PREDICTING IMPLIED VOLATILITY IN THE COMMODITY FUTURES OPTIONS MARKETS

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Abstract

Both academics and practitioners have a substantial interest in understanding patterns in implied volatility that are recoverable from commodity futures options. Such knowledge enhances their ability to accurately forecast volatility embedded in these high-risk options. This paper examines option-implied volatility contained in the heavily traded September corn futures option contracts for the ten-year period, 1991-2000. We also test whether a "weekend effect" exists in the market for these contracts. We evaluate the performance of various measures widely employed in the literature to estimate historical volatility. We further report the na-

ture of profits from a short straddle strategy which seeks to exploit differences between option-implied and historical volatility.

Keywords: commodity futures options, implied volatility

JEL Codes: G10/G12/G13

1. Introduction

A call option gives an option holder the right to buy an asset at a price pre-specified in the option contract on or before the option's expiration date. The option holder is not obligated to exercise the option. However, the option holder exercises the option only to increase his own wealth. Because the option premium reveals the investor's expectation regarding future price movement by the asset, observed option prices contain information about the market's expected price as well as the volatility of the underlying asset. If an option pricing model works well to price options, then an investor can use the observed option prices to invert the option pricing model and obtain the market's estimate of the underlying asset's volatility. This volatility is referred to as the option implied volatility.

The importance and usefulness of option implied volatility has been extensively recognized in the academic literature. Canina and Figlewski (1993) and Fleming (1996, 1998) examine implied volatilities using S&P 100 stock index options (OEX) while Beckers (1981) and Lamoureux and Lastrapes (1993) consider options on individual stocks. Day and Lewis (1993) investigate the nature of implied volatilities on crude oil futures while Jorion (1995) examines foreign currency futures and Ferri (1996) analyzes foreign currency options. Findings from Black and Scholes (1973), Merton (1973), Manaster and Rendleman (1982), Day and Lewis (1992), Ederington and Lee (1996), and Christensen and Prabhala (1998) show that implied volatilities contain information about the expected variance of stock returns. More recent work by Mayhew and Stivers (2001) describes the properties of the forecasts contained in option implied volatilities while Ferson, Heuson, and Su (2001) examine the relation between volatility in stock returns and implied standard deviations.

But the study of implied volatilities has not been limited to equity markets. Wilson and Fung (1990) examine the information content of volatility implied by options on grain futures. Nelson (1996) studies the relation between option implied volatility and the underlying contract activity in the live cattle market. Kenyon and Beckman (1997) analyze multiple-year pricing opportunities for corn and soybeans spot, futures, and futures options markets.

Option implied volatility is of great importance to traders, whether they are hedgers or speculators. The absolute price level is of secondary importance to traders. It is the change in price of a futures contract that is important because such changes generate capital gains or losses. These, in turn, produce trading profits or losses. In addition, fundamental factors such as supply and demand, traders often look for relationships between prices, volumes, open interests, or volatility. Existing option pricing theories such as Black and Scholes (1973) or Merton (1973) suggest for instance that there is a positive relation between volatility and option price. When volatility increases, option prices increase as well and vice versa. Anticipated changes in volatility generate changes in option prices.

Some commodity traders and academic researchers (Wilson and Fung, 1990; Nelson, 1996) suspect that implied volatility in commodity futures options is seasonal because weather and other seasonal factors that have the potential to impact crop growth exhibit behaviors that are predictable in calendar time. If implied volatility is seasonal, then traders can predict volatility changes based on seasonal patterns. Thus, the first contribution of this study is a test for seasonality patterns in implied volatilities in corn futures options. We elect to focus on corn futures contracts since they are the most actively traded agricultural futures contracts on the Chicago Board of Trade (CBOT). Indeed, the average trading volume for this commodity exceeds 50,000 contracts per day during our sample period, 1991-2000.

Our specific focus is on the September futures option contracts that expire in August. Volatility in the September futures contracts is the hardest to predict among all such contracts because of the corn pollination that occurs in July and August. The success of this pollination period is highly uncertain, thus making the size of the future harvest difficult to project. Consequently, September futures contracts are perceived to have a much higher implied volatility than any other corn futures options. Traders have a substantial interest in the implied volatility patterns recovered from September futures options because such knowledge enhances their ability to accurately forecast the volatility embedded in these high-risk options.

Previous studies of the equity market such as French (1980), Lakonishok (1982), Keim, Stambaugh, and Rogalski (1984) report evidence of a weekly pattern in index returns. This anomaly is termed the "weekend effect". Jaffe and Westerfield (1985) and Jaffe, Westerfield, and Ma (1989) find limited evidence of this effect in international stock markets while Dyl and Maberly (1986) and Chang, Jain, and Locke (1995) present findings suggesting its presence in the market for sock index futures.

In this study, we test for a weekend effect in the commodity futures option market by investigating whether implied volatility is higher on Fridays than Mondays due to added uncertainty resulting from the market's weekend closure. Such information will be useful for traders seeking to find entry or exit points to the market, or to speculate on volatility changes on a short-term basis.

The final contribution of this study is our analysis of forecasting performance using alternative measures of historical volatility. We report the forecasting performance of four commonly used historical volatility measures, measured across ten and twenty day moving windows. In addition, we report the results from executing a short straddle trading strategy using empirical data. We find positive trading profits when options are within four months to expiration. We conclude that differences in implied volatilities and historical volatilities lead to positive trading profits.

We organize the remainder of the paper in the following manner. In section 2 we introduce our methodology while in section 3 we describe our data and sample construction. We present our empirical findings in section 4. We discuss the trading implications of our results in section 5. We conclude with a brief summary in section 6.

2. Methodology

2.1 *Implied volatility estimation*

Given an option pricing model and an option contract information, the implied volatility parameter equates the theoretical option price to the observed market option price. The implied volatility is regarded as the market's expected volatility of returns for the underlying asset over the remaining life of the option.

The Black (1976) option pricing model for futures options is a variant of the Black-Scholes (1973) option pricing model for equity options. Similar to the Black-Scholes model, a futures price, a strike price, an interest rate, time to maturity, and volatility are used to compute a futures option price. The first four variables are directly observable from the market. However, a trader has to estimate the asset return volatility to use any option pricing model. If the market prices futures options according to the Black model, then the market observed option price, Cobs should be equal to the theoretical option price, CBlack, generated from the Black model.

We use the Black model to recover implied volatilities. The procedure generally requires a numerical search routine to accomplish this task. Solving the Black model backward from the observed option prices thus provides an estimate for the option implied volatility.

Because the Black (1976) model is for European style options and the corn futures options are American style, the binomial pricing model is more appropriate. Other things held constant, an American style option is always worth more than an otherwise identical European style option. This is because an American style option can be exercised on or before the expiration date while a European style option can be exercised only on expiration. Thus for commodity futures options, the implied volatility recovered from the Black model is upward biased. This bias however is of minor consequence because most traders are fully aware of it. Hence, they adjust their estimates accordingly. Furthermore, traders are more concerned with changes in implied volatility than the absolute level of implied volatility.

2.2 *Historical volatility estimates*

Historical volatility is estimated by two different procedures: a "standard" procedure and a "zero-mean" procedure. Figlewski (1997) discusses both procedures in detail. We summarize these methodologies as follows.

2.2.1 *The standard procedure*

We begin with a set of historical futures closing prices $\{S_0, S_1, ...S_T\}$. We then estimate a set of log price relatives, i.e., $R_t = \ln (S_t/S_{t-1})$ for t from 1 to T. To obtain historical volatility on a ten-day moving window basis, the log price relative series is then decomposed into ten-day internals on a moving window basis. That is, $\{R_1, R_2, ...R_{10}\}$, $\{R_2, R_3, ...R_{11}\}$, and so on. The historical volatility estimates are the annualized standard deviations of returns for these ten-day intervals. The numerical expression for the procedure is:

$$\sigma_t = \sqrt{\frac{\sum_{j=t}^{j=t+9} (R_j - \bar{R})^2}{9} \times 252}\ , t = 1, 2, ..., T\text{-}9 \quad (1)$$

where 252 is the number of trading days in a year. $\overline{R}$ is the mean return for a 10-day interval which is equal to:

$$\frac{\sum_{j=t}^{j=t+9} R_j}{10} \quad (2)$$

2.2.2 *The zero mean procedure*

Figlewski (1997) reports that the mean return of the series is in fact determined only by the first price observation St-1, the last observation in the price series S_{t+9}, and the length of the interval:

$$\bar{R} = \frac{\sum_{j=t}^{j=t+9} R_t}{10} = \frac{\sum_{j=t}^{j=t+9} (\ln S_t - \ln S_{t-1})}{10} = \frac{\ln S_{t+9} - \ln S_{t-1}}{10} \quad (3)$$

Estimating a sample mean based on equation (1) hence can be quite inaccurate. Since the volatility does not depend heavily on the mean, Figlewski (1997) suggests imposing a sample mean as zero in the calculation so that historical volatility is estimated by:

$$\sigma = \sqrt{\frac{\sum_{j=t}^{j=t+9} R_t^{\ 2}}{10} \times 252} \quad (4)$$

Figlewski (1997) argues that "using elaborate models for mean returns is unlikely to be worth the effort in terms of any improvement in accuracy". Note that the denominator in equation (4) is ten instead of nine since the mean is not estimated from the sample. Thus, no observations are lost.

Historical volatilities on a 20-day moving window basis are estimated similarly. In the standard mean procedure,

$$\sigma = \sqrt{\frac{\sum_{j=t}^{j=t+19} (R_t - \bar{R})^2}{19} \times 252} \qquad (5)$$

and in the zero mean procedure:

$$\sigma = \sqrt{\frac{\sum_{j=t}^{j=t+19} R_t^{\,2}}{20} \times 252} \qquad (6)$$

To examine the forecasting performance of the above four historical volatility measures, we use estimated volatility from a given interval as the volatility forecast for the next interval. We record the deviations between forecast and realized volatilities. We repeat the above procedure using 10- and 20-day moving window measures. Root-mean-squared-errors (RMSEs) summarize all corresponding recorded volatility deviations. In the zero mean procedure, we compute both realized and forecast volatility in the forecasting period assuming a zero-mean.

3. Data and Sample Description

3.1 *Data description*

We obtain data for our sample from the Chicago Board of Trade (CBOT). Our data contain all daily closing prices of September futures and futures option from January to July for the period of 1991-2000. The specific commodity is grade number two yellow corn. We exclude all options contracts prior to January because of thin trading volume on the option contracts. We further remove all observations after July due to the short remaining time to expiration.

The underlying asset of a September futures option is September futures contract. For the futures options, we have data concerning the option premium, strike price, maturity month, underlying security price, and T-bill rates. We recover the option implied volatility from at-the-money options. When the futures price does not exactly equal any strike price, we use a near the money option to approximate an at-the-money option. The Black (1976) model requires a market interest rate to compute an option price. We first use a six percent constant risk free rate in the Black model. Some traders use a constant interest rate because the impact of interest rate on the recovered implied volatility is believed to be trivial and should not materially impact trading decisions. We also use yields on 90-day Treasury bills as more elaborate proxies for market interest rates. Our tables present results from both sets of market interest rate proxies.

3.2 *Nature of the contract*

The September corn futures contracts are introduced in May each year and expire in September of the following year. The contract size is 5,000 bushels and the tick size is 1/4 cent per bushel. The daily price limit is 20 cents per bushel above or below the previous day's settlement price. Limits are lifted two business days before the spot month begins.

Options on the September futures are introduced in June and expire in mid-August of the following year. Option exercise results in an underlying futures market position. The tick size is 1/8 cent per bushel. The strike price interval is five cents per bushel for the most current two months and ten cents per bushel for all other months. At the commencement of trading, five strikes above and five strikes below at the money are listed. Except on the last trading day, options are subjected to a daily price limit of 20 cents per bushel above or below the previous day's settlement premium. Both the futures contracts and futures option contracts are traded simultaneously in open outcry from 9:30 a.m. to 1:15 p.m. This characteristic reduces potential noise that could result from non-synchronous trading, as occurs in index and index options.

4. Empirical results

4.1 *Implied volatility*

We use the Black (1976) model to estimate option implied volatility of September corn futures options. First, for each trading day, our sample provides us with a set of input variables. They include the September corn futures closing price, option time to maturity, option strike price, market interest rate, and option premium. Second, we program a numerical search routine to compute an asset return volatility that equates the Black futures price to the observed market price. Since the option price is monotonic in volatility, the search routine quickly converges to a unique solution. We repeat the procedure for each trading day in our sample and document all daily implied volatilities in our ten-year sample period for further analysis.

4.2 *Patterns in annual implied volatilities*

Table 1 reports the average implied volatility over each month during our sample period. Figure 1 is a graphical presentation of those results. Over our ten-year sample period, we observe a rising trend in volatility from January to July. Implied volatilities are the lowest in January and increase steadily from January to May. They continue to increase from the planting season in May and remain high going into the July pollination season. The mean option implied volatility increases by more than 25% from January (23.00%) to May (29.15%). The results are robust with respect to the selection of an interest rate proxy.

We plot annual implied volatility patterns in Figure 1. In 1991, implied volatility started at around 20% and gradually rose to over 30% in mid-July during the pollination period. In 1993, implied volatility remained at the 20% level for the beginning of the year, increased in March, declined and then temporarily jumped to slightly over 30% going into July and finally fell to below 30% during pollination. The implied volatility patterns are somewhat similar for 1992 and 1994. In both years, implied volatility dramatically rose in May and remained high until the end of June before declining to around 20% in July. This suggests that the market expected high uncertainty in corn yield in May, but the uncertainty was reduced during pollination. In 1995, volatility started to increase in mid-March and remained high as pollination approached. The year 1996 experienced a high level of volatility. Volatility rose dramatically in mid-April and stayed high as pollination approached, but fell slightly during the actual pollination season. In 1997, higher uncertainty occurred during pollination period. In 1998, the market started on the high end of the volatility range from the beginning and ended lower in late July. In 1999, volatility consistently increased throughout the first half of the year with high volatility entering July. The pattern in year 2000 is different from that of the other years. Market implied volatility started from above 30% at the beginning of the year. It went up to as high as over 40% in May, and remained above 30% before finally dropping below 30% in late July.

Our findings suggest that it is difficult to find evidence of seasonal patterns that apply to even a majority of our sample years. Weather,

Figure 1
Option implied volatility for September corn futures, 1991-2000

We use the Black [1976] model to estimate the option implied volatility. Specifically, we program a numerical search routine to compute an asset return volatility that equates a Black futures price to an observed market price. The procedure is repeated for each trading day in our sample. Daily ATM option implied volatility (IV) is reported below with IV on the vertical axis, and year and months on the horizontal axis. Yields on 90-day T-bill are used as market interest rate proxies.

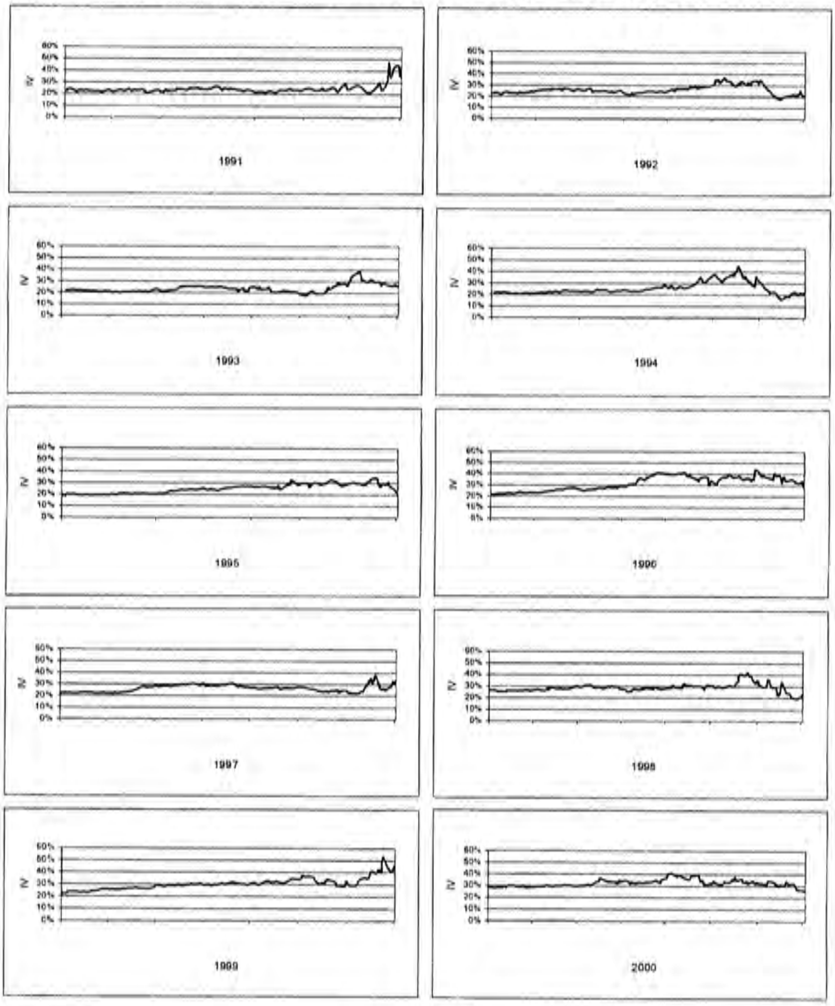

Table 1
Mean implied volatility based on at-the-money calls by month for 1991-2000

The Black (1976) model is used to estimate the option implied volatility of September corn futures options. For each trading day, our sample provides us with a set of input variables including futures closing price, option time to maturity, option strike price, market interest rate, and option premium. We program a numerical search routine to compute an asset return volatility that equates the Black futures price to the observed market price. We repeat the procedure for each trading day in our sample and document all daily implied volatilities in our ten-year sample period.

Panel A: The interest rate is derived from yields on 90-day T-bills

Year	January	February	March	April	May	June	July
1991	0.2278	0.2293	0.2391	0.2420	0.2261	0.2479	0.3036
1992	0.2289	0.2565	0.2479	0.2343	0.2727	0.3275	0.2260
1993	0.2112	0.2015	0.2351	0.2364	0.2213	0.2272	0.3006
1994	0.2075	0.2201	0.2290	0.2441	0.2856	0.3508	0.2102
1995	0.1943	0.2035	0.2286	0.2547	0.2725	0.2969	0.2943
1996	0.2214	0.2512	0.2668	0.3536	0.3746	0.3699	0.3579
1997	0.2236	0.2449	0.2899	0.2902	0.2670	0.2539	0.2807
1998	0.2578	0.2752	0.2953	0.2737	0.2971	0.3323	0.2655
1999	0.2390	0.2593	0.2921	0.3016	0.3196	0.3310	0.3845
2000	0.2875	0.2963	0.3244	0.3316	0.3723	0.3367	0.3109
1991-2000 average	0.2300	0.2441	0.2647	0.2765	0.2915	0.3076	0.2936

Panel B: The interest rate is set at six percent

Year	January	February	March	April	May	June	July
1991	0.2280	0.2296	0.2379	0.2425	0.2265	0.2483	0.3037
1992	0.2320	0.2596	0.2501	0.2363	0.2745	0.3290	0.2268
1993	0.2150	0.2054	0.2370	0.2390	0.2233	0.2276	0.3015
1994	0.2115	0.2236	0.2317	0.2461	0.2874	0.3524	0.2103
1995	0.1950	0.2047	0.2288	0.2537	0.2728	0.2973	0.2945
1996	0.2224	0.2526	0.2672	0.3560	0.3756	0.3670	0.3582
1997	0.2249	0.2461	0.2910	0.2903	0.2682	0.2538	0.2810
1998	0.2594	0.2764	0.2964	0.2750	0.2983	0.3330	0.2658
1999	0.2411	0.2614	0.2937	0.3031	0.3210	0.3320	0.3849
2000	0.2885	0.2974	0.3247	0.3325	0.3736	0.3369	0.3107
1991-2000 average	0.2313	0.2460	0.2658	0.2777	0.2927	0.3080	0.2941

price stagnation, and the pace of planting are all factors that significantly impact corn yield. While current production plus ending stock from prior year establish the supply side of the equation, domestic usage and global demand determine demand. The imbalance between supply and demand result in changes in market price as well as market implied volatility. Kluis (1998) notes that technological changes, the impact of commodity funds, and international trade combine to make the commodity market more sensitive and responsive to new, economically relevant information. These changes result in higher short-term market volatility. These market volatility changes are then captured in the annual volatility patterns discussed above.

4.2 *Weekend effect*

Another question that puzzles commodity traders is whether implied volatility is higher on Fridays than on Mondays due to the uncertainty resulting from a market that has been closed over the weekend. In short, is there a weekend effect in implied volatilities? Insights on this question are useful as traders seek to find market entry or exit points or to speculate on short-term volatility changes.

Table 2 reports the means in weekday volatility. We find that the mean volatility on Friday (27.49%) is slightly higher than that on Monday (27.21%). This result is consistent with Chang, Jain, and Locke (1995) who find that Friday's close is the period of highest volatility in the S&P 500 futures market. The differences between the Friday and Monday means however are small and statistically insignificant. Although economically relevant activity might occur during the weekend, the mean option implied volatility does not appear to be affected. We conclude that there is not a weekend effect in option implied volatilities.

Table 2
Mean implied volatility based on at-the-money calls by day of week, 1991-2000

The Black (1976) model is used to recover implied volatilities. Solving the Black model backward from the observed option prices provides an estimate for the option implied volatility.

Panel A: The interest rate is derived from yields on 90-day T-bills

	Monday	Tuesday	Wednesday	Thursday	Friday
Mean	0.2721	0.2731	0.2728	0.2721	0.2749
Standard Dev.	0.0518	0.0531	0.0529	0.0520	0.0568

Panel B: The interest rate is set at six percent

	Monday	Tuesday	Wednesday	Thursday	Friday
Mean	0.2741	0.2744	0.2738	0.2727	0.2753
Standard Dev.	0.0520	0.0525	0.0529	0.0517	0.0565

4.3 *Historical volatility*

Historical volatility in general begins at a lower level during the early part of the year, rises at a faster pace than option implied volatility does during mid-year, but approaches implied volatility near the option expiration date. Figure 2 illustrates monthly averages of ten and twenty day moving window historical standard volatility measures and the mean option implied volatility. Since historical volatility measures are estimated from historical futures prices, a possible explanation for lower historical volatility in the early part of a year is the "non-trading effect" (Figlewski, 1997). When the futures markets are relatively less active at the beginning of the year, the full impact of a large information event tends to spread over two or more days' recorded closing prices, which would result in positive autocorrelation in returns. The autocorrelation in return reduces estimated volatility. When the futures markets become more active, futures prices become more volatile and we observe higher historical volatilities.

Figure 2
Mean monthly volatility, 1991-2000

We used the Black (1976) model to estimate option implied volatility of September corn futures options. In the standard procedure, we estimate historical volatility by $\sigma_t = \sqrt{\frac{\sum_{j=1}^{j=N} (R_j - \bar{R})^2}{N} \times 252}$, where N = 10 (20) in the 10 (20) - day moving average procedure; 252 is the number of trading day in a year; $\bar{R}$ is the mean return for a N-day interval which is equal to $\frac{\sum_{j=1}^{j=N} R_j}{N}$. In the zero mean procedure, sample mean is assumed to be zero and historical volatility is estimated by $\sigma = \sqrt{\frac{\sum_{j=1}^{j=N} R_j^2}{N} \times 252}$.

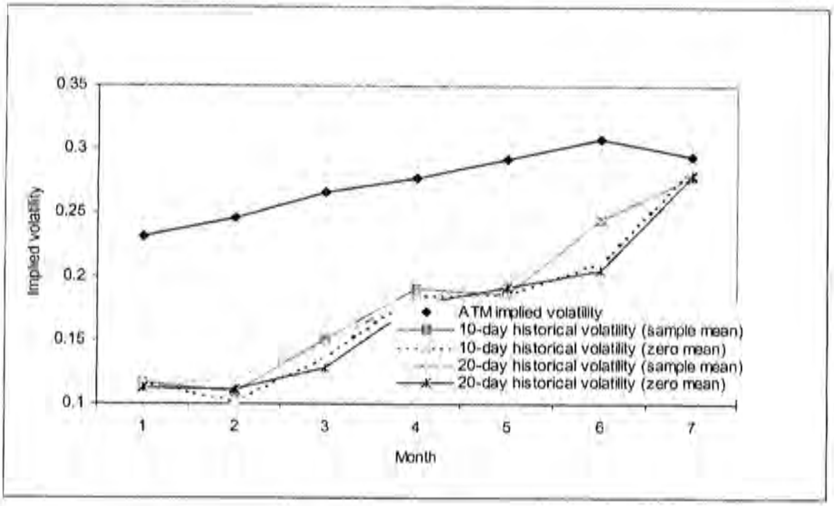

Table 3 reports the average historical volatilities by month for each year. We also observe an increasing trend in the realized historical volatilities from January to July. The results are consistent with those presented in Table 1.

Table 4 reports the forecasting performance of the four different historical volatility measures. The root-mean-squared-errors (RMSEs) measure the forecasting performance of our alternative measures. The smaller the RMSE, the better the forecast. RMSE indicate that the 20-day zero mean historical volatility gives best forecasting results among all four historical volatility measures. The 20-day standard historical volatility performs the second best.

Table 3
Mean historical volatility by month, 1991-2000

In the *standard* procedure, we estimate historical volatility by $\sigma_t = \sqrt{\frac{\sum_{j=t}^{j=t+9}(R_j-\bar{R})^2}{9}\times 252}$, t = 1, 2, ..., T-9, where 252 is the number of trading day in a year. $\bar{R}$ is the mean return for a 10-day interval which is equal to $\frac{\sum_{j=t}^{j=t+9} R_j}{10}$. In the zero mean procedure, sample mean is assumed to be zero and historical volatility is estimated by $\sigma = \sqrt{\frac{\sum_{j=t}^{j=t+9} R_j^2}{\ldots}\times 252}$.

Historical volatilities on a 20-day moving window basis are estimated similarly.

	Standard procedure				*Zero mean procedure*			
	10-day historical volatility				10-day historical volatility (zero mean)			
Month	Max	Min	Mean	Std.	Max	Min	Mean	Std.
Jan	0.2405	0.0358	0.1171	0.0528	0.2322	0.0350	0.1173	0.0534
Feb	0.3154	0.0280	0.1094	0.0552	0.2039	0.0279	0.1024	0.0389
Mar	0.4142	0.0483	0.1506	0.0781	0.2883	0.0473	0.1361	0.0538
Apr	0.5735	0.0489	0.1905	0.1026	0.5659	0.0471	0.1853	0.1020
May	0.3915	0.0775	0.1860	0.0687	0.3786	0.0761	0.1856	0.0685
Jun	0.8618	0.0639	0.2445	0.1578	0.4592	0.0733	0.2114	0.0798
Jul	0.4926	0.0814	0.2792	0.0969	0.5021	0.1166	0.2847	0.0935

	20-day historical volatility				20-day historical volatility (zero mean)			
Month	Max	Min	Mean	Std.	Max	Min	Mean	Std.
Jan	0.1918	0.0521	0.1130	0.0376	0.1932	0.0517	0.1127	0.0377
Feb	0.2266	0.0449	0.1198	0.0490	0.1988	0.0441	0.1113	0.0381
Mar	0.3120	0.0577	0.1461	0.0667	0.2497	0.0577	0.1286	0.0456
Apr	0.4353	0.0672	0.1843	0.0803	0.4356	0.0716	0.1781	0.0820
May	0.4227	0.0975	0.1932	0.0743	0.4120	0.0952	0.1918	0.0733
Jun	0.6381	0.0972	0.2454	0.1390	0.3700	0.0947	0.2057	0.0662
Jul	0.4362	0.1435	0.2831	0.0708	0.4280	0.1407	0.2796	0.0680

5. Trading implications

While some corn traders suspect that corn futures option implied volatility might be seasonal due to the fact that corn growth is affected by many seasonal factors, a close examination of the volatility pattern for the decade of the 1990s reveals that volatility is not as seasonal as suspected. The volatility is largely affected by the impact of weather on the planting, pollination, and growth of the corn crop. Although a general rising trend of implied volatility from January to July is observed, time decay may offset the gains in option prices that result from higher volatility.

Traders frequently compare implied volatility with historical volatility from the same period from prior years to predict short-term implied volatility changes. Historical volatility tends to be lower than implied volatility in the early part of a year. This pattern, however, does not necessarily imply a trading opportunity. Still, we are curious

Table 4
Forecasting performance of historical volatility estimates for 1991-2000

We use estimated volatility from a given interval as the volatility forecast for the next interval. We record the deviations between forecast and realized volatilities. We repeat the above procedure using 10- and 20-day moving window measures. Root-mean-squared-errors (RMSEs) summarize all corresponding recorded volatility deviations. In the zero mean procedure, we compute both realized and forecast volatility in the forecasting period assuming a zero-mean.

	10-day (actual mean)	20-day (actual mean)	10-day (zero mean)	20-day (zero mean)	Realized volatility (January – July)
Year	RMSE	RMSE	RMSE	RMSE	MEAN
1991	0.0519	0.0665	0.0535	0.0652	0.1866
1992	0.0724	0.0504	0.0689	0.0447	0.1651
1993	0.0793	0.0580	0.0784	0.0573	0.1386
1994	0.1024	0.0635	0.1018	0.0637	0.2206
1995	0.0628	0.0478	0.0571	0.0461	0.1417
1996	0.0790	0.0828	0.0680	0.0816	0.2734
1997	0.0803	0.0754	0.0724	0.0724	0.2061
1998	0.0806	0.0809	0.0754	0.0774	0.2095
1999	0.0685	0.0737	0.0708	0.0751	0.2271
2000	0.1600	0.1469	0.1613	0.1443	0.2304
Averages:	0.0837	0.0746	0.0808	0.0728	0.1999

about the potential for profit resulting from the difference in implied and realized volatilities. If implied volatility is consistently larger than realized volatility in futures contracts, then the futures options will tend to be over-priced.

A short options straddle, which involves a short call option and a short put option on the same underlying asset, with the same time to maturity and exercise price, should generate a profit. These short straddles are also called volatility strategies, or volatility plays. Holders of short straddles gain if the market price at maturity stays within a narrow range around the straddle's strike price. This assumes that the positions are held to maturity without delta neutral hedging[1].

We simulate this trading strategy with empirical futures and futures options data. On each trading day in our sample, we construct a short straddle by using an at-the-money call and a put option pair. The call and the put share the same at-the-money strike price and the same maturity month (September). We collect options premiums ($C_0 + P_0$) for the call and the put on the set up day. We hold the short straddle until the options matures and then compute the payoff, which is $|F_T - X|$. This strategy generates a dollar profit/loss of W and a percent return of R:

$$W = C_0 + P_0 - |F_T - X| \quad (7)$$
$$R = W / (C_0 + P_0) \quad (8)$$

We define C_0 as the call option premium on the set up day, P0 as the put option premium on the set up day, F_T as the futures price on the expiration day, and X as the strike price of the call and put.

Table 5 contains the average dollar and percent returns across each of the months during our sample period. We report the results by month. Average dollar profits are quoted on a cents per bushel basis while percent return is quoted as a percent of the initial call and put premiums collected, as defined in equation (8). In the first three months of each year, the average dollar profits are negative, suggesting that the short straddles lose money on average. The results are not surprising because of the long holding period. There is a lot of risk in the underlying futures contract. Holding a short straddle on these contracts involves is risky. Our empirical results show that there is no benefit, on average, in a short straddle strategy during the months of January, February, and March. However, average trading profits for the months between April and July are significantly positive. The highest average trading profit occurs in the month of April. The mean is 6.87 cents per bushel, which corresponds to a return of 16.32%. These statistics are both statistically and economically significant. Consider a six-cent per bushel profit. Since the contract size of corn futures is 5,000 bushels, the profit directly translates to \$300 per contract (\$0.06′5,000 = \$300).

We argue that the positive trading profits are closely related to the fact that option implied volatilities are visibly larger than realized volatilities as presented in Figure 2. High implied volatility leads to high option prices, which lead to profits on short options straddles. Since realized volatilities are lower than implied volatilities, the underlying futures contracts do not generate the degree of movement anticipated by option traders. Consequently, short straddles produce positive profits.

However, we need to interpret these results with caution. First, in our computation, we ignored market frictions, including but not limited to, bid/ask spread and transaction costs. Including such factors will clearly reduce profits and increase losses as traders incur these costs of transacting. Spread and transaction adjusted profits and losses are

Table 5
Average trading profits of a short straddle strategy across calendar months

We set up short straddle positions using at-the-money options for each trading day. We hold the short straddles until the options' maturity day and compute gains or losses. The table reports the average trading profits/losses and returns during each month in our sample period between 1991 and 2000. Profits are quoted on a cents per bushel basis. Return is measured as the percent of initial call and put option premiums collected when we set up the short straddle. ** indicates that the average is significant different from zero at the 0.01 significance level

Panel A: Dollar trading profits

Month	Profit	St. dev.	Min	Max
January	-0.96	22.63	-40.00	35.25
February	-0.82	22.83	-40.50	35.25
March	-1.14	21.03	-40.00	33.75
April	6.87**	23.95	-38.25	64.50
May	4.29**	20.60	-42.00	60.13
June	2.55**	15.91	-33.75	44.25
July	2.90**	11.63	-36.25	30.00
Overall	2.09**	19.26	-42.00	64.50

Panel B: Percentage trading returns

Month	Return	St. dev.	Min	Max
January	1.25%	63.03%	-98.56%	98.58%
February	3.05%	63.21%	-94.37%	98.51%
March	-0.10%	57.82%	-89.89%	98.43%
April	16.32%**	61.01%	-93.51%	98.39%
May	16.08%**	60.81%	-111.81%	99.03%
June	8.08%**	56.21%	-142.03%	98.89%
July	14.69%**	65.19%	233.87%	98.99%
Overall	10.49%**	60.32%	-233.87%	99.03%

more meaningful in such a calculation. Second, options on futures are highly risky securities. Short futures option straddles are highly risky speculative positions. A close examination of Table 5 reveals the standard deviations of the trading returns are in the neighborhood of 60%, and the maximum loss can go well beyond -100% (-233.87% in the month of July). It is true that the average trading profits are positive. However, it is not clear that the average *risk-adjusted* returns on the short straddles are still positive.

6. Conclusion

This paper examines volatility embedded in the September corn futures option markets for the sample period, 1991-2000. Our analysis focuses on corn futures contracts since they are the most actively traded agricultural futures contract on the CBOT. We find an increase trend in both the implied volatility and historical volatility in September corn futures contract over January to July period. We fail to find however evidence of any other seasonal patterns that applies to all of our sample years.

We also examine whether there is a day-of-the-week effect present in the market for these options. We find that implied volatility on Friday, in general, is higher than that on Monday. The difference however is small and statistically insignificant.

Further, we explore the relative performance of alternative techniques to estimate historical volatility. We find that historical volatility is lower than option implied volatility in the earlier part of the year. Historical volatility however rises at a faster pace than implied volatility during mid-year and approaches implied volatility near the option expiration date. We conclude that the twenty day zero mean historical volatility is the best performing estimator for historical volatility.

Given the differences between implied and realized volatility, we test whether one can profit from these divergences. We examine the profits from a short straddle position and find that such a trading strategy does produce positive profits. It is likely however that after adjusting for the transaction costs of trading that these profits will vanish.

Endnotes

1. Traders are likely to create a delta neutral hedge to protect against losses from an adverse movement in futures prices. A delta-neutral hedge involves a long position in a fraction of a unit of the underlying asset and a short call contract. For small changes in the underlying asset, the overall portfolio value is unchanged. Consequently, the portfolio is called a hedged portfolio. Delta refers to the hedge ratio, i.e., the fraction of shares that needs to hedge a short call.

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