The Information Content of Implied Volatility in the Crude Oil and Natural Gas Markets

Duong Le
Marietta College

This paper explores the forecasting power of implied volatilities (IVs) in the crude oil and natural gas options markets from 2005 through 2012. In these markets, IVs are efficient forecasts of future volatility. The information content of oil and gas IVs differs substantially and systematically by strike price displaying a "frown" pattern which is roughly the mirror image of the IV smile pattern. For crude oil options, the most informative in terms of predicting future volatility are IVs on nearby group and deep in-the-money options. For natural gas options, IVs from near-the-money options contain considerable information regarding future volatility.

INTRODUCTION

This paper explores the forecasting power of implied volatilities calculated from crude oil and natural gas call options traded on the New York Mercantile Exchange (NYMEX) from January 2005 through December 2012. Volatility is a key input into option pricing formulas, value-at-risk modeling, portfolio allocation, and risk management and therefore, an accurate volatility forecast is essential to market participants.

Forecasting volatility has traditionally been done using the generalized autoregressive conditional heteroscedasticity (GARCH) approach by Bollerslev (1986) and Engle (1982). The GARCH framework is also used in energy commodity markets (see, for example, Marzo and Zagaglia, 2010 and Wei et al., 2010). It has long been documented that there are other sources of information about future volatility than GARCH-based forecast. A natural candidate is implied volatility, the volatility that equates the theoretical price of an option according to an option pricing formula with the observed market price, which reflects the market's expectation of future volatility over the life of the option. Theoretically, implied volatility has a number of practical advantages over GARCH models. Implied volatility uses a larger information set and furthermore, it can also take into account events such as announcements of macroeconomic indicators (see Jorion, 1995) or releases of oil and gas storage reports.

If markets are efficient and the option pricing model is correct, implied volatilities should be unbiased forecasts of future volatility and should fully subsume all available information, including the underlying asset's price history. However, numerous studies find that, when realized volatility is regressed on implied volatility and measures of historical volatility, (1) the coefficient of implied volatility is invariably less than one, implying that implied volatility is a biased estimator and (2) historical volatility often has a significant positive coefficient, indicating that implied volatility does not efficiently impound all information in the historical record (see, for example, Bollerslev et. al, 2013 and references within).

The forecasting power of implied volatility calculated from option prices has been a subject of intense research activity in recent decades. 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[1], foreign exchange options market[2], futures options markets[3], Eurodollar options market[4], etc. In contrast to the literature on equity and other financial options, research on crude oil and natural gas options markets has been quite sparse. This is particularly surprising for the crude oil and natural gas markets considering the economic importance of these energy markets 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.

This study is motivated by the limited nature of previous research on the information content of crude oil and natural gas implied volatilities. Day and Lewis (1993) find that crude oil IV outperforms historical volatility in forecasting future volatility. Szakmary et al. (2003) report that IV calculated from crude oil and natural gas options is a biased but still efficient forecast of future volatility. Martens and Zein (2004) find that both realized volatility and IV contain useful information in forecasting crude oil volatility. Agnolucci (2009) documents that GARCH-type models seem to perform better than IV. Haugom, Langeland, Molnar, and Westgaard (2014) find evidence that IV significantly improves daily and weekly volatility forecasts. However, the results in previous studies are limited to IVs calculated from nearby at-the-money options. This limitation is due to the data sets used in those studies which only include nearby at-the-money options. On the contrary, in this study, we construct a dataset that includes IVs across various strike prices for a range of terms to maturity to (1) examine the forecasting power of IV across strike prices and terms to maturity and (2) explore whether IV calculated from a strike price and maturity group is an unbiased and/or efficient forecast of actual volatility. This research is motivated by the results from Ederington and Guan (2005) for the stock index options. Contrary to the conventional notion that at-the-money IVs are the most informative, Ederington and Guan (2005) find significant evidence that for stock index options, IVs calculated from 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.

While the forecasting performance of oil and gas IVs from nearby at-the-money options has been the subject of previous research, we 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 us to consequently explore the differences in the forecasting power of oil and gas IVs by strike price and maturity. The main findings and contributions to the literature can be summarized as follows. Although the unbiasedness of crude oil and natural gas IVs depends on the term to maturity and moneyness of the options, IV is a fairly efficient forecast of future volatility in these markets. 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. Consequently, results in this study have implications for market practitioners who need to better understand the behavior of oil and gas IVs for valuation purposes.

The paper is organized as follows. The data and sampling procedure are provided in Section 2. Section 3 presents the model framework. The forecasting performance of oil and gas IVs is reported in Section 4. Section 5 concludes the paper.

DATA AND SAMPLING PROCEDURE

The data

Actual and implied volatilities are calculated from daily settlement prices of light, sweet crude oil and natural gas futures and call options written on these futures contracts traded on the New York Mercantile Exchange (NYMEX) from January 3, 2005 through December 31, 2012. According to NYMEX, crude oil and natural gas futures and options are the world's most and third-largest physical commodity futures and option contracts in the world by volume. For example, in 2013, daily average trading volume of crude oil is 900,000 futures and options contracts and the largest open interest for both contracts reached 7.5 million lots. Price data on oil and gas futures and futures options traded on the NYMEX over the sample assessed in this study have been obtained from the Commodity Research Bureau (http://www.crbtrader.com).

There are a number of advantages to using the NYMEX options on futures. First, the NYMEX futures and options on futures closing prices are observed at the same time and therefore, we can avoid the nonsynchronous data problem. Second, since the underlying futures and options are traded side by side in a very liquid market with minimal transaction costs, it is unlikely that the market will suffer from asymmetric information dissemination which is the main source of measurement errors in examining implied volatility (Jorion, 1995).

Two exclusionary criteria are applied to the data. First, we eliminate options with less than 7 calendar days 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, we 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 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 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 call 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.

We denote the "moneyness" bin as GIk or GOk, where "I" or "O" indicates whether the call 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 $F \cdot \left\{1 - \frac{4(k-1)}{100}\right\}$.

We 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.

Realized volatility

We 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.

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

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*.

Implied volatility

Using Black's (1976) model for options on futures, day *t* closing prices for both the futures and call options on futures, and risk-free interest rate, we 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. While Black model ISDs may not be the most appropriate, these are the ISDs used in previous literature so we continue this approach for comparability[5]. In the case of a call option, ISD can be obtained by inverting $C = [F_t N(d_1) - X N(d_2)]e^{-rT}$ where *C* is the price of the call, F_t is the current futures price, *T* is the time to expiration of the option, *X* is the strike price of the option, *r* is the risk-free interest rate, while *N* indicates the value of the cumulative normal distribution evaluated at $d_1 = [ln(F_t / X) + (\sigma_t^2 / 2)T] / \sigma_t\sqrt{T}$ and $d_2 = d_1 - \sigma_t\sqrt{T}$. The term σ_t denotes the standard deviation of the futures contract, i.e., our unknown variable. Following Day and Lewis (1993), we compute the risk-free interest rate from the US Treasury bill with closest maturity but following the expiration date. Data on the US Treasury bill have been obtained from the US Treasury (www.treasurydirect.gov). For easier interpretation, these ISDs are annualized by being multiplied by the square root of 252.

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). Le (2015) finds that in the crude oil market, the three-day weekend return variance is 18.32% higher than the average weekday variance, which is still not as large as the calendar day assumption implies.

Consequently, we adjust $ISD_{i,j,t,C}$ to a trading day basis. In particular, we 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. We use $ISD_{i,j,t,T}$ throughout this study and omit the subscript *T* for simplicity.

Table 1 reports the summary statistics of crude oil and natural gas ISDs for the sample period.

TABLE 1
SUMMARY STATISTICS

This table presents the summary statistics of crude oil and natural gas implied standard deviations calculated from daily settlement prices of nearby, second-, third-, and fourth-month futures and call options on futures from January 03, 2005 to December 31, 2012.

Crude Oil	2005	2006	2007	2008	2009	2010	2011	2012
Mean	0.3516	0.3152	0.3502	0.3708	0.3595	0.3418	0.3205	0.2479
Median	0.3571	0.3113	0.3153	0.3615	0.3295	0.3445	0.3209	0.2524
Maximum	0.5452	0.5794	0.9832	0.8582	0.7968	1.2222	1.1841	0.3446
Minimum	0.1090	0.1215	0.0848	0.1910	0.1929	0.0635	0.0851	0.0858
Std. Dev.	0.0429	0.0507	0.0986	0.0491	0.0796	0.0495	0.0323	0.0287
Skewness	-0.6924	0.3348	1.0978	0.6272	1.6052	2.7198	0.5415	-1.0748
Kurtosis	4.15	3.73	3.50	4.04	5.49	4.01	6.50	5.12
Number of Obs	1,756	7,050	6,989	8,647	10,085	13,195	18,143	8,739
2nd decile	0.3188	0.2756	0.2755	0.3282	0.3016	0.3033	0.2985	0.2287
4th decile	0.3469	0.3010	0.3024	0.3507	0.3202	0.3321	0.3144	0.2462
6th decile	0.3678	0.3228	0.3297	0.3752	0.3432	0.3573	0.3275	0.2582
8th decile	0.3871	0.3543	0.4538	0.4175	0.4188	0.3792	0.3432	0.2703
Natural Gas								
Mean	0.5518	0.5555	0.6033	0.5409	0.5367	0.4701	0.4024	0.5618
Median	0.5649	0.5519	0.5961	0.5409	0.5260	0.4335	0.3866	0.5526
Maximum	0.7272	1.4800	1.4296	1.0262	1.2022	0.9732	0.9371	0.8885
Minimum	0.2383	0.1126	0.1820	0.2625	0.2039	0.1508	0.1293	0.2031
Std. Dev.	0.0778	0.1694	0.1335	0.0621	0.1074	0.1376	0.0889	0.1035
Skewness	-0.7014	1.2046	0.5247	0.0460	0.9612	0.8213	0.9885	0.0913
Kurtosis	3.48	6.21	3.16	3.55	5.52	2.81	4.13	2.36
Number of Obs	1,425	8,111	8,481	10,883	15,615	15,384	11,938	7,324
2nd decile	0.4869	0.4232	0.4865	0.4900	0.4512	0.3518	0.3324	0.4678
4th decile	0.5422	0.5216	0.5629	0.5255	0.5020	0.3986	0.3683	0.5162
6th decile	0.5825	0.5811	0.6231	0.5567	0.5524	0.4717	0.4054	0.5971
8th decile	0.6176	0.6472	0.7039	0.5923	0.6137	0.5995	0.4603	0.6601

MODEL FRAMEWORK

If markets are efficient and the option pricing model is correct, 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).

$$\sigma_{j,t} = \alpha + \beta_1 \cdot ISD_{j,t} + u_{j,t} \quad (2)$$

and

$$\sigma_{j,t} = \alpha' + \beta_1' \cdot ISD_{j,t} + \beta_2' \cdot HIS_{j,t} + u_{j,t} \quad , \quad (3)$$

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 α = 0 and β_1=1 in Equation (2) and α' = 0, β_1'=1 in Equation (3). If IV efficiently impounds all available information included in historical volatility, β_2' should be zero in Equation (3). Virtually all studies find that 0<β_1<1 and 0<β_1'<1 and most find that α >0 (Ederington and Guan, 2005, Haugom et al., 2014). Thus, the evidence in most options markets implies that IV is a biased predictor of realized volatility. There is mixed evidence of whether IV is efficient, i.e., whether β_2' is significant in Equation (3)[6].

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

$$\sigma_{i,t}(\tau) = \alpha + \beta_1 \cdot ISD_{i,j,t} + u_{i,j} \quad (2)$$

and

$$\sigma_{i,t}(\tau) = \alpha' + \beta_1' \cdot ISD_{i,j,t} + \beta_2' \cdot HIS_{i,j,t} + u_{i,j} \quad (3)$$

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. We 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: $R_t = \text{Ln}\left(\frac{F_t}{F_{t-1}}\right)$ 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 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, we employ Hansen's correction, (see Hansen, 1992), the most common procedure in the literature[7].

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 (3)]. X is the $N \times 2$ matrix of the X_n. [X is the $N \times 3$ for regressions based on Equation (3)]. 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, we compute

$$\hat{\Psi} = \sum_{n=1}^{N} (\hat{u}_n)^2 X'_n X_n + \sum_{k=1}^{N} \sum_{n=k+1}^{N} Q(k,n) \hat{u}_k \hat{u}_n (X'_n X_k + X'_k X_n), \qquad (6)$$

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 variable of the overlap between observations k and n. For observations on options with the same expiry observed on the same day, $Q(k,n) = 1$ if there is an overlap between the periods to expiration for the two options, and if there is no overlap, $Q(k,n) = 0$.

The corrected variance-covariance matrix for the estimated coefficients is

$$\hat{\Omega} = (X'X)^{-1}\hat{\Psi}(X'X)^{-1}, \quad (7)$$

We report the t-statistics based on the corrected standard errors after applying the Hansen correction.

RESULTS

TABLE 2
REALIZED VOLATILITY REGRESSED ON IMPLIED VOLATILITY

The table reports regression results from Equation (2): $\sigma_t(\tau) = \alpha + \beta_1 \cdot ISD_{i,j,t} + u_{i,j,t}$, for each of the subsample defined by maturity and "moneyness" of oil and gas options between January 3, 2005, and December 31, 2012. 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	GI6	GI5	GI4	GI3	GI2	GI1	GO1	GO2	GO3	GO4	GO5
α		0.1678**	0.1561**	0.0928*	0.0497	0.0342	0.0283	0.0314	0.0285	0.0414	
s.e		0.0462	0.0430	0.0448	0.0456	0.0462	0.0473	0.0481	0.0522	0.0579	
β_1		0.4494**,††	0.4930**,††	0.6917**,†	0.8179**	0.8717**	0.8851**	0.8614**	0.8486**	0.7881**	
s.e		0.1306	0.1321	0.1418	0.1439	0.1473	0.1498	0.1497	0.1581	0.1692	
Adj.R^2		0.0785	0.1085	0.1727	0.2158	0.2287	0.2304	0.2303	0.2257	0.2081	
Y ratio		0.9161	0.9212	0.9379	0.9662	0.9993	1.0002	0.9990	0.9890	0.9730	
Second											
α	0.2155**	0.1862**	0.2059**	0.1442**	0.1214*	0.1075*	0.1066*	0.0981*	0.0924	0.0877	0.0588**
s.e	0.0732	0.0553	0.0532	0.0514	0.052	0.0504	0.0492	0.048	0.0481	0.0487	0.0494
β_1	0.3726*,††	0.4343**,††	0.4144**,††	0.5924**,††	0.6584**,†	0.7024**,†	0.7031**,†	0.7211**,†	0.7283**,†	0.7301**,†	0.7793**,†
s.e	0.2137	0.1668	0.1599	0.1509	0.1539	0.1493	0.1438	0.1388	0.1376	0.1375	0.1328
Adj.R^2	0.1478	0.1583	0.1362	0.2285	0.2541	0.2780	0.2774	0.2908	0.2972	0.299	0.3607
Y ratio	0.9120	0.9071	0.9020	0.9434	0.9734	1.0011	1.0012	1.0213	1.0259	1.0256	1.0240
Third											
α	0.2085**	0.2216**	0.2474**	0.2113**	0.1826**	0.1642*	0.1513*	0.1471*	0.1371	0.1341	0.1355
s.e	0.0949	0.053	0.0525	0.0612	0.0635	0.0689	0.0706	0.0715	0.0717	0.0735	0.0814
β_1	0.3628	0.3165*,††	0.2723*,††	0.3803*,††	0.4732**,††	0.5341**,†	0.5711**,†	0.5787**,†	0.6023**,†	0.6058**,†	0.5880**,†
s.e	0.3115	0.1777	0.1648	0.1774	0.1868	0.2076	0.212	0.2135	0.2117	0.214	0.2288
Adj.R^2	0.1414	0.1268	0.082	0.1222	0.1646	0.1927	0.2114	0.2158	0.229	0.2319	0.2310
Y ratio	1.0874	0.9024	0.9152	0.9638	0.9798	0.9859	1.0103	1.0134	1.0240	1.0424	1.0338

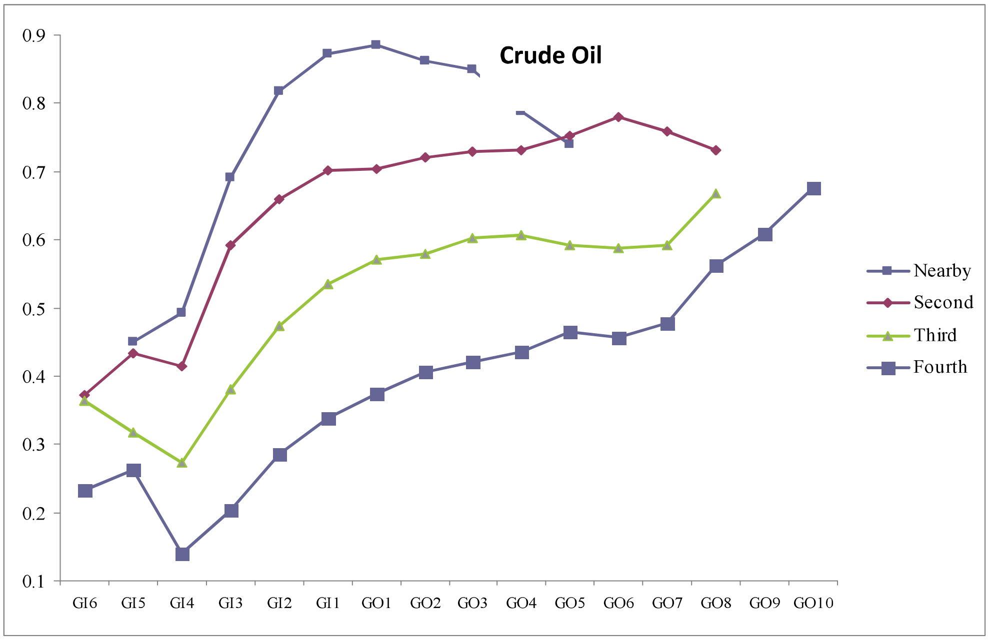
Fourth											
α	0.2522**	0.2377**	0.2797**	0.2627**	0.2410**	0.2257**	0.2143**	0.2029*	0.1973*	0.1908**	0.1795
s.e	0.0669	0.0589	0.0659	0.065	0.0706	0.0804	0.0832	0.0825	0.0816	0.0736	0.0959
β_1	0.2331††	0.2631	0.1393	0.2044	0.2858	0.3390	0.3738	0.4062	0.4199*,††	0.4348*,††	0.4567*,†
s.e	0.2363	0.1999	0.2098	0.1969	0.2092	0.2453	0.2542	0.2506	0.2445	0.2168	0.2723
Adj.R^2	0.0683	0.0779	0.0269	0.0428	0.0706	0.0855	0.1001	0.1161	0.1258	0.1299	0.1349
Y ratio	1.1163	0.9743	0.9796	0.9819	0.9886	0.9914	1.0009	1.0153	1.0239	1.0280	1.0305

Natural Gas

Nearby	GI7	GI5	GI4	GI3	GI2	GI1	GO1	GO2	GO3	GO4
α		0.2060*	0.1180*	0.0752	0.0622	0.0587	0.0488	0.0693	0.1065	0.1351
s.e		0.0885	0.0578	0.0463	0.0509	0.0514	0.0559	0.0640	0.0747	0.0891
β_1		0.6949**,†	0.8193**,†	0.8581**,†	0.8709**	0.8685**	0.8684**	0.8092**,†	0.7458**,†	0.6874**,††
s.e		0.1451	0.0955	0.0712	0.0829	0.0775	0.0851	0.0953	0.1106	0.1300
Adj. R^2		0.1385	0.2613	0.3465	0.3188	0.3276	0.3174	0.2676	0.2255	0.2162
Y ratio		0.9757	0.9991	1.0116	1.0072	1.0030	0.9993	0.9947	0.9878	0.9911
α	0.2852	0.1160*	0.1136	0.0892	0.0810	0.0824	0.0760	0.0841	0.0742	0.0587
s.e	0.1757	0.0516	0.0588	0.0606	0.0622	0.0598	0.0638	0.0644	0.0700	0.0759
β_1	0.5092	0.8184**	0.8084**	0.8412**	0.8436**	0.8276**	0.8279**	0.7935**	0.7982**	0.8119**
s.e	0.3579	0.1164	0.1234	0.1252	0.1274	0.1211	0.1275	0.1252	0.1348	0.1444
Adj. R^2	0.0682	0.4499	0.4485	0.4554	0.4516	0.4487	0.4347	0.4201	0.4036	0.3898
Y ratio	0.9938	0.9820	0.9921	0.9868	0.9950	1.0113	0.9961	0.9771	0.9740	0.9609
α	0.3072**	0.2271**	0.2084**	0.1908**	0.1843**	0.1715*	0.1668*	0.1546*	0.1533*	0.1550*
s.e	0.0870	0.0615	0.0614	0.0645	0.0644	0.0702	0.0717	0.0759	0.0748	0.0751
β_1	0.3467*,††	0.5049**,††	0.5277**,††	0.5613**,††	0.5671**,††	0.5937**,††	0.5928**,††	0.6081**,††	0.5985**,††	0.5852**,††
s.e	0.2026	0.1344	0.1319	0.1381	0.1358	0.1484	0.1487	0.1572	0.1526	0.1495
Adj. R^2	0.1030	0.2895	0.3125	0.3199	0.3236	0.3239	0.3209	0.3160	0.3099	0.3009
Y ratio	0.9562	0.9615	0.9861	0.9896	0.9948	1.0027	0.9983	0.9921	0.9819	0.9713
α	0.2588**	0.2573**	0.2145*	0.1842*	0.1778*	0.1605	0.1454	0.1345	0.1278	0.1219
s.e	0.0921	0.0972	0.0865	0.0863	0.0859	0.0850	0.0856	0.0860	0.0869	0.0893
β_1	0.4565*,††	0.4323*,††	0.5180**,††	0.5790**,†	0.5788**,†	0.6145**,†	0.6367**,†	0.6473**,†	0.6482**,†	0.6468**,†
s.e	0.2284	0.2281	0.2049	0.1998	0.1949	0.1904	0.1887	0.1871	0.1863	0.1902
Adj. R^2	0.1382	0.1593	0.2245	0.2648	0.2679	0.2898	0.3076	0.3171	0.3202	0.3158
Y ratio	0.8268	0.9137	0.9407	0.9609	0.9815	0.9890	1.0057	0.9981	0.9946	0.9882

FIGURE 1
THE SLOPE COEFFICIENT OF IMPLIED VOLATILITY BY "MONEYNESS"

The slope coefficient, $\hat{\beta}_1$ from estimations 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.



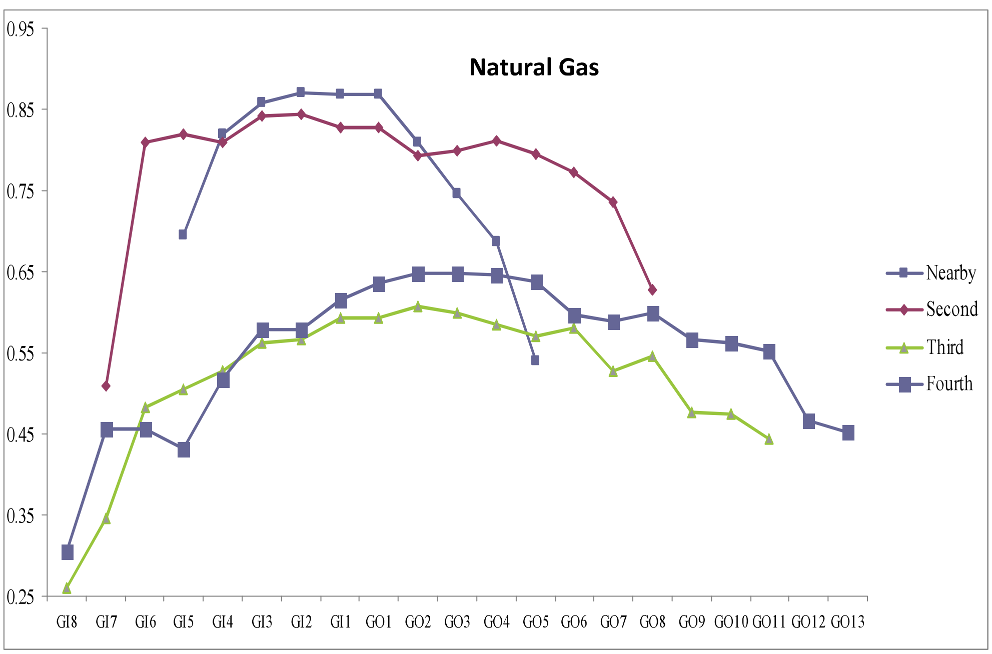
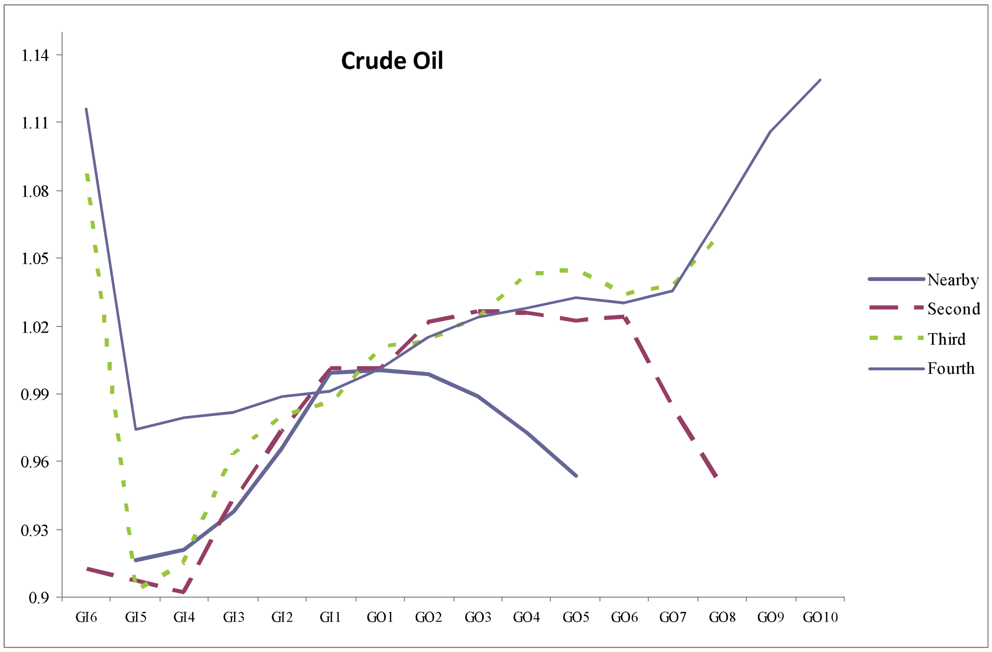
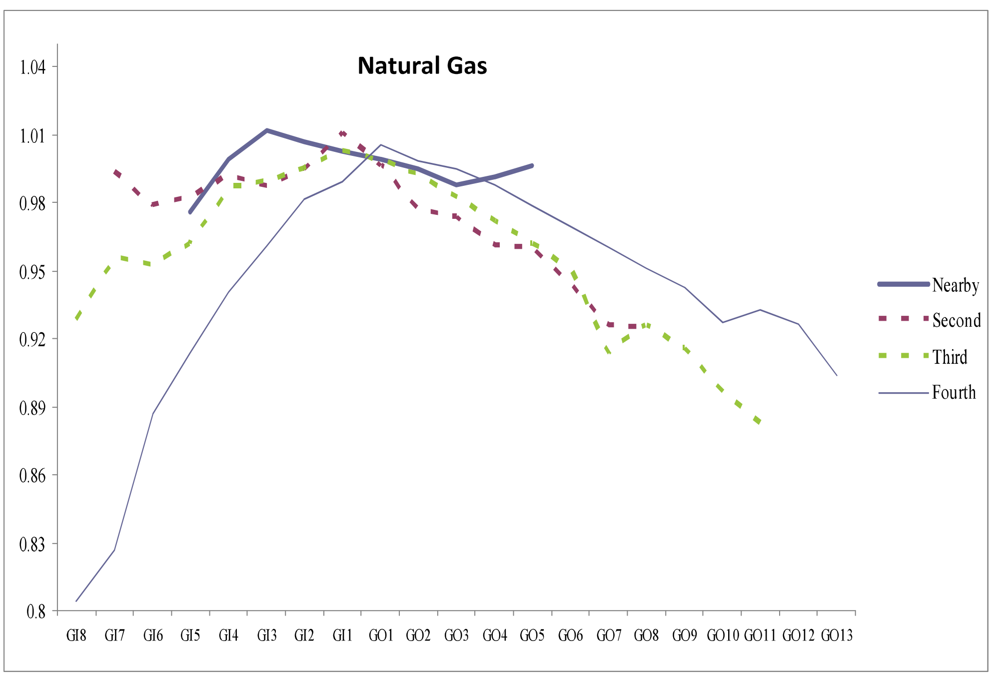


FIGURE 2
THE INFORMATION "FROWN" IN OPTION PRICES: RELATIVE FORECASTING POWER OF THE IMPLIED VOLATILITY BY "MONEYNESS"

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.





Bias and information content differences across maturities and moneyness

Estimations of Equation (2) for oil and gas IVs are reported in Table 2 and Figures 1 and 2. Apparently, the patterns of the parameter estimates differ by time to expiration. Consider the results for crude oil ISDs. For the nearby group, the 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.

We plot $\hat{\beta}_1$ from crude oil options as a function of "moneyness" in Figure 1. For the nearby group, $\hat{\beta}_1$'s display a "frown" image[8] 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 1, the ISD coefficients for natural gas nearby options also display a "frown" pattern where $\hat{\beta}_1$ is highest for the near-the-money groups. $\hat{\beta}_1$ 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 2, the 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 a 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, we follow Ederington and Guan (2005) and calculate the relative forecasting power for each "moneyness" group. First we 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 2, we then form the ratio $Y_{i,j} = \sum u(\text{ATMa})^2_{i,t} \big/ \sum u^2_{i,j,t}$ 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 2 and graphed in Figure 2, Y pattern varies by time-to-maturity. For crude oil nearby options, relative R^2s are highest for ATM options. However, for longer term crude oil options, R^2s are generally higher for OTM options. For natural gas nearby options, relative R^2s 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 of 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 ISDs calculated from option prices of the nearby group, except for deep ITM options. For natural gas options, the most informative in terms of forecasting future volatility are ISDs calculated from 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 2 is consistent with the hypothesis that IVs are unbiased predictors of actual volatility as 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 option groups, the hypothesis that IVs are unbiased predictors of future volatility is rejected. The prices of options in those groups are apparently heavily influenced by factors other than the market’s expectation of future volatility.

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 2 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.

Efficiency

Next we test whether oil and gas IVs efficiently impound all the historical information by estimating Equation (3) where a measure of historical volatility is added to the equation. For historical volatility, we use the volatility forecast over the life of the options generated by a GARCH-type model developed by Glosten, Jagannathan, and Runkle (1993)[9]. Results are reported in Table 3. 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 of 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 option 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), Fleming (1998), Blair et al. (2001), Szakmary et al. (2003), Corrado and Miller (2003) and Ederington and Guan (2005).

TABLE 3
REALIZED VOLATILITY REGRESSED ON IMPLIED VOLATILITY AND HISTORICAL VOLATILITY

The table reports regression results from Equation 3: $\sigma_t(\tau) = \alpha + \beta_1 \cdot ISD_{i,j,t} + \beta_2 \cdot HIS_{i,j,t} + u_{i,j,t}$ for each of the subsample defined by maturity and “moneyness” of oil and gas options between January 03, 2005, and December 31, 2012. $ISD_{i,j,t}$ 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	GI6	GI5	GI4	GI3	GI2	GI1	GO1	GO2	GO3	GO4
α		0.0359	0.0202	0.0069	-0.0107	-0.0107	-0.0049	-0.0011	-0.0143	-0.0089
s.e		0.0544	0.0607	0.0582	0.0527	0.0538	0.0600	0.0642	0.0652	0.0678
β_1		$0.3585^{**,\dagger\dagger}$	$0.4343^{**,\dagger\dagger}$	$0.5678^{**,\dagger\dagger}$	$0.7045^{**,\dagger}$	0.7774^{**}	0.8040^{**}	0.7820^{**}	0.7455^{**}	$0.5809^{**,\dagger}$
s.e		0.1271	0.1263	0.1509	0.1699	0.1793	0.1865	0.1857	0.1939	0.2026
β_2		$0.4409^{**,\dagger\dagger}$	$0.4178^{**,\dagger\dagger}$	$0.3428^{*,\dagger\dagger}$	0.2643	0.2039	0.1609	0.1581	0.2086	0.3361
s.e		0.1522	0.1597	0.1709	0.1774	0.1802	0.2035	0.2187	0.2244	0.2465
Adj.R^2		0.1113	0.1419	0.1861	0.2235	0.2336	0.2336	0.2335	0.2313	0.2024
Second										
α	0.1736^{*}	0.1438^{**}	0.1569^{*}	0.1242^{*}	0.1221^{*}	0.1098^{*}	0.1062^{*}	0.1001^{*}	0.0964^{*}	0.0754
s.e	0.0734	0.0548	0.0613	0.0548	0.0505	0.0461	0.0436	0.0437	0.0441	0.0448
β_1	0.3406	$0.3964^{*,\dagger\dagger}$	$0.3638^{*,\dagger\dagger}$	$0.5633^{**,\dagger\dagger}$	$0.6418^{**,\dagger}$	0.7079^{**}	0.7018^{**}	0.7266^{**}	0.7395^{**}	0.7550^{**}
s.e	0.2481	0.2012	0.1843	0.1797	0.1923	0.1888	0.1869	0.1781	0.1737	0.1666
β_2	0.1540	0.1625	0.1941	0.0869	0.0146	-0.0122	0.0026	-0.0113	-0.0228	-0.0069
s.e	0.2858	0.2247	0.2046	0.1751	0.1654	0.1422	0.1359	0.1296	0.1213	0.1184
Adj.R^2	0.1545	0.1661	0.1428	0.2299	0.2500	0.2781	0.2774	0.2908	0.2974	0.3227
Third										
α	0.2403^{**}	0.2333^{**}	0.2132^{**}	0.1917^{**}	0.1689^{*}	0.1541^{*}	0.1463^{*}	0.1452	0.1341	0.1307
s.e	0.0758	0.0635	0.0772	0.0721	0.0730	0.0747	0.0739	0.0766	0.0766	0.0812
β_1	0.3837	0.3259	0.2399	$0.3537^{*,\dagger\dagger}$	$0.4473^{*,\dagger\dagger}$	$0.5134^{*,\dagger}$	$0.5595^{*,\dagger}$	$0.5744^{**,\dagger}$	$0.5949^{**,\dagger}$	$0.5778^{**,\dagger}$
s.e	0.2394	0.2060	0.1829	0.2036	0.2092	0.2360	0.2468	0.2419	0.2399	0.2402
β_2	-0.1217	-0.0465	0.1406	0.0881	0.0686	0.0522	0.0271	0.0103	0.0170	0.0316
s.e	0.2762	0.2598	0.2536	0.2278	0.2072	0.2072	0.2077	0.2043	0.1999	0.2046
Adj.R^2	0.1454	0.1276	0.0870	0.1242	0.1659	0.1934	0.2116	0.2158	0.2291	0.2310
Fourth		GI5	GI4	GI3	GI2	GI1	GO1	GO2	GO3	GO5
α	0.2488^{**}	0.2378^{**}	0.2741^{**}	0.2514^{**}	0.2350^{**}	0.2172^{**}	0.2037^{*}	0.1946^{*}	0.1857^{*}	0.1683
s.e	0.0643	0.0636	0.0626	0.0643	0.0758	0.0821	0.0852	0.0867	0.0854	0.0940
β_1	0.2321	0.2632	0.1371	0.2003	0.2832	0.3338	0.3659	0.4006	$0.4101^{*,\dagger}$	$0.4567^{*,\dagger}$
s.e	0.2409	0.2403	0.2132	0.1990	0.2096	0.2469	0.2556	0.2505	0.2437	0.2644
β_2	0.0120	-0.0005	0.0203	0.0405	0.0217	0.0324	0.0421	0.0325	0.0472	0.0408
s.e	0.1153	0.0958	0.0785	0.0809	0.0834	0.0757	0.0781	0.0813	0.0795	0.0788
Adj.R^2	0.0667	0.0779	0.0271	0.0436	0.0707	0.0859	0.1008	0.1165	0.1269	0.1435

Natural Gas

Nearby	GI7	GI5	GI4	GI3	GI2	GI1	GO1	GO2	GO3	GO4
α		0.1766*	0.1022	0.0618	0.0507	0.0505	0.0420	0.0627	0.1044	0.1398
s.e		0.0862	0.0584	0.0483	0.0542	0.0524	0.0571	0.0655	0.0772	0.0928
β_1		0.4919*,†	0.6940**,†	0.7492**	0.7593**	0.7579**	0.7694**	0.7097**	0.6326**,†	0.545**,†
s.e		0.2384	0.1813	0.1587	0.1501	0.1631	0.1723	0.1792	0.1893	0.2123
β_2		0.2084	0.1303	0.1173	0.1187	0.1132	0.1029	0.1050	0.1126	0.1325
s.e		0.1587	0.1553	0.1559	0.1472	0.1492	0.1569	0.1554	0.1493	0.1478
Adj. R^2		0.1534	0.2647	0.3511	0.3236	0.3316	0.3208	0.2715	0.2302	0.2243
Second										
α	0.3489	0.1416*	0.1395*	0.1174	0.1076	0.1086	0.0927	0.0987	0.0899	0.0708
s.e	0.1785	0.0679	0.0694	0.0682	0.0680	0.0657	0.0717	0.0719	0.0757	0.0824
β_1	0.6259*	0.8839**	0.8792**	0.9287**	0.9296**	0.9094**	0.8798**	0.8364**	0.8492**	0.8510**
s.e	0.3763	0.1466	0.1578	0.1638	0.1685	0.1607	0.1724	0.1712	0.1865	0.1921
β_2	-0.2016	-0.1032	-0.1111	-0.1323	-0.1292	-0.1258	-0.0809	-0.0694	-0.0803	-0.0622
s.e	0.1588	0.1566	0.1548	0.1506	0.1487	0.1460	0.1693	0.1708	0.1788	0.1874
Adj. R^2	0.0914	0.4523	0.4513	0.4597	0.4558	0.4527	0.4360	0.4210	0.4049	0.3903
Third										
α	0.2804**	0.2077**	0.1984**	0.1803*	0.1715*	0.1592*	0.1596*	0.1433	0.1436	0.1371
s.e	0.1061	0.0702	0.0693	0.0742	0.0748	0.0763	0.0806	0.0832	0.0833	0.0839
β_1	0.3157	0.4659**,††	0.5062**,††	0.5382**,††	0.5393**,††	0.5631**,†	0.5759**,†	0.5777**,†	0.5714**,†	0.5326**,†
s.e	0.2252	0.1733	0.1732	0.1783	0.1747	0.1987	0.1922	0.2105	0.2088	0.2070
β_2	0.0778	0.0736	0.0400	0.0431	0.0527	0.0548	0.0315	0.0537	0.0478	0.0917
s.e	0.1936	0.1642	0.1641	0.1759	0.1791	0.1906	0.1935	0.2103	0.2199	0.2235
Adj. R^2	0.1068	0.2925	0.3130	0.3204	0.3247	0.3243	0.3210	0.3163	0.3099	0.3032
Fourth										
α	0.2531*	0.2544**	0.2228**	0.1999*	0.1894*	0.1716*	0.1591	0.1478	0.1415	0.1322
s.e	0.1020	0.0977	0.0854	0.0849	0.0831	0.0837	0.0837	0.0833	0.0839	0.0870
β_1	0.4486*,†	0.4265	0.5365*,†	0.6190**	0.6065**	0.6410**	0.6707**	0.6815**	0.6846**	0.6714**
s.e	0.2693	0.2816	0.2670	0.2633	0.2571	0.2483	0.2491	0.2486	0.2490	0.2484
β_2	0.0193	0.0118	-0.0363	-0.0744	-0.0538	-0.0519	-0.0660	-0.0659	-0.0701	-0.0501
s.e	0.2158	0.2086	0.2083	0.2073	0.2047	0.2018	0.2040	0.2055	0.2085	0.2106
Adj. R^2	0.1375	0.1588	0.2247	0.2673	0.2690	0.2908	0.3094	0.3188	0.3222	0.3166

CONCLUSIONS

This paper explores the forecasting power 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 January 2005 through December 2012, we have shown that (1) oil and gas IVs are efficient forecasts of future volatility across terms to maturity and (2) the information content of oil and gas IVs differs substantially and systematically by strike price displaying a "frown" pattern which is roughly the mirror image of the well-documented IV smile pattern. For crude oil options, the most informative in terms of predicting future volatility are IVs on nearby group and deep ITM options. For natural gas options, IVs calculated from the near-the-money options in the nearby group and in the second-month group contain considerable information regarding future volatility. Finally, evidence in this paper suggests that in testing whether IV is an unbiased and efficient forecast of future volatility, it is essential to estimate separate coefficient for each strike price.

ENDNOTES

1. See, for example, Day and Lewis (1993), Lamoureux and Lastrapes (1993). Canina and Figlewski (1993), Christensen and Prabhala (1998), etc.
2. Jorion (1995)
3. See, Day and Lewis (1993), Martens and Zein (2004), Szakmary, Ors, Kim, and Davidson (2003)
4. Amin and Ng (1997)
5. Black's (1976) model is a simplified version of B-S adjusted for the facts that (1) futures pay no dividends, and (2) futures entail no investment at time *t*. 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).
6. Canina and Figlewski (1993), Day and Lewis (1993), Ederington and Guan (2002) and Martens and Zein (2004) observe significant values for $\beta_2^{'}$ in Eq. (3) in at least some data sets 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.
7. Examples are Canina and Figlewski (1993), Jorion (1995), Ederington and Guan (2005) and others.
8. The information "frown" is first explored in Ederington and Guan (2005).
9. We use the GJR (Glosten et al., 1993) model to forecast historical volatility over the life of the option. The GJR specification is $h_t = \omega + \gamma_1 \varepsilon_{t-1}^2 + \gamma_2 h_{t-1} + \gamma_3 \eta_t \varepsilon_{t-1}^2$, (6) where $\eta_t = 1$ if $\varepsilon_{t-1} < 0$ and 0 otherwise.

The regression estimates from (6) 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.

REFERENCES

Agnolucci, P. (2009). Volatility in crude oil futures: a comparison of the predictive ability of GARCH and implied volatility models. *Energy Economics*, 31, (2), 316-321.

Amin, K.I. & Ng, V.K. (1997). Inferring future volatility from the information in implied volatility in Eurodollar options: A New Approach. *Review of Financial Studies*, 10, 333-367.

Black, F. (1976). The pricing of commodity contracts. *Journal of Financial Economics*, 3, 167-179.

Blair, B., Poon, S. & Taylor, S. (2001). Forecasting S&P 100 volatility: The incremental information content of implied volatilities and high frequency index returns. *Journal of Econometrics*, 105, 5–26.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroscedasticity. *Journal of econometrics*, 31, (3), 307-327.

Bollerslev, T., Osterrieder, D., Sizova, N. & Tauchen, G. (2013). Risk and return: Long-run relations, fractional cointegration, and return predictability. *Journal of Financial Economics*, 108, (2), 409-424.

Canina, L. & Figlewski, S. (1993). The informational content of implied volatility. *Review of Financial Studies*, 6, 659–681.

Christensen, B.J. & Prabhala, N.R. (1998). The relation between implied and realized volatility. *Journal of Financial Economics*, 50, 125–150.

Corrado, C. & Miller, T. (2003). The forecast quality of CBOE implied volatility indexes. *University of Auckland working paper*.

Day T.E. & Lewis, C.M. (1993). Forecasting futures market volatility. *Journal of Derivatives*, 1, 33-50.

Ederington, L. & Lee, J.H. (1996). The creation and resolution of market uncertainty: The impact of information releases on implied volatility. *Journal of Financial and Quantitative Analysis*, 31, 513-539.

Ederington, L. & Guan, W. (2002). Why are those options smiling?. *Journal of Derivatives*, 10, 9-34.

Ederington, L.H. & Guan, W. (2005). The information frown in option prices. *Journal of Banking & Finance*, 29, 1429-1457.

Engle, R.F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the Econometric Society*, 987-1007.
Fleming, J., Ostdiek, B. & Whaley, R. (1995). Predicting stock market volatility: A new measure. *Journal of Futures Markets*, 15, 265-302.
Fleming, J. (1998). The quality of market volatility forecasts implied by S&P 100 index option prices. *Journal of Empirical Finance*, 5, 317–345.
French, K. & Roll, R. (1986). Stock return variances: The arrival of information and the reaction of traders. *Journal of Financial Economics*, 17, 5-26.
Glosten, L.R., Jagannathan, R. & Runkle, D.E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The journal of finance*, 48, (5), 1779-1801.
Hansen, L. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, 50, 1029–1054.
Haugom, E., Langeland, H., Molnár, P. & Westgaard, S. (2014). Forecasting volatility of the US oil market. *Journal of Banking & Finance*, 47, 1-14.Jorion, P. (1995). Predicting volatility in the foreign exchange market. *Journal of Finance*, 50, 507-528.
Lamoureux, C.G. & Lastrapes, W.D. (1993). Forecasting stock return variance: Toward an understanding of stochastic implied volatilities. *Review of Financial Studies*, 6, 293-326.
Le, D.T. (2015). Ex-ante determinants of volatility in the crude oil market. *International Journal of Financial Research*, 6, (1), 1-13.
Martens, M. & Zein, J. (2004). Predicting financial volatility: High-frequency time-series forecasts vis-à-vis implied volatility. *Journal of Futures Markets*, 24, 1005-1029.
Marzo, M. & Zagaglia, P. (2010). Volatility forecasting for crude oil futures. *Applied Economics Letters*, 17, (16), 1587-1599.
Mincer, J. & Zarnowitz, V. (1969). The evaluation of economic forecasts in J. Mincer (ed.). *Economic Forecasts and Expectations*, NBER, New York, 3-46.
Szakmary, A., Ors, E., Kim, J.K. & Davidson III, W.N. (2003). The predictive power of implied volatility: Evidence from 35 futures markets. *Journal of Banking and Finance*, 27, 2151-2175.
Wei, Y., Wang, Y. & Huang, D. (2010). Forecasting crude oil market volatility: Further evidence using GARCH-class models. *Energy Economics*, 32, (6), 1477-1484.