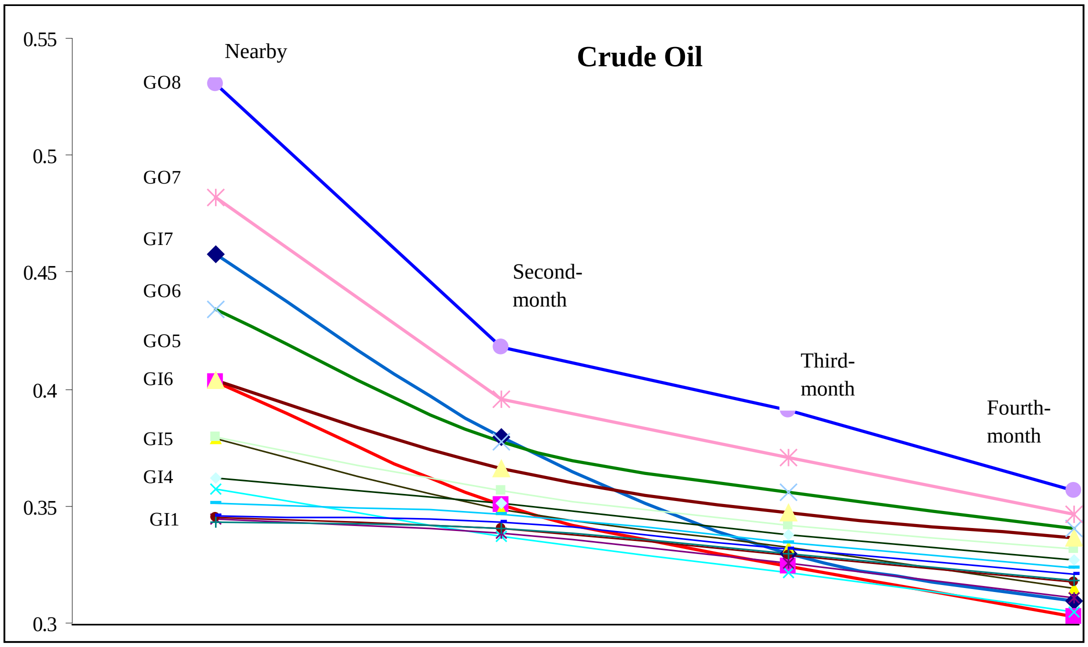
Figure 9. Time-of-the-year pattern



This figure presents the month-of-the-year pattern according to the estimates in the third column of Panel B in Table 2. The vertical axis depicts the ratio of the average variance of natural gas volatility on the futures contract expiring in a certain month to that on the futures contract expiring in June.

Figure 10. Implied Volatility Term Structure

This figure presents the mean ISD of each "moneyness" subsample in each maturity group. "I" or "O" indicates whether the call option is ITM (low-strike calls) or OTM (high-strike calls) and the third digit denotes the "moneyness" where "1" is the closest to the money. The *Y*-axis measures the mean ISD for each strike price at each maturity.



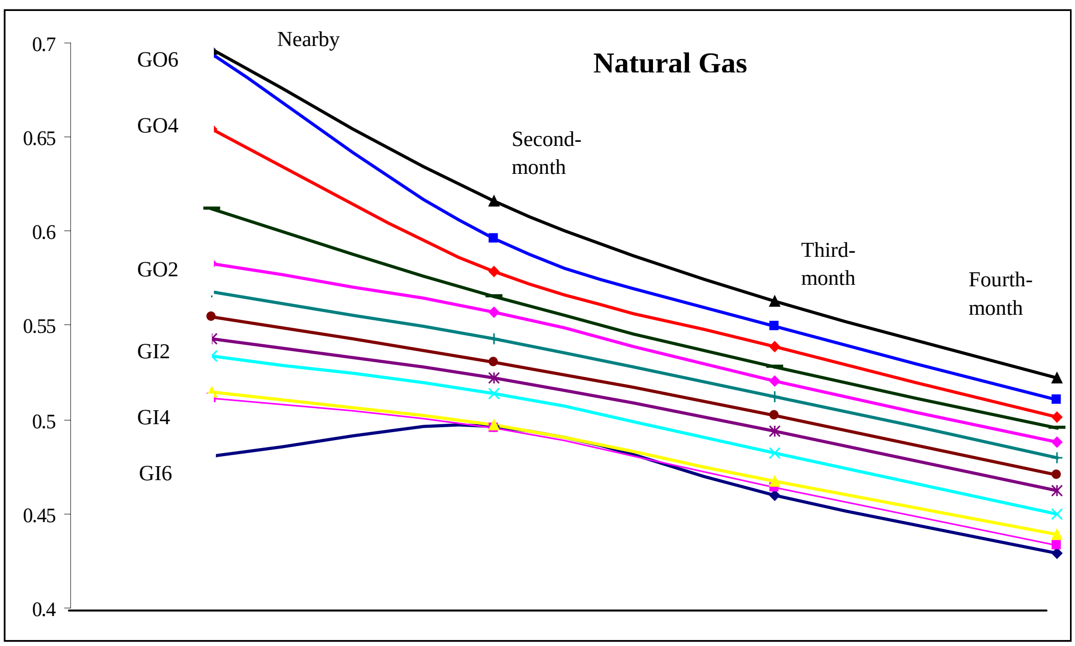
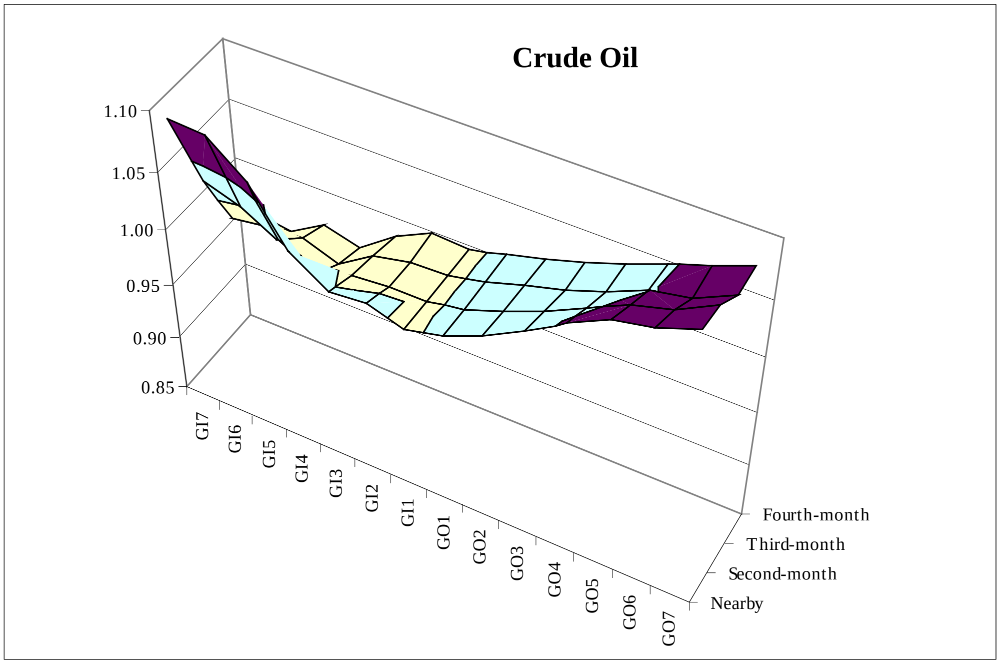


Figure 11. Volatility Surface

This figure presents surface plots showing the mean relative ISD graphed against each "moneyness" group and time-to-maturity. "I" or "O" indicates whether the call option is ITM (low-strike calls) or OTM (high-strike calls) and the third digit denotes the "moneyness" where "1" is the closest to the money. The vertical axis measures the mean ratio of the ISD for that strike price relative to the average of the two nearest-the-money options, i.e, GI1 and GO1.



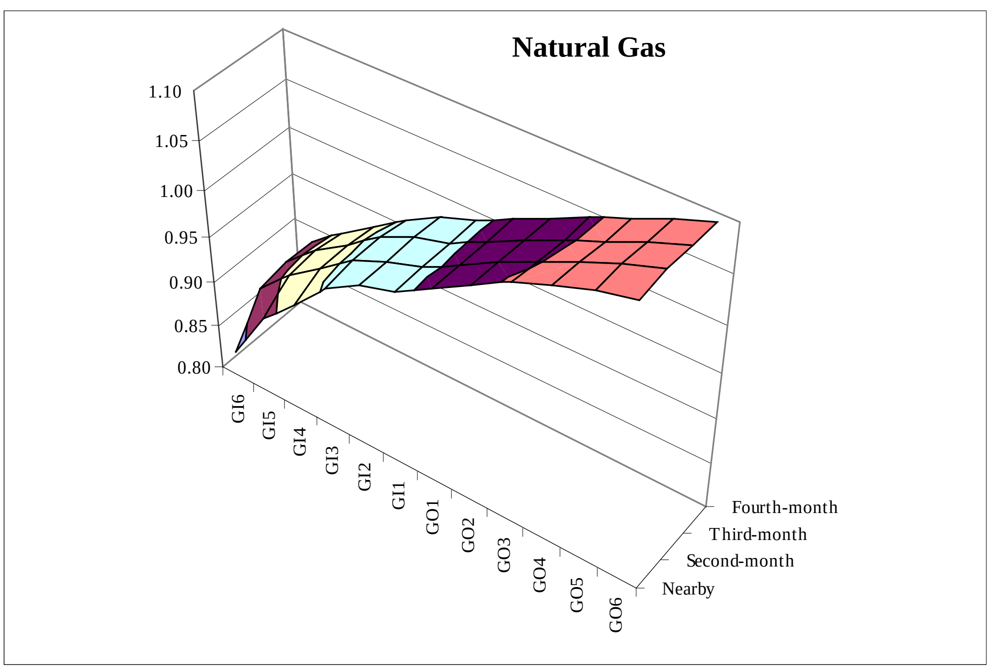
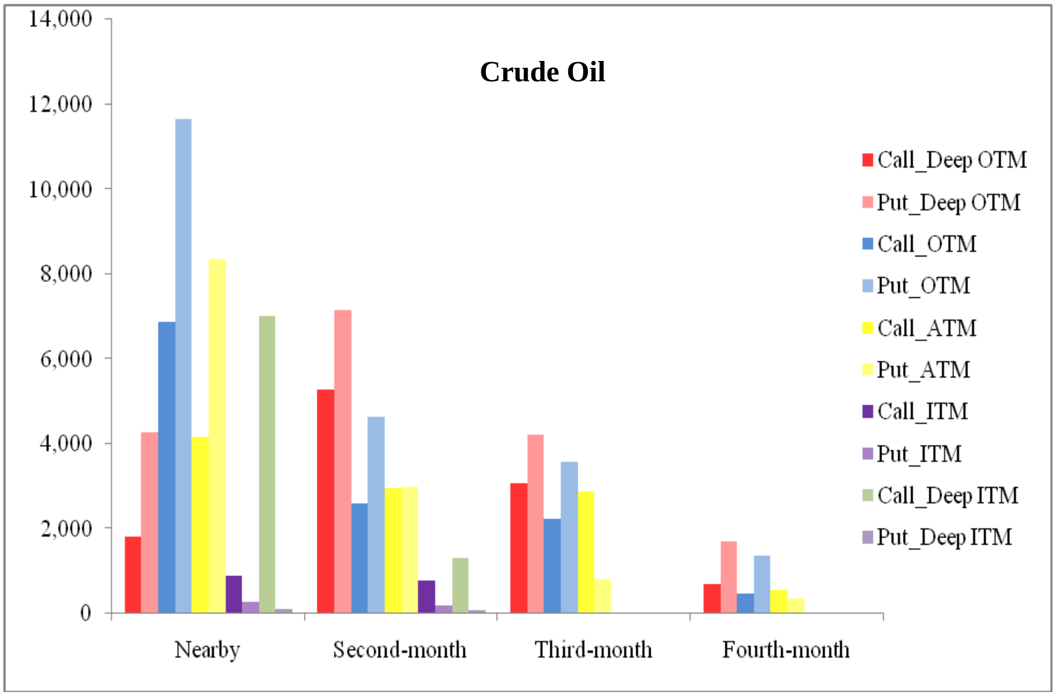


Figure 12. Average Trading Volume

This figure presents the average number of crude oil and natural gas call and put options traded per day during the period from September 1999 through June 2006.



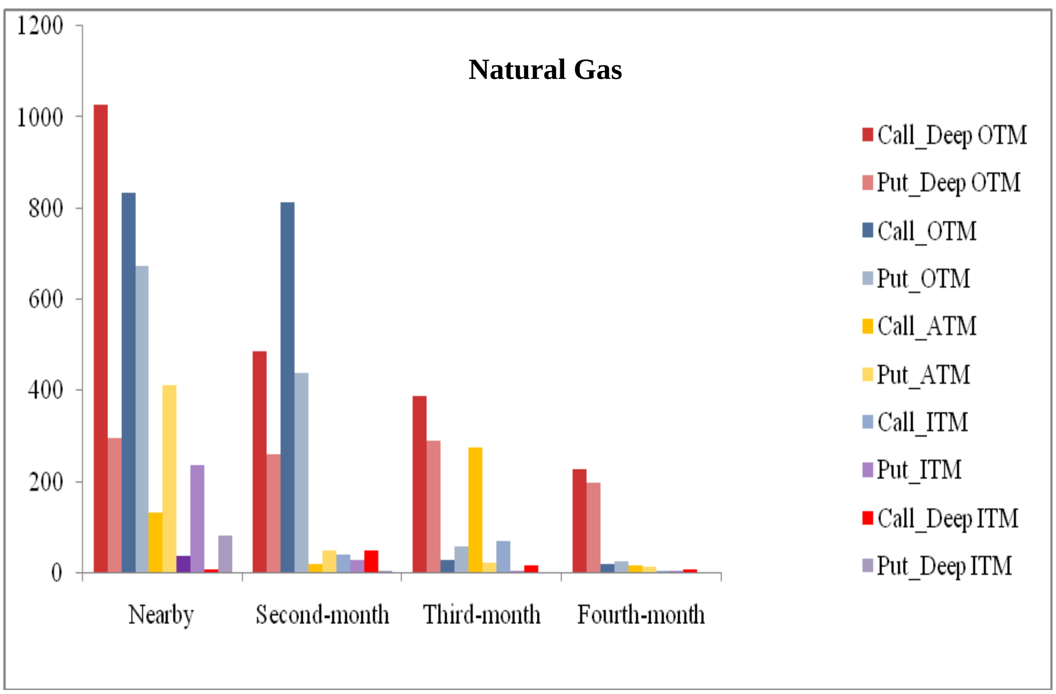
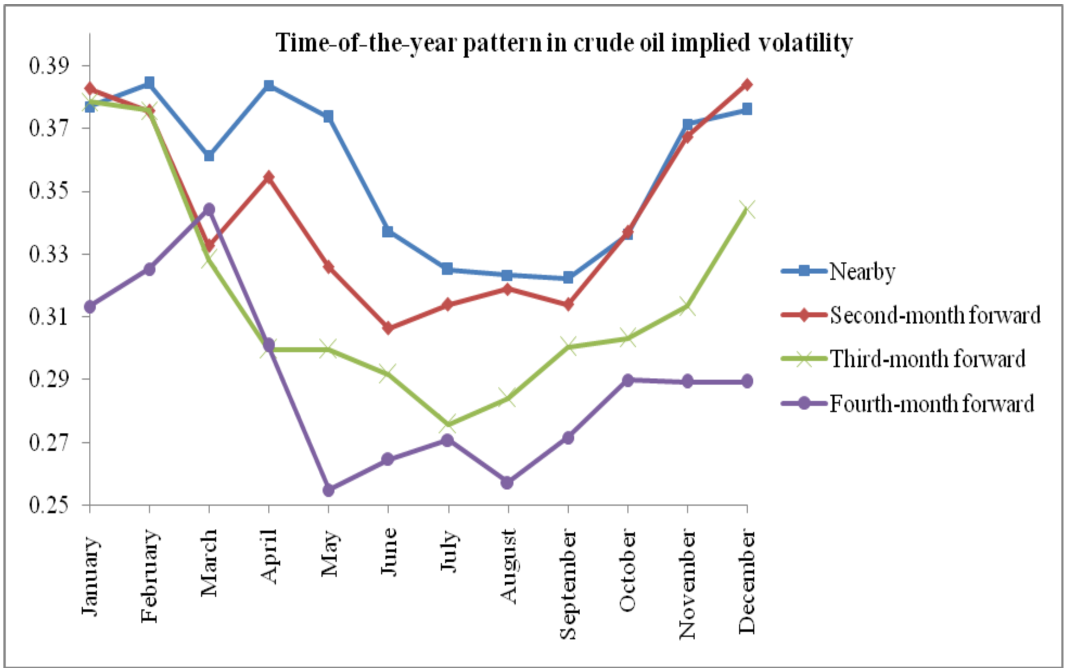


Figure 13. Time-of-the-year pattern in implied volatility

These graphs present mean values of the implied forward volatility by month-of-the-year. The horizontal axis presents the expiration month of the option contract.



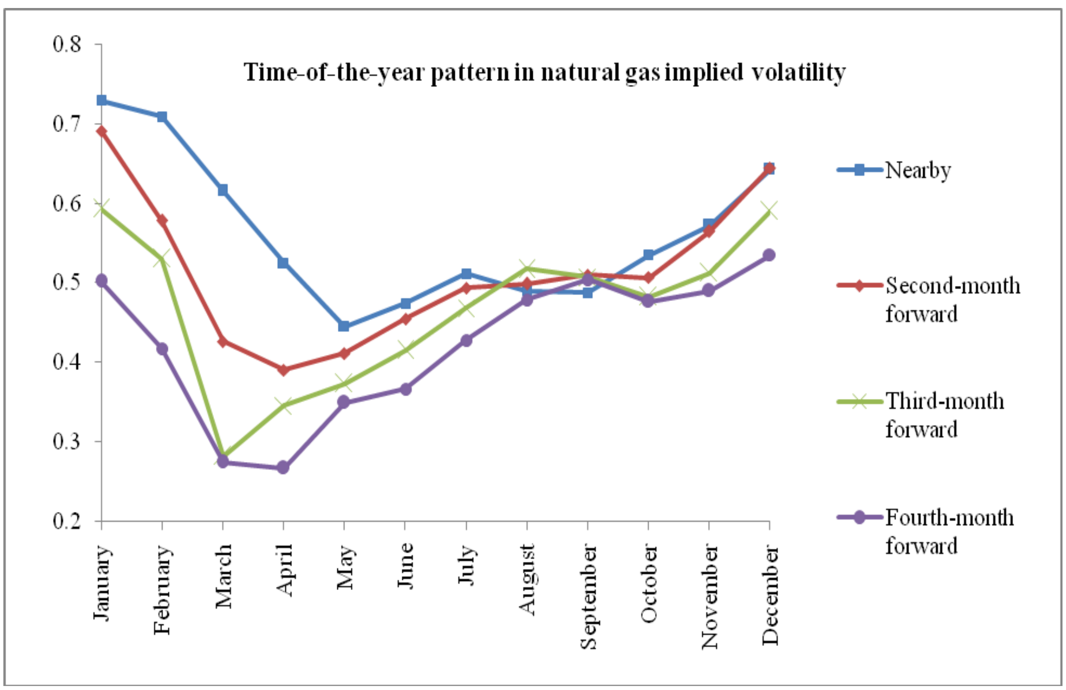
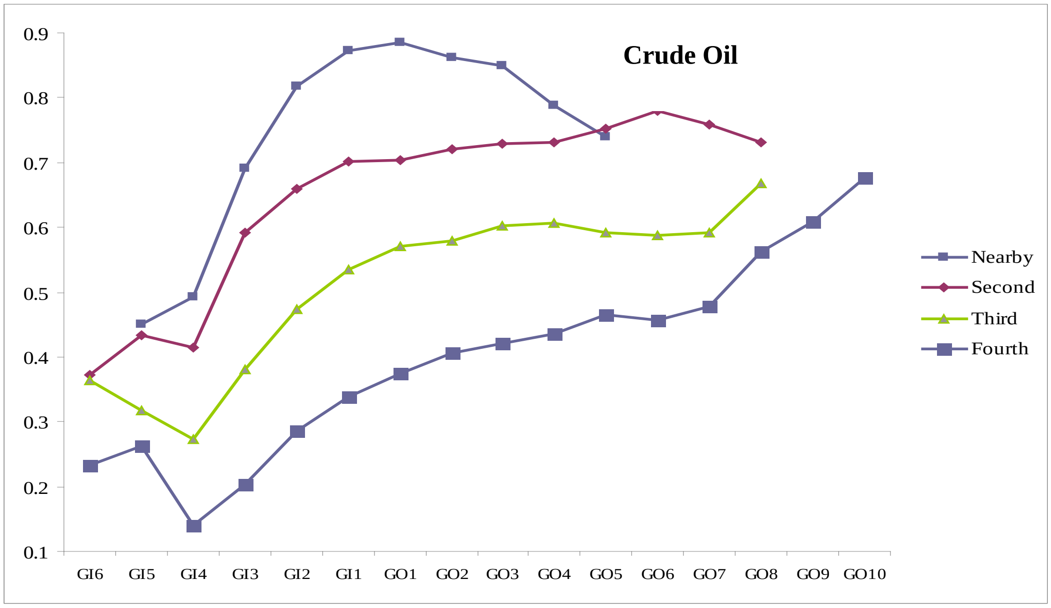


Figure 14. The Slope Coefficient of Implied Volatility by "Moneyness"

The slope coefficient, $\hat{\beta}_1$ from estimation results of the equation $\sigma_t(\tau) = \alpha + \beta_1 \cdot ISD_{i,j,t} + u_{i,j,t}$, is graphed against the "moneyness" bin for each maturity group. The X-axis represents the "moneyness" bin and the Y-axis measures the slope coefficient of implied volatility for that "moneyness" bin.



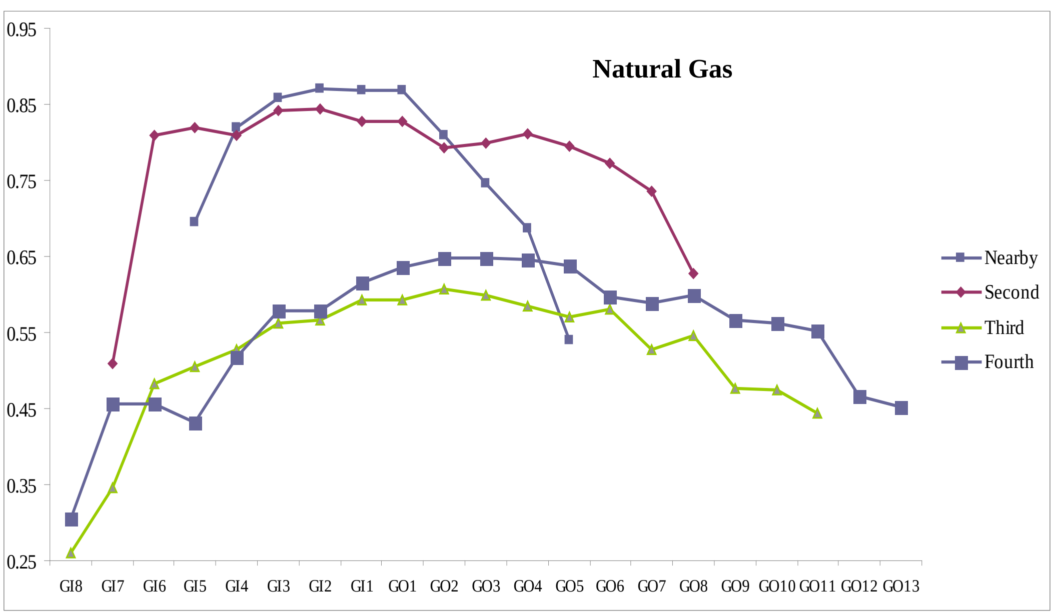


Figure 15. The information "frown" in option prices: relative forecasting power of the implied volatility by "moneyness"

The forecasting power of the equation $\sigma_t(\tau) = \alpha + \beta_1 \cdot ISD_{i,j,t} + u_{i,j,t}$, is graphed against the "moneyness" for each maturity group. The *X*-axis represents each "moneyness" bin, the *Y*-axis measures relative forecasting power as the reciprocal of the ratio of the sum of squared errors (SSE) from the regression (2) for each "moneyness" bin *j* to the SSE for a regression with the average ISD for ATM options as the independent variable over observations common to both regressions.