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Are Agricultural Options Overpriced?

Hernán A. Urcola and Scott H. Irwin

As agricultural options markets grow, perceptions of overpricing persist among market participants. This study tests the efficiency of corn, soybean, and wheat options by computing trading returns. Several call and put option strategies yield significant profits, but returns are influenced by movements in the futures price, and straddle trading does not lead to significant returns. The combined analysis of put, call, and straddle returns indicates that significant returns can be attributed to drifts in the underlying futures, and that the corn, soybean, and wheat options markets are efficient.

Key Words: agricultural options, mispricing perceptions, trading returns

Introduction

Trading in options on futures contracts was banned during the Great Depression due to allegations of manipulation and abuse, but trading resumed on October 31, 1984. By buying put options, farmers can hedge the price risk of their crops. Put options generate increasing pay-offs as a commodity price decreases without limiting upward commodity price gains by allowing an owner to sell a futures contract at a specified strike price. Unlike short hedging, agricultural producers can establish a minimum selling price for commodities while retaining opportunities to participate in price increases. Similarly, agricultural commodity purchasers can establish price ceilings on commodity prices by purchasing call options, giving the holder the right to buy a futures contract at a specified strike price. Unlike a long hedge, a call option does not prevent its owner from participating in lower commodity prices. These opportunities have caused increases in agricultural options trading volume and open interest. For instance, the trading volume for corn, soybeans, and wheat options has increased 40, 11, and 390 times, respectively, from the first full year of trading in each market to 2009.

As these markets grow, one issue remains stubbornly persistent. Specifically, some market participants argue that agricultural options are overpriced relative to the price insurance being provided. Irwin (1990) reports that farmers, agribusiness dealers, and traders almost unanimously believe that option sellers earned substantial risk premiums. Several prominent market advisory services recommend that clients do not use options outright because of high premiums (Williams, 2003, p. 14), and the Chicago Board of Trade (CBOT, 2004, p. 1) acknowledges that producers may feel the option premiums are too costly. In general, if options are mispriced, then one side of the market consistently makes or loses money. Risk-averse farmers or grain processors might be willing to pay for insurance, but if options are overpriced, the price for this insurance might be higher than its fair market value. If options are overpriced enough, their cost can offset (or more than offset) the benefit of reducing risks.

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The perception that agricultural options are overpriced is consistent with a growing body of evidence which documents anomalies in the pricing of certain financial futures options. Several studies have shown that excess returns of about 100% can be made by selling options on the S&P 500 futures through simple trading schemes (Constantinides, Jackwerth, and Perrakis, 2009; Coval and Shumway, 2001; Bollen and Whaley, 2004). It is also interesting to note mispricing concerns in the investment industry that parallel those in agriculture. The education section of the exchange-traded funds (ETF) center of Yahoo Finance (2006) advises investors against routinely using options on ETFs because their price is usually too high.

Option mispricing is especially interesting to academic researchers because of competing theoretical models of asset pricing. For some time, the main model used to describe the behavior of market prices has been the Efficient Market Hypothesis (EMH) (Fama, 1970). The EMH predicts that prices always reflect the true value of the assets, and it is not possible to obtain systematic arbitrage profits. Any mispricing would create riskless arbitrage opportunities. Traders would immediately take advantage of these opportunities, arbitraging the mispricing away, and bringing prices back into alignment. This process guarantees that market participants correct any mispricing by pursuing profitable trades.

Branger and Schlag (2005) argue that the seeming overpricing of options is caused by the path-peso problem. Under the path-peso problem, options appear overpriced because option sellers consider rare, but possible, underlying price paths when pricing options. As opposed to buying options, selling options entails significant risk. Therefore, option sellers have important incentives to price them accurately. However, because such rare price events are not usually observed, the true probability distribution cannot be estimated with precision from a sample of observed prices, and important characteristics of the true underlying distribution remain unknown. Yet, option sellers know that such price paths are theoretically possible and price options accordingly. Bates (1991) documents how market crash fears affect option premiums in the S&P 500 futures market. Nonetheless, other authors question the validity of the EMH and propose alternative models of market behavior. As Barberis and Thaler (2003) contend, many of the opportunities perceived to be pure arbitrage are in fact risky and costly, and therefore unattractive to many investors. They discuss several risks faced by arbitrageurs when trying to exploit seemingly riskless opportunities. As a result, arbitrage may be limited, and mispricing can remain unchallenged and persist through time.

To empirically test the validity of the EMH in options markets, researchers have used two approaches. The first is based on the prediction that implied volatility (IV) should be an unbiased forecast of subsequent realized volatility (RV) under market efficiency; otherwise, the options market may not correctly price options. Implied volatility can be obtained by inverting a given option pricing model and solving for the standard deviation. The forecasting ability of IV is also tested relative to alternative forecasts, such as historical volatility (HV). The second approach computes returns to different simulated trading schemes using historical end-of-day or intraday option prices. Returns are computed using a riskless trading strategy or raw returns are adjusted for risk. In general, market efficiency requires that expected risk-adjusted returns equal zero.

Existing evidence regarding options markets for corn, soybeans, and wheat is largely based on the IV approach, and most studies indicate some degree of mispricing.[1] Myers et al. (1996) report that historical volatility can improve the forecast of the volatility of soybean futures given by implied volatility. Simon (2002) uses options data from January 1988 through

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[1] Also, recent evidence of mispricing has been reported for live cattle options markets (Brittain, Garcia, and Irwin, 2009).

September 1999, and applies the IV approach to options on corn, soybean, and wheat futures. He concludes soybean and wheat markets are efficient. For the case of corn only, Simon simulates trading returns and reports that corn options are efficiently priced. More recent studies, however, reveal contrasting results. Szakmary et al. (2003) find that IV provides a biased volatility forecast for corn, soybeans, and wheat. Similarly, Egelkraut and Garcia (2006) observe that IV provides a biased forecast of the RV prevalent in intermediate time intervals for soybeans and wheat, but not for corn. Results for all but one of the aforementioned studies indicate some degree of mispricing in agricultural options.

Moreover, it is worth noting that the IV approach has some important limitations. In particular, it is not possible to conclude from IV forecast results whether mispricing is large enough to generate consistent trading profits. The fact that options volatility forecasts are biased constitutes a necessary condition for market inefficiency, but it is not sufficient given that a biased forecast does not immediately mean systematic trading profits can be obtained. Also, the IV approach requires the use of an option pricing model. Thus, volatility biases can be caused by using the wrong pricing model, and are not necessarily explained by market inefficiency. Further, because trading returns are not computed, the effect of transaction costs on trading returns cannot be quantified.

The above discussion indicates the existing evidence about the efficiency of corn, soybean, and wheat option markets is mixed, and to a large extent based on IV tests with the attendant limitations of such tests. A direct test for these options has not been implemented for all three markets. Since the pricing of agricultural options is an important issue for farmers, grain processors, and traders in general, the objective of this study is to test the efficiency of corn, soybean, and wheat options markets utilizing returns from simulated trading strategies.

The simulated trading approach is model-free and allows the effect of transaction costs to be quantified. A drawback of this approach is that returns may be influenced by movements in the underlying price. To remove this influence, returns to straddle strategies are also computed. Straddles are nondirectional trades that remove the influence of price trends on returns, and the extent to which option premiums correspond to the risk in the market becomes more evident. This approach has been recently employed by Brittain, Garcia, and Irwin (2009) and Urcola and Irwin (2010). Using a data set that begins at the resumption of trading, we find corn and soybean options are efficient. Wheat calls and puts yield significant returns, but wheat straddle returns are not statistically significant once transaction costs have been subtracted. This finding suggests wheat options price market risk efficiently. Mispricing claims regarding corn, soybean, and wheat options can be caused by biases in agents' perceptions of futures price distributions.

Data

The analysis uses daily settlement prices and volume for corn, soybean, and wheat options obtained from the CBOT and from Barchart. The data set includes daily settlement prices for the underlying futures contract and daily interest rates for three-month Treasury Bills obtained from the Federal Reserve Bank. Data on options and futures prices start on February 27, 1985, February 19, 1985, and November 17, 1986, respectively, for corn, soybeans, and wheat. The data set for all three commodities ends on December 31, 2009. Option contracts traded at the CBOT are one of two types, "standard" and "serial." A standard option contract exercises on the underlying futures in each corresponding contract month. Serial option contracts are listed in months where there is no futures contract and exercise into the nearby futures (i.e., an August corn option contract exercises into September futures). In this way, there is an option contract available for each month of the year since 1998.[2]

Daily settlement prices of options are used in the analysis. Compared to closing prices, settlement prices do not suffer from nonsynchronous/stale trading, and are less likely to have rounding errors or to violate basic nonarbitrage restrictions. This is because settlement prices at the CBOT are scrutinized at two different levels of control at the close of each trading day.[3] First, a designated group of traders, the "pit committee members," propose settlement prices for each option traded. In proposing settlement prices, pit committee members exert mutual control over one another since they are immersed in a conflict of interests. Settlement prices are used by the clearing corporation to compute margin requirements. These margins determine the amount of money traders must maintain on deposit, and in some situations margin calls might drive traders into bankruptcy. The second level of control is exerted by the exchange through a computer software program. Proposed settlement prices are verified by software, operated by an exchange staff member, which checks basic nonarbitrage restrictions.[4]

Previous studies of financial and agricultural options filter out of the data set those options with very low trading volume or premiums and options violating no-arbitrage relationships (Coval and Shumway, 2001; Egelkraut, Garcia, and Sherrick, 2007). However, in order to assess the impact of every trade on market efficiency, our study includes options that have been traded at least once on the day positions are established, regardless of premium level. Violations of no-arbitrage bounds—such as maximum and minimum option premiums and strike-premium relationships—are checked through the data set. These relationships determine bounds on option premiums that identify whether riskless profit opportunities exist. A large number of observations violating these relationships can indicate potential recording errors in the data set. McDonald (2003, ch. 9) discusses these relationships in detail and presents the corresponding formal proofs. For example, no-arbitrage bounds imply the premium for a call option cannot be negative, since the call need not be exercised if the futures price is less than the strike price. Similarly, the call premium cannot exceed the futures price, because the holder of a call will end up owning the future if the call expires in-the-money.

Option premiums must also vary according to established no-arbitrage relationships across options. First, a call option with a low strike price should be worth at least as much as an otherwise identical call (i.e., another call with the same underlying asset and expiration date) with a higher strike price. Second, the premium difference between two otherwise identical calls with different strike prices cannot be greater than the difference in strike prices. Finally, call premiums should decrease at decreasing rates for calls with progressively increasing strike prices. If these relationships do not hold, different combinations of options (i.e., spreads) would exist that would always yield positive profits. Equivalent relationships can be derived for put options. In the data set employed here, less than 1% of the observations violate one of these relationships. Such observations were not included in the return computations.

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[2] There is a tendency for observations to be more numerous in recent years, due to the increase in liquidity over time. However, there is no evidence of nonrandomness in the distributions of return observations over time. Therefore, results are not driven by observations from any particular subperiod of the data set.

[3] Details about options settlement procedures at the CBOT were obtained from interviews with the Vice President for Investigations and Audits and with commodity option traders.

[4] Control software was introduced by exchanges to minimize opportunities to manipulate option settlement prices. The program allows a preestablished margin of discrepancy between theoretical and proposed settlement prices, but pit committee representatives must either adjust the settlement price within the theoretical values, or justify in writing why the option was settled outside the program parameters.

Option Return Computations

Observed trading returns are computed by buying options approximately 30 and 90 calendar days prior to expiration and holding the positions until expiration. At expiration, a new set of option contracts having the same amounts of time left to expiration as the previously held option is purchased and held until expiration, and so on. The returns computed here are relevant for any rational risk-averse investor who invests a share of his or her wealth with the goal of maximizing profits. The 30-day holding period maximizes the number of nonoverlapping return observations and minimizes the effects of transaction costs and/or bid-ask spreads because it involves trading once. The 90-day strategies are informative about the pricing of options with a longer time horizon. The option returns computed here are model free, since the computations do not require the specification of any option pricing model. Consequently, results are not affected by the choice of a particular pricing model.

These trading strategies involve taking long positions. For the case of put (call) options, long positions earn (lose) money when the underlying futures price decreases. In contrast, long put (call) positions lose (make) money when the price of the underlying futures increases. Note that when long positions make money, short positions lose money. If the bid/ask spread is symmetrical around the option's settlement price, then profits computed from settlement prices for an off-floor seller are equal and of opposite sign to profits for an off-floor buyer of the option. If the bid/ask spread is not symmetric around the options settlement price, then the profits of buyers and sellers are not equal and of opposite sign, and some errors in the estimation of profits will exist. However, because of the multiple layers of scrutiny to which settlement prices are subjected, settlement prices are normally set close to the bid/ask spread midpoint, and they reflect prices at which options could actually have been traded. Thus, determining that long positions consistently make money indicates short positions consistently lose money, and vice versa.

The percentage returns to a put (r_p) and to a call (r_c) are computed, respectively, as $r_p = (\max(K - F_T, 0)/p_{K,t} - 1) * 100$ and $r_c = (\max(F_T - K, 0)/c_{K,t} - 1) * 100$, where $p_{K,t}$ and $c_{K,t}$ are the price of the put and of the call with strike price K at time t, and F_T is the price of the underlying futures at the expiration of the option. The percentage returns for calls and puts can be expressed in dollars per contract as $r_c/100 * c_{K,t} * 5{,}000$ and $r_p/100 * p_{K,t} * 5{,}000$, respectively, where 5,000 is the contract size in bushels.

Trading costs in options markets can be broadly divided into two categories: brokerage commissions and the bid-ask spread.[5] Brokerage commissions are readily available from brokerage service providers. Estimates of bid-ask spreads for agricultural options markets are scarce.[6] In this study, we compute trading returns, excluding all trading costs (brokerage fees and bid/ask spread) from the analysis. Then, if trading profits are found, the level of transaction costs that would eliminate those profits is determined.

Straddles are formed by an equal number of calls and puts with the same strike prices and with the same amount of time to expiration. The simulation of long straddles complements the strategy of buying puts and calls individually because straddles do not require a forecast of the direction of futures price movements. Straddles are nondirectional trades and profit from futures price movements in either direction, but losses occur if the futures remain at similar levels. Furthermore, straddles constitute a useful device to analyze the influence of futures price movements on option returns (Brittain, Garcia, and Irwin, 2009). During periods of increasing futures prices, calls (puts) will yield positive (negative) returns, and vice versa for periods of decreasing futures. However, when straddles are simulated, the influence of the underlying futures price movement is removed, and the ability of the options to price market risk is highlighted. Under this framework, options market efficiency should be gauged analyzing both individual option returns and straddle returns. For instance, significant returns of individual calls or puts combined with insignificant straddle returns would suggest that option returns are caused primarily by movements of the futures price, but that options are not mispriced in aggregate. In contrast, significant straddle returns indicate options are mispriced relative to risk in the market.

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[5] The bid-ask spread cost is also referred to as execution cost, liquidity cost, or skid error. There are also other costs such as clearing, exchange, and floor brokerage fees. These, however, are a very small percentage of total trading costs (Wang, Yau, and Baptiste, 1997).

[6] Shah, Brorsen, and Anderson (2009) estimate for the first time the liquidity costs for an agricultural options market, the wheat options traded at the Kansas City Board of Trade. Their findings reveal that options liquidity costs are two to three times higher than the typical liquidity costs for the underlying futures.

Long straddles are formed by purchasing one nearest-to-the-money call and one nearest-to-the-money put with 30 or 90 days remaining to expiration. Straddle positions are held until the option's expiration date. Returns to long straddles are computed in percentage terms as:

$$(1) \qquad r_{st} = \left(\frac{c_{K1,T} + p_{K2,T}}{c_{K1,t} + p_{K2,t}} - 1 \right) * 100.$$

Similarly, straddle returns are expressed in dollars per contract as $(r_{st}/100 * (c_{K1,t} + p_{K2,t})) * 5{,}000$, where $c_{K1,T} = \max(F_T - K, 0)$ and $p_{K2,T} = \max(K - F_T, 0)$ are the premiums for calls and puts at expiration. The purchase prices of calls and puts at time t are denoted by $c_{K1,t}$ and $p_{K2,t}$, with $K_1 \approx K_2$.

Straddle strategies profit from increases in implied volatility. For instance, if IV increases once the position has been established, the value of both calls and puts will rise and the strategy can be offset at a profit. Therefore, it might be wise to buy straddles when the trader expects an increase in IV. In order to test whether volatility changes may be used to exploit any mispricing, different entry rules for increasing the possibility of profitable trades are simulated. First, straddles are initiated with options having one or three months to expiration, regardless of volatility levels. Second, straddles are initiated only on days where the 30-day moving average of realized futures volatility (RV) is below average. This strategy profits from mean-reverting volatility behavior. Indeed, inspection of the RV and of IV patterns through the sample reveals cycles around a long-term mean. Realized volatility is computed as the standard deviation of the continuously compounded daily returns, with daily returns calculated as the log of the ratio of the futures price at t and at $t-1$, and annualized by multiplying by the square root of 252 (the typical number of trading days per year). Third, straddles are initiated only on days where the at-the-money (ATM) implied volatility is below the sample average IV. This strategy generates profits when IV increases after the position has been established. Implied volatilities are computed as the average of the IV for the nearest-to-the-money call and for the nearest-to-the-money put, using Black's (1976) future options pricing model. Similar trading decision rules have been used in previous option research studies (e.g., Simon, 2002; Urcola and Irwin, 2010).

Options market efficiency tests are implemented by testing whether expected returns equal zero. If expected option returns are statistically different from zero, this would imply option prices do not reflect all available information about the commodity, and the options market is inefficient (Fama, 1970). In order to test whether expected option returns are statistically different from zero, bootstrapped confidence intervals are constructed. Bootstrapping uses the sample data to obtain a description of the sampling properties of empirical estimators when asymmetries in the return distribution might limit the reliability of the usual *t*-statistic. Bootstrapped confidence intervals are not affected by asymmetries in the distribution of returns. Given a sample of reasonable size and a consistent estimator, the asymptotic distribution of the estimator can be approximated by drawing observations from the data a given number of times. Then, the estimator is computed from each of the bootstrapped samples (Greene, 1997). Since the mean is a consistent estimator, observations are drawn with replacement from each of the return vectors for calls, puts, and straddles. The mean return is then computed from the bootstrapped vectors. This process is repeated 2,000 times. Finally, the 2.5% and 97.5% percentiles for the distribution of the mean return are computed. These percentiles identify with 95% confidence the range within which the true mean return lies.

Time and Information Effects

Given the nature of agricultural production, it is possible that option returns are affected by time trends, time of year, or the release of production forecasts. Regression analysis is used to investigate these effects. Market behavior might change over time as traders learn and liquidity increases. Egelkraut and Garcia (2006) document different volatility patterns across the production cycle of the commodities studied here. Such patterns may significantly impact option returns. Finally, the release of acreage and production reports from the U.S. Department of Agriculture (USDA) are carefully watched by market participants, and these announcements have a strong influence on agricultural futures prices (Isengildina-Massa et al., 2008).

Option returns would vary systematically if any of these effects are substantial. In order to test for these effects, the following regression model is estimated for the full sample period for the returns of calls, puts, and straddles in each respective market:

$$r_j = a + bx_j + b2x_j^2 + \sum_{q=2}^{4} c_q D_{j,q} + dAnn_j + \varepsilon_j , \tag{2}$$

where r_j is the per contract return for the jth call, put, or straddle; a is the intercept; b and $b2$ are the linear and quadratic trend parameters; x_j is a time trend; c_q is the parameter for quarter q; and $D_{j,q}$ is a dummy variable equal to one if option j expires in quarter q, and zero otherwise. For the quarter dummy variables, the January-February-March quarter is the base. The variable Ann_j is a dummy equal to one if the holding period for return j contains the date of one of the production forecast reports, and zero otherwise; and d is the announcement coefficient. The Gaussian error term is represented by ε_j.

Results

Returns are presented and analyzed from the buyer's perspective. Thus, a positive return indicates a profit to the buyer and a loss to the seller, and vice versa for a negative return. Results were computed and grouped into moneyness categories. The moneyness, or leverage, is a measure of the ability of the option to magnify gains and losses, and it varies directly with the relationship K/F_t. Options with different moneyness levels have different behavior. For instance, the sensitivity of the option price to changes in the price of the underlying futures (the option delta and gamma) and to changes in its volatility (the option vega) changes with

Table 1. Corn, Soybean, and Wheat Option Empirical Returns

Description	Dollar Returns Mean	Dollar Returns Std. Dev.	Percentage Returns Mean	Percentage Returns Std. Dev.	No. of Observs.
Corn (2/27/1985–12/31/2009):					
30-Day Calls	14	1,082	−9.0	579	1,771
90-Day Calls	−10	613	5.3	155	1,316
30-Day Puts	162*	1,120	6.0	305	1,470
90-Day Puts	76*	697	11.9*	117	913
Soybeans (2/19/1985–12/31/2009):					
30-Day Calls	−177*	2,045	−32.3*	185	2,361
90-Day Calls	−15	915	−1.6	191	1,676
30-Day Puts	85	1,955	−6.0	287	1,796
90-Day Puts	36	1,051	−5.1	86	1,092
Wheat (11/17/1986–12/31/2009):					
30-Day Calls	−175*	1,458	−1.7	525	1,814
90-Day Calls	−94*	626	−5.1	130	1,442
30-Day Puts	29	2,457	2.9	176	1,490
90-Day Puts	110*	846	1.8	69	1,082

Notes: An asterisk (*) denotes statistical significance at the 5% level. Ninety-five percent confidence intervals for the mean returns are constructed using a bootstrap procedure with 2,000 repetitions. Bootstrapped confidence intervals test the null hypothesis that the mean return equals zero.

the moneyness ratio (see McDonald, 2003, ch. 12, for a detailed discussion of these concepts). Studies of financial options have found consistent differences in the returns of options with different moneyness (e.g., Bollen and Whaley, 2004). However, no consistent trends or patterns across moneyness categories were found in returns computed here. Therefore, returns are presented pooled across moneyness categories, without reference to moneyness bins.

Observed Returns

Return distributions for options on corn, soybean, and wheat futures share some common features (table 1). Trading volume tends to increase as the option expiration date approaches, so there are more observations for 30-day returns than for 90-day returns. In general, option returns are highly variable. In percentage terms, the standard deviation of returns is largest on average for corn and smallest for wheat. Also, option returns usually include some extreme return observations, implying the buyers of these options frequently lose the premiums, but occasionally obtain large gains (figure 1).

For corn and soybeans, put options tend to favor buyers, as all 30- and 90-day put dollar returns are positive. However, percentage put returns are positive for corn and negative for soybeans. Corn and soybean calls tend to favor sellers, as most call returns are negative or slightly positive (table 1). Some of the percentage returns for corn and soybean options appear fairly large in absolute value and suggest one side of the market could potentially make consistent profits. Corn puts, in both holding periods, appear to be significantly underpriced, but dollar and percentage returns indicate significant overpricing in 30-day soybean calls.

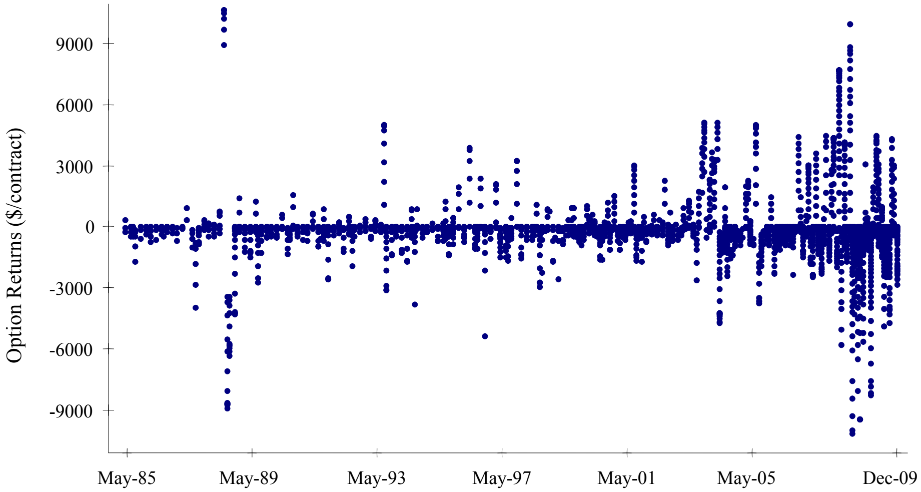

Figure 1. Dollar returns for 30-day soybean calls, March 1985−December 2009

Option returns would be reduced by transaction costs. While transaction costs have not been directly included, their impact on returns can be illustrated. Consider a typical bid/ask spread for grain options of two ticks. Implementing the strategy employed here would cost one tick (since options are traded only once, half of the bid/ask spread is paid, and one tick equals $6.25/contract). Also, consider that one-half tick is paid to offset the futures position once the option has been exercised (i.e., $3.125 per contract). Commission costs have declined in recent years to about $25 per contract, but these costs were higher at the beginning of the sample period. Therefore, average commission costs of about $50 per contract are likely a good approximation for a medium-size off-floor trader. Thus, it would amount to $59.375 per contract to set up and close the trading strategies used for calls and puts. This level of transaction cost would easily eliminate the significant profits of the 90-day corn puts, but unrealistically high levels of transaction costs would be required to eliminate the profits found in 30-day corn puts and in 30-day soybean calls.

Wheat option returns appear to differ by option type; buying calls tends to be unprofitable, but buying puts tends to be profitable (table 1). All wheat call returns are negative, and all wheat put returns are positive. Wheat futures increased to a maximum of $12.825/bu. in March 2008, then descended rapidly to $7.90/bu. by May 1 of the same year. The price decrease continued, with some reversals, until December 2008 (figure 2). If the market did not anticipate this decrease in price, this large and rapid decrease in the futures price could have caused the negative returns for calls and positive returns for puts. Dollar returns are statistically significant for calls in both holding periods and for 90-day puts. The overpricing of wheat calls appears more severe for the 30-day returns than for the 90-day returns. The overpricing of wheat options does not disappear after including transaction costs. Call dollar returns and 90-day put dollar returns remain statistically significant after accounting for transaction costs of $59.375 per contract.

Results show that buying straddles using different decision rules does not generally produce large economic gains (table 2). Buying corn and soybean straddles systematically yields small absolute values, indicating that neither buyers nor sellers would obtain excess returns once transaction costs are subtracted. Thirty-day wheat straddles appear underpriced,

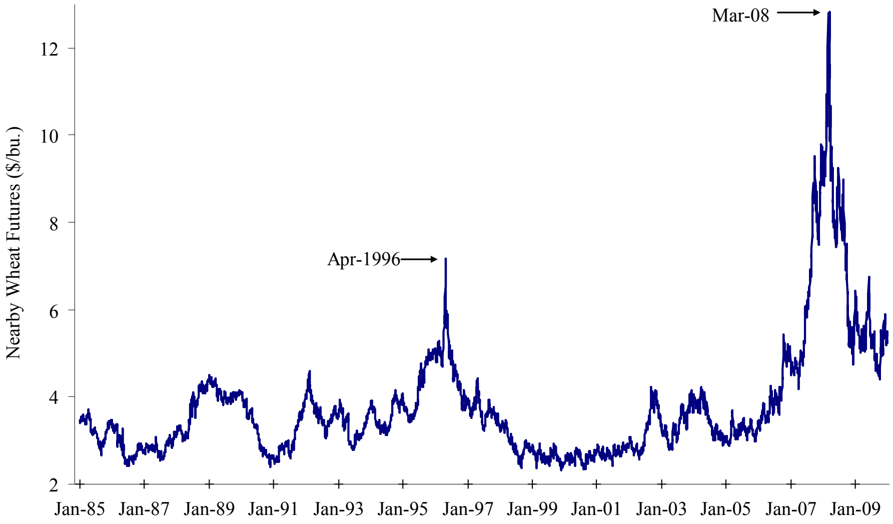

Figure 2. Nearby wheat futures, January 1985–December 2009

Table 2. Corn, Soybean, and Wheat Straddle Returns with Different Trading Rules

	No Volatility Rules[a] (systematically buy & hold)		RV Is Below the 30-Day Moving Average[b]		IV Is Below the Sample Mean[c]	
Description	%	$/Contract	%	$/Contract	%	$/Contract
Corn Straddle:						
30-Day	−3	58	−16*	−72	−8	−17
No. of Observs.	(274)		(154)		(139)	
90-Day	5	95	4	84	7	86
No. of Observs.	(128)		(69)		(72)	
Soybean Straddle:						
30-Day	−8	−35	−14*	−173	−11	−95
No. of Observs.	(376)		(225)		(222)	
90-Day	−1	−0.3	−0.03	25	−0.1	21
No. of Observs.	(154)		(96)		(90)	
Wheat Straddle:						
30-Day	9	207*	7	125	4	96
No. of Observs.	(274)		(144)		(155)	
90-Day	0.2	58	1	22	0.04	−1
No. of Observs.	(148)		(82)		(89)	

Note: An asterisk (*) denotes that the bootstrapped 95% confidence interval for the mean return, constructed using 2,000 repetitions, does not include zero.

[a] Indicates that straddle trading is initiated systematically for options with 30 or 90 days left.

[b] Indicates that straddle trading is initiated only for options having 30 or 90 days left and on days when realized volatility (RV) is below its 30-day moving average.

[c] Indicates that straddle trading is initiated only for options having 30 or 90 days left and on days when implied volatility (IV) is below its sample mean.

producing statistically significant returns. Nevertheless, the statistical significance of wheat straddle returns is heavily dependent on the level of transaction costs considered. Two options are traded with straddles, so transaction costs for the entire sample would average about $100 per contract. Subtracting $100 per contract makes expected returns for 30-day wheat straddles statistically insignificant. Furthermore, total transaction costs as low as $38 per contract are enough to make expected returns for 30-day wheat straddles not statistically different from zero. This result highlights the influence of futures price movements on call and put returns, and confirms that traders cannot obtain systematic after-transaction-costs profits in the long run by trading wheat options.

Results from straddle trading do not show much difference when the trigger for entering the market is an RV smaller than the 30-day moving average, or a below-average IV. Using the RV rule, the only statistically significant returns are those for 30-day corn and 30-day soybean straddles, in percentage terms. However, transaction costs of about 6% would be enough to eliminate the significance of these returns. When IV is used to decide when to enter the long straddle positions, returns do not show consistent increases from the previous decision rules, and none of the IV-based returns are statistically significant (table 2).

Overall, results show a tendency for long call returns to be negative and for long put returns to be positive. Statistically significant returns were generated by corn puts, 30-day soybean calls, wheat calls, and 90-day wheat puts. Most of these returns can be attributed to movements of the underlying futures, but wheat option returns reveal that average call prices are too high and that average put prices are too low. The combined analysis of call, put, and straddle returns indicates a strong influence of future price drift on wheat options, but suggests wheat options are priced efficiently, once transaction costs are accounted for.

The sensitivity of wheat results to extreme price shocks is tested by removing observations around the wheat futures rally of March 2008. Specifically, 21 return observations within the September 21, 2007 to August 22, 2008 time window are removed and results are recomputed (roughly, this time window contains observations whose futures price are above $8.50/bu.). This period of time is characterized by an increased market uncertainty, reflected by a higher futures price volatility. In annualized terms, the average RV from September 21, 2007 to August 22, 2008 is 23%—about 30% higher than the sample average RV of 18%. Straddle returns become insignificant after removing observations contained in the aforementioned time interval, which suggests the wheat market's ability to estimate subsequent price movements can be affected in times of increased volatility. Similar findings have been reported for live cattle options (Brittain, Garcia, and Irwin, 2009).

Time and Information Results

Regression analysis shows that time, time of the year, and the release of USDA production reports explain little of the option return variations.[7] Only a few of the estimated coefficients for quarter of the year variables reflect significant effects (tables 3–5). However, no consistent effect of a particular quarter was found across options of a given commodity or across commodities. Similarly, all coefficients of determination are very low for the estimated models, with the largest R^2 being 7.59% for corn puts (table 3).[8]

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[7] Only regression results for 30-day returns are presented here. Results for 90-day returns show similar qualitative results and are available from the authors upon request.

[8] The Newey-West procedure was used to adjust standard errors when autocorrelation was detected using the Ljung-Box-Pierce and ARCH tests.

Table 3. Parameter Estimates for Call, Put, and Straddle Returns and Variables for Time, Quarter, and Crop Report Releases for Corn Futures Options (2/27/1985–12/31/2009)

	CALLS		PUTS		STRADDLES	
Variable	Parameter Estimate	*t*-Ratio	Parameter Estimate	*t*-Ratio	Parameter Estimate	*t*-Ratio
Constant	−130.63	−0.69	117.81	0.71	−21.15	−0.10
Linear Trend	1.28	0.39	−4.20	−1.49	−0.94	−0.16
Quadratic Trend	0.001	−0.03	0.03	1.69	0.02	0.45
$Q2$	116.44	0.53	−125.05	−0.81	−227.20	−1.26
$Q3$	−381.40*	−2.46	802.15	1.75	316.92	0.47
$Q4$	−68.75	−0.41	703.20*	2.04	409.67	0.93
Ann	143.15	1.12	−658.10	−1.49	−366.38	−0.57
R^2	2.35		7.59		3.41	
No. of Observs.	1,771		1,470		274	

Notes: An asterisk (*) denotes statistical significance at the 5% level. The regression model is expressed as:

$$r_j = a + bx_j + b2x_j^2 + \sum_{q=2}^{4} c_q D_{j,q} + d\,Ann_j + \varepsilon_j ,$$

where r_j is the per contract return for the *j*th call, put, or straddle combination; *a* is the intercept; *b* and *b*2 are the linear and quadratic trend parameters; x_j is a time trend; c_q is the parameter for quarter *q*; $D_{j,q}$ is a dummy variable equal to one if option *j* expires in quarter *q*, and zero otherwise. For the quarter dummy variables, the quarter January-February-March is the base. The variable Ann_j is a dummy equal to one if the holding period for return *j* contains the data of one of the production forecast reports, and zero otherwise; and *d* is the announcement coefficient. The Gaussian error term is represented by ε_j.

Table 4. Parameter Estimates for Call, Put, and Straddle Returns and Variables for Time, Quarter, and Crop Report Releases for Soybean Futures Options (2/19/1985–12/31/2009)

	CALLS		PUTS		STRADDLES	
Variable	Parameter Estimate	*t*-Ratio	Parameter Estimate	*t*-Ratio	Parameter Estimate	*t*-Ratio
Constant	−464.77	−0.86	303.53	0.79	116.95	0.22
Linear Trend	13.16	1.83	−4.58	−0.90	5.52	0.69
Quadratic Trend	−0.05	−1.81	0.02	0.86	−0.01	−0.32
$Q2$	12.77	0.03	−803.03*	−2.40	−918.81	−1.55
$Q3$	−1,098.40*	−2.60	163.08	0.43	−864.2	−1.88
$Q4$	−270.02	−0.70	−52.45	−0.15	−284.94	−0.66
Ann	−35.09	−0.12	251.25	0.72	−104.55	−0.23
R^2	6.53		6.05		4.50	
No. of Observs.	2,361		1,796		376	

Notes: An asterisk (*) denotes statistical significance at the 5% level. See footnote to table 3 for the regression model and definitions of terms.

Table 5. Parameter Estimates for Call, Put, and Straddle Returns and Variables for Time, Quarter, and Crop Report Releases for Wheat Futures Options (11/17/1986–12/31/2009)

	CALLS		PUTS		STRADDLES	
Variable	Parameter Estimate	*t*-Ratio	Parameter Estimate	*t*-Ratio	Parameter Estimate	*t*-Ratio
Constant	−250.90	−1.00	108.08	0.52	−325.53	−1.04
Linear Trend	2.42	0.63	−2.00	−0.41	−5.89	−0.75
Quadratic Trend	−0.02	−0.69	0.01	0.20	0.07	1.25
*Q*2	12.00	0.04	−13.26	−0.04	633.87*	2.23
*Q*3	478.41	1.72	−148.00	−0.69	188.45	0.39
*Q*4	196.82	0.73	76.42	0.42	102.69	0.31
Ann	−251.21	−1.17	159.88	0.84	16.22	0.04
R^2	0.85		0.20		5.21	
No. of Observs.	1,814		1,490		274	

Notes: An asterisk (*) denotes statistical significance at the 5% level. See footnote to table 3 for the regression model and definitions of terms.

Returns to buying corn (table 3), soybean (table 4), and wheat (table 5) options appear stable through time, as no time effect was found. Some returns appear to differ with the quarter of the year. Corn calls (puts) returns are significantly lower (higher) than the first-quarter returns. Also, third-quarter soybean calls and second-quarter soybean puts are statistically lower than first-quarter returns. Finally, second-quarter wheat straddle returns are higher than first-quarter returns. Quarter effects appear to be randomly distributed across options type and options market without a consistent pattern.

The release of USDA crop reports does not have a significant influence on the returns of corn, soybean, and wheat options. Based on our results, the pricing ability of corn, soybean, and wheat option markets is stable, and time, time of the year, and production forecast announcements cause little to no effect on the degree of market efficiency.

Conclusions

This study empirically evaluates the claim that agricultural options are overpriced by simulating returns from different trading strategies. Corn puts, 30-day soybean calls, wheat calls, and 90-day wheat puts yielded significant returns. However, buying corn and soybean straddles does not lead to large economic gains, even before accounting for customary transaction costs. Wheat options exhibit the largest number of significant returns, indicating call prices are too high and put prices are too low, on average. Nonetheless, 30-day wheat straddles do not yield excess returns after accounting for transaction costs, suggesting wheat options price market risk efficiently. The combined analysis of call and put returns and of straddle returns shows that corn, soybean, and wheat returns are primarily influenced by the fluctuations experienced by futures prices, but that these options markets are efficient. Further, our results establish that large price shocks can markedly change volatility and the market's estimation of additional price movements. In such uncertain periods, forecasting might be more difficult than usual, and the degree of market efficiency can be reduced.

Szakmary et al. (2003) report that corn, soybean, and wheat options provide a biased volatility forecast, and Egelkraut and Garcia (2006) find that soybean and wheat options' implied volatility provides a biased forecast for the intermediate realized volatility. While a biased volatility forecast constitutes a precondition for options market inefficiency, according to our findings, any bias in the implied volatility forecast is not large enough to generate consistent speculative profits, either for sellers or buyers of the options analyzed. Also, this study augments Simon's (2002) analysis by including 13 additional years of data. Our results agree with those of Simon, but provide a more detailed explanation of the returns for calls, puts, and straddles separately and determine that the degree of market efficiency can be influenced by futures price movements.

Our results are substantially different from those found for options on the S&P 500 futures. Differences between the efficiency of agricultural option markets and S&P 500 option markets might be explained by the different underlying assets. Agricultural options are written on a single asset, as opposed to options on index futures. Comparing returns to index options with those of stock options, Bollen and Whaley (2004) conclude the mispricing of S&P 500 options is due to excess buying pressure that market makers are not able to arbitrage away. This explanation suggests S&P 500 futures options have more natural buyers (i.e., investors in all 500 stocks) compared to agricultural options (i.e., investors in a single asset).

Finally, results of this study contrast with the perception that agricultural options are overpriced. This seeming disparity can be explained because individuals' subjective probability assessment of the futures price distribution does not agree with the actual futures price distribution. This mis-assessment of the actual distribution has been formally proposed by Tversky and Kahneman (1974) and has been documented empirically for U.S. farmers and grain merchandisers. Eales et al. (1990) find a systematic disagreement between the future price volatility expected by farmers and merchandisers and the corn and soybean IV, and Kenyon (2001) documents that farmers consistently expect higher than actual prices and underestimate the future price volatility. A lower than actual price volatility may lead economic agents to believe that put and call options are overpriced. Alternatively, if the subjective probability distribution is skewed toward higher prices, producers will see put options as being overpriced. Therefore, our results suggest the mispricing claims are caused by biases in the agents' perceptions of futures price distributions.

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