Are Agricultural Options Too Expensive?

by

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Abstract: As agricultural options markets grow, perceptions of overpricing persist among market participants. This article tests the efficiency of corn, soybean and wheat options by computing trading returns. Results indicate that corn and soybean options are efficient, but that wheat calls yield significant returns to option sellers. These returns, however, can be attributed to trends in the futures price and wheat options price the market risk efficiently. Our findings suggests that agricultural options markets are efficient.

Key words: mispricing perceptions, agricultural options, trading returns.

Trading in options on futures contracts was banned during the Great Depression due to allegations of manipulation and abuse, but trading resumed on October 31st, 1984. By buying a put option an agricultural producer can acquire the right to sell futures at a specified price while retaining the right to sell at a higher price should the market price exceed the strike price. A buyer of a call option can lock in the purchase price of the futures by paying only the option premium, which is a small fraction of the futures purchase price. Because of these features, agricultural options have experienced major increases in trading volume and open interest since the resumption of trading. For instance, the trading volume for corn, soybeans and wheat options has increased 57, 12 and 436 times, respectively, comparing 2008 to the first full year of trading in each market.

As these markets grow, one issue remains stubbornly persistent. Specifically, some market participants argue that agricultural options are too expensive. 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 (i.e., the selling side or the buying side) consistently makes or loses money. For instance, farmers that hedge the value of their crops or grain processors who hedge input purchases may lose substantial amounts of money when using options. Risk-averse farmers 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. This situation is the equivalent of buying expensive insurance, and if this insurance is expensive enough, the cost can offset (or more than offset) the benefit of reducing risks.

The perception that agricultural options are overpriced is consistent with a growing body of evidence that 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 mis-pricing concerns in the investment industry that parallel those in agriculture. For example, the education section of the exchange-traded funds (ETF) center of Yahoo Finance (2006) advises investors not to routinely use options on ETF's because their price is usually too expensive.

Option mispricing is especially interesting to academic researchers because of competing theoretical models of asset pricing. Traditional theory postulates that market prices are right. While some individual traders might incorrectly assess expected prices, in aggregate the market makes no systematic pricing mistakes. The efficient markets hypothesis (EMH) (Fama, 1970) predicts that prices always reflect the true value of the assets, and hence, it is not possible to obtain systematic arbitrage profits. However, the EMH hypothesis rests on several assumptions about economic agents and their trading environment. For instance, the EMH assumes frictionless markets in which traders have no transaction costs and all existing information is costlessly available to them. The hypothesis postulates that under these conditions 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.

In order to empirically test the validity of the EMH in options markets, researchers have used two basic approaches. The first 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 adjusted for risk. In general, market efficiency requires that expected risk-adjusted returns equal zero. The second approach 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 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).

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 (2001) applies the IV approach to options on soybeans and wheat and concludes that these markets are efficient. For the case of corn only, the author simulates trading returns concluding that corn options are efficiently priced. However, more recent studies report contrasting results. Szakmary et al. (2003) find that IV provides a biased volatility forecast for corn, soybeans and wheat. Similarly, Egelkraut and Garcia (2006) find that IV provides a biased forecast of the RV prevalent in intermediate time intervals for soybeans and wheat, but not for corn. The above discussion reveals that results of all but one of the aforementioned studies indicate some degree of mispricing in agricultural options.

Furthermore, it is worth noting that the IV approach has some important limitations. In particular, it is not possible to conclude from the IV forecast results whether the mis-pricing 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 that systematic trading profits can be obtained. Also, because trading returns are not computed, the effect of transaction costs on trading returns can not be quantified.

This discussion indicates that the existing evidence about the efficiency of corn, soybeans 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 article is to test the efficiency of corn, soybean and wheat options markets by testing returns to 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 non-directional 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).

Using a data set that begins at the resumption of trading, we find that corn and soybean options are efficient. Thirty-day wheat calls yielded significant gains to option sellers, but these returns can be attributed to trends in the futures price. In aggregate, wheat options price the market risk efficiently. Our results suggests that mispricing claims are caused by biases in the agents' perceptions of futures price distributions.

The rest of the article is organized as follows: The next two sections describe the data, the computation of trading returns and the analysis of different market conditions on option returns. The fourth section presents the empirical results and the last section summarizes the conclusions of the article.

Data

The analysis uses daily settlement prices and volume for corn, soybean and wheat options obtained from the CBOT. The dataset includes daily settlement prices for the underlying futures contract and daily interest rates for 3-month Treasury Bills obtained from the Federal Reserve Bank. Data on options and futures prices start on 2/27/1985, 2/19/1985 and 11/17/1986 for corn, soybeans and wheat, respectively. The dataset for all three commodities ends on 12/31/2005. Option contracts traded at the CBOT are one of two types, "standard" and "serial." A standard option contracts 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] While most option pricing theory is developed for European-type options, the markets analyzed here trade American-type options. European options can only be exercised at expiration date. Instead, American options can be exercised at any time prior to expiration. This research does not employ any option pricing models, thus results computed here are not affected by option type problems.

Daily settlement prices of options are used in the analysis. Compared to closing prices, settlement prices do not suffer from nonsynchronous/stale trading, are less likely to have rounding errors, or to violate basic non-arbitrage restrictions. The reason is that 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," proposes settlement prices for each option traded. In proposing settlement prices pit committee members exert mutual control over each other 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 margins 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 a software, which operated by an exchange staff member, checks basic non-arbitrage restrictions.[4]

The dataset is filtered according to minimum volume traded, strike price convexity and minimum option premium. Similar filters have been applied in studies of options on financial and agricultural derivatives (Coval and Shumway, 2001; Egelkraut, Garcia, and Sherrick, 2007). The analysis uses options that, for any given day, have been traded above an established minimum volume. Prices of lightly traded options may contain little to no information, as they may not reflect a true agreement between buyers and sellers that actively negotiate the fair market value of the asset. There is no established criterion to set the minimum volume figure. This depends on the specific market being analyzed and on the time period under study. In this research the minimum trading volume is set to five contracts a day. This filter of five contracts assures that the option has been traded on the day of the purchase, leaving a reasonable number of observations available. Options whose trading volume is below this minimum are not used in the analysis.[5]

Strike price convexity constitutes a basic no-arbitrage relationship. It shows that options prices must be convex functions of their strike prices, K, and that the slope of these functions should be less than one in absolute value. In practice some option settlement prices violate no-arbitrage relationships due to institutional issues, recording errors, etc. However, those prices do not come from a true negotiation process, and can be seen as outliers that can potentially bias the analysis. Thus, those observations are excluded. Also, options with very low prices are usually very illiquid and few of these observations have the potential to heavily bias the computations toward extremely high returns. Therefore, options with prices less than three times the minimum tick size are also excluded from the analysis.

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. Then, 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 that invests a share of his/her wealth with the goal of maximizing profits. The 30 calendar-day holding period is selected because it maximizes the number of non-overlapping return observations and minimizes the effects of transaction costs and/or bid-ask spreads because it involves trading once. The 90 calendar-day strategies are informative about the pricing of options with a longer time horizon.

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. On the contrary, 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, 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 settlement prices have to go through, settlement prices are normally set close to the bid/ask spread midpoint and they reflect prices at which options could have been actually traded. Thus, determining that long positions consistently make money indicates that 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 as $r_c = (\max(F_T - K, 0)/c_{K,t} - 1) * 100$ where

$p_{K,t}$ and $c_{K,t}$ are respectively 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, $r_p/100 * c_{K,t} * 5000$ and $r_c/100 * p_{K,t} * 5000$, respectively, where 5000 is the contract size in bushels.

Options markets trading costs can be broadly divided into two categories, brokerage commissions and the bid-ask spread.[6] Brokerage commissions are readily available from brokerage service providers. Estimates of bid-ask spreads for agricultural options markets are scarce.[7] In this study, the approach used is to 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 needed to eliminate those profits will be determined.

The computations of returns to long straddle positions is described next. 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 simulations of long straddles complements the strategy of buying puts and calls individually because straddles do not require a forecast on the direction of futures price movements. Straddles are non-directional trades and profit from futures price movements in either direction, but losses occur if the futures remains 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 movements is removed, and the ability of the options to price the market risk is highlighted. Under this framework, options market efficiency should be gauged analyzing both individual options returns and straddle returns. For instance, significant returns of individual calls or puts combined with insignificant straddle returns would indicate that option returns are caused primarily by movements of the futures price, but that, on aggregate, the options are not mispriced. On the contrary, significant straddle returns would indicate that options are mispriced relative to risk in the market.

Long straddles are formed by purchasing one nearest-to-the-money call and one nearest-to-the-money put with 30 or 90 days left and held until the options expiration. Returns to long straddles are computed in percentage terms as,

$$r_{st} = \left(\frac{c_{K_1,T} + p_{K_2,T}}{c_{K_1,t} + p_{K_2,t}} - 1 \right) * 100. \tag{1}$$

Similarly, straddle returns are expressed in dollars per contract as, $(r_{st}/100 * (c_{K_1,t} + p_{K_2,t})) * 5000$, where $c_{K_1,T} = \max(F_T - K, 0)$ and $p_{K_1,T} = \max(K - F_T, 0)$ are, respectively, the premiums for calls and puts at expiration. The purchase price of calls and puts at time t is denoted $c_{K_1,t}$ and $p_{K_2,t}$, respectively, 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 that increase the possibilities 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 would profit from a mean-reverting volatility behavior. Indeed, inspection of the RV and of IV patterns through the sample indicates cycles around a long-term mean. Realized volatility is computed as the standard deviation of the continuously compounded 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 ATM implied volatility is below the sample average IV. This strategy will generate profits when IV increases once 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 computed using the Black's (1976) future options pricing model. Similar trading decision rules have been used in previous option research studies (e.g., Simon, 2001).

Options market efficiency tests are implemented by testing whether expected observed returns equal zero. That expected options returns are not statistically different from zero would imply that option prices do not reflect all available information about the commodity and that 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, from each of the bootstrapped samples the estimator is computed (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. Then, the mean return is computed from the bootstrapped vectors. This process is repeated 2,000 times. Next, the 2.5% and 97.5% percentiles for the distribution of the mean return are computed. These percentiles indicate the range within which the true mean return lie, with 95% confidence.

Time and Information Effects

Given the nature of agricultural production, it is possible that option returns are affected by time, 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 production cycle of the commodities studied here. Such patterns may impact option returns significantly. Finally, the release of acreage and production reports from the United States 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).

Options returns would vary systematically if any of these effects is substantial. In order to test for any of 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,

$$r_j = a + b\, x_j + b2\, x_j^2 + \sum_{q=2}^{4} c_q\, D_{j,q} + d\, Ann_j + \epsilon_j \tag{2}$$

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, $D_{j,q}$ is a dummy variable that equals 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 that equals 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

The first part of this section presents the observed returns of individual puts, calls and straddle trading. The second part presents the analysis of time, season and arrival of information on the level of market efficiency. Returns are presented and analyzed from the buyers perspective, thus a positive return indicates a profit to the buyer and a loss to the seller, and vice versa for a negative return. While results were computed and analyzed grouped into moneyness categories, no identifiable patterns or trends were detected across categories. Therefore, only returns pooled across moneyness categories are reported, without reference to moneyness bins.

Observed Returns

Return distributions for options on corn, soybean and wheat futures share some common features. As expected, 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 for corn and smallest for wheat, on average. Also, option returns usually include some extreme return observations, indicating that the buyers of these options lose the premiums frequently, but obtain large gains on occasions (figure 1).

Corn and soybean option returns tend to favor sellers, both in percentage and dollar terms. For instance, percentage returns are negative or slightly positive for both commodities, and five of the eight dollar returns for corn and soybeans are negative (table 1). Some of the percentage returns for corn and soybean options appear fairly large in absolute value and suggest that one side of the market could potentially make consistent profits. However, returns are highly variable with the result that only the dollar return for 30-day corn calls and for 90-day corn puts are statistically different from zero.

Also, note that option returns would be further reduced by transaction costs. While transaction costs have not been directly included, their impact on returns can be illustrated considering a typical bid/ask spread for grain options of two ticks, one tick to open the position and one tick to close it. Also, consider that one half tick is paid to offset the futures position once the option has been exercised. This would amount to \$59.375/contract to set up and close the trading strategies employed here. Such costs correspond to \$6.25 for buying the option, \$3.125 for offsetting the futures plus a \$50/contract brokerage fee for buying the option and offsetting the futures after the option is exercised.[8] The described costs would easily eliminate the significant returns from trading corn and soybean options.

Wheat option returns appear to differ by option type, buying calls tends to be unprofitable but buying puts tends to be profitable. All wheat call returns are negative, and all wheat put returns are positive (table 1). Wheat call returns are smaller than returns for corn and soybean calls. Wheat futures increased to a maximum of $7.165/bu in April, 1996 and then descended rapidly to about $4/bu by October of that year. The price decrease continued, with some reversals, until August 1998 (figure 2). This large and rapid decrease in the futures price is likely to have caused the negative returns for calls and positive returns for puts if the market did not anticipate this decrease in price. Dollar call returns are statistically significant for both holding periods, and the 30-day percentage call return is also significant. The overpricing of wheat calls appears more severe for the 30-day returns than for the 90-day returns. For puts, the only significant case is the 30-day dollar return.

In most cases, the overpricing of wheat options disappears after including transaction costs. For instance, 90-day calls yield a $71 gain to option sellers, but substracting a per contract transaction cost of $59.375 yields a net gain to sellers of $11.625, not statistically significant. However, including transaction costs does not eliminate the overpricing of 30-day calls, neither in percentage, nor in dollar terms. For these options, the after transaction costs percentage and dollar returns are, respectively, -19.9% and $-94.57, both statistically significant.

Next, the returns to buying corn, soybean and wheat straddles using three trading rules are investigated (table 2). Results indicate that buying straddles using different decision rules does not produce large economic gains. For instance, buying straddles systematically produces significant returns only in the case of 30-day corn options. For soybean and wheat straddles, average returns are negative or small positive values, but neither buyers nor sellers of these options would obtain excess returns once transaction costs are subtracted.

Average returns tend to be larger for the 30-day options than for the 90-day options.

Also, results do not show much difference when the trigger for buying the straddles is a RV smaller than the 30-day moving average, or when the decision rule is an IV below the average IV. Using the RV rule, average returns tend to be larger than returns to buying straddles systematically, but in no case are economically important or statistically significant (table 2). When IV is used to decide when to enter the long straddle positions, returns do not show substantial increases from the previous decision rule. The percentage return for the 30-day soybean straddle is statistically significant, but not large enough to pay for customary transaction costs.

Overall, observed option returns indicate that corn and soybean options are efficiently priced. Wheat option returns indicate that call prices are too high and that put prices are too low, on average. However, only wheat calls for the shorter trading horizon exhibit returns that are larger than typical trading costs. Furthermore, straddle returns suggest that the pattern of wheat options returns is caused by the movements of the underlying futures, and that wheat options price the market risk correctly. The next section analyzes the effect of different market conditions on option returns.

Time and Information Results

This section analyzes the effects of time, time of the year, and the release of USDA production reports on option returns. Regression results show that independent variables explain little of the return variations as few of the calculated t-ratios are statistically significant and coefficients of determination are very low for the estimated models (tables 3 through 5).

Returns to buying corn calls and puts appear stable through time, time of year and are not affected by the release of USDA crop-specific reports. Corn straddle returns exhibit a significant negative quadratic trend, suggesting that returns increased during a period of time and then reverted back towards zero. Also, fourth quarter straddle returns appear significantly larger than first quarter returns (table 3). Soybean options and straddle returns appear not to be affected by the described effects, and only the returns for calls in the third quarter exhibit a significant difference with the first quarter call returns (table 4).

Wheat options are the ones presenting the largest number of significant coefficients among the three markets. Wheat put returns show a significant increasing trend. However, the estimated coefficients indicate that the put returns tend to zero over time, approaching zero from negative values at a decreasing rate. Consequently, put returns do not increase without bound (table 5). Straddle returns exhibit a time pattern similar to that of put returns.

The release of USDA crop reports does not have a significant influence on the returns of corn, soybean and wheat options. Results presented suggest that the pricing ability of corn and soybean option markets is stable and that time, time of the year, and production forecast announcements cause little to no effect on the degree of market efficiency. Mild evidence of time effects is found for wheat puts.

Conclusions

This article evaluates empirically the claims that agricultural options are too expensive by simulating trading returns from different strategies. For most options, expected returns are not statistically different from zero. Thirty-day wheat calls yielded significant net gains to option sellers. Wheat straddles indicate that call returns are affected substantially by movements of the underlying futures and that wheat options price the market risk accurately. These results indicate that the analyzed markets are efficient.

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, findings of this article indicate that 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.

Our results agree with those of Simon (2001) regarding corn and soybean options and provide a more detailed explanation of the returns of wheat options. Simon (2001) analyzes the power of the volatility implied by corn, soybeans and wheat options to forecast the futures RV. Regarding wheat, the author concludes that options IV provides an unbiased forecast of the futures RV. However, results presented here describe call and put returns separately, and identify the probable causes of such returns.

Finally, our results are substantially different than those found for options on the S&P500 futures. Differences between the efficiency of agricultural option markets and S&P500 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 that the mispricing of S&P500 options is due to an excess buying pressure that market makers are not able to arbitrage away. This explanation suggests that S&P500 futures options have more natural buyers (i.e., investors in all 500 stocks) than what agricultural options have (i.e., investors in a single asset).

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 US 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 expected higher than actual prices and underestimated the future price volatility. A lower than actual price volatility may lead economic agents to believe that put and call options are overpriced. Or, if the subjective probability distribution is skewed toward higher prices, producers will see put options as being overpriced. Therefore, our results suggest that the mis-pricing claims are caused by biases in the agents' perceptions of futures price distributions.

Footnotes

1. Also, recent evidence of mispricing has been reported for live cattle options markets (Brittain, Garcia, and Irwin, 2009)
2. There is a tendency for the observations to be more numerous in recent years due to the increase in liquidity over time. However, there is no evidence of non-randomness in distribution of return observations over time. Therefore, results are not driven by observations from any particular subperiod of the dataset.
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 the opportunities to manipulate option settlement prices. The program allows a pre-established 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.
5. The same qualitative results can be obtained computing option returns with a minimum trading volume of 1 and 10 contracts a day.
6. The bid-ask spread cost is also referred to as execution cost, liquidity cost, or skid error. There 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).
7. Recently, Shah, Brorsen, and Anderson (2009) estimate for the first time the liquidity costs for an agricultural option market, the wheat options traded at the Kansas City Board of Trade.
8. Note that, since options are traded only once, half of the bid/ask spread is paid. Trading commissions are surveyed from several brokerage services and the \$50/contract fee represents typical trading commissions for the sample period analyzed. Recent option studies have used similar trading commissions (Simon, 2001).

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Table 1: Corn, Soybeans, and Wheat Options Empirical Returns

	Dollar Returns		Percentage Returns		
	Mean	Std. Dev.	Mean	Std. Dev.	n
Corn					
Thirty-day Calls	-60*	627	-9.2	374.1	519
Ninety-day Calls	-9	1084	0.8	212.0	336
Thirty-day Puts	-2	409	-7.7	163.0	480
Ninety-day Puts	35*	763	2.1	144.9	317
Soybeans					
Thirty-day Calls	-99	1494	-13.3	176.8	686
Ninety-day Calls	-29	2450	1.4	224.9	449
Thirty-day Puts	36	1232	-12.4	183.2	705
Ninety-day Puts	40	1625	-3.2	157.4	396
Wheat					
Thirty-day Calls	-154*	863	-29.9*	189.2	587
Ninety-day Calls	-71*	1191	-5.2	190.2	418
Thirty-day Puts	92*	665	10.8	155.5	583
Ninety-day Puts	27	947	1.1	132.2	394

Corn, soybeans and wheat data covers, respectively, 2/27/1985 – 12/31/2005, 2/19/1985 – 12/31/2005, and 11/17/1986 – 12/31/2005.

Ninety-five percent confidence intervals for the mean returns are constructed using bootstrap with 2,000 repetitions. Bootstrapped confidence intervals test the null hypothesis that the mean return equals zero. Asterisks (*) indicate significance at 5% level.

n denotes the number of observations

Table 2: Corn, Soybeans, and Wheat Straddle Returns with Different Trading Rules

	No volatility rules: buy and hold systematically		RV is below the 30 day MA		IV is below the sample mean	
	%	$/contract	%	$/contract	%	$/contract
Corn Straddle						
Thirty-day	-20*	-117*	-15	-45	-12	-45
n	131	131	76	76	69	69
Ninety-day	3	39	3	37	4	38
n	83	83	46	46	46	46
Soybean Straddle						
Thirty-day	-14	-151	9	1	-14*	-110
n	196	196	121	121	113	113
Ninety-day	-1	2	-2	-20	2	79
n	95	95	55	55	50	50
Wheat Straddle						
Thirty-day	-2	7	9	99	6	81
n	127	127	72	72	67	67
Ninety-day	-1	-19	1	19	4	62
n	97	97	59	59	52	52

Trading rules denote, respectively, that straddle trading is initiated systematically for options with 30 or 90 days left, or that straddles are initiated only for options having 30 or 90days left and on days when RV is below its 30-day moving average, or that straddles are initiated only for options having 30 or 90days left and on days when IV is below its sample mean.

Asterisks (*) indicate that the bootstrapped 95% confidence interval for the mean return, constructed using 2,000 repetitions, does not include zero.

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 – 12/31/2005

	Calls		Puts		Straddle	
	Parameter Estimates	t-ratio	Parameter Estimates	t-ratio	Parameter Estimates	t-ratio
Constant	7.10	0.05	-5.27	-0.06	-157.00	-1.52
Linear Trend	1.15	0.31	-2.91	-1.05	6.67	1.93
Quadratic Trend	-0.01	-0.62	0.02	1.01	-0.06*	-2.25
Q2	-3.68	-0.03	73.01	1.27	-95.56	-1.34
Q3	-301.03	-1.61	166.78	1.47	-200.28	-1.27
Q4	-184.42	-1.14	55.80	0.87	-283.90*	-3.00
Ann	143.61	0.97	4.87	0.09	195.93	1.69
R^2	2.38		2.75		5.83	
n	519		480		131	

The regression model is,

$$r_j = a + b\ x_j + b2\ x_j^2 + \sum_{q=2}^{4} c_q\ D_{j,q} + d\ Ann_j + \epsilon_j$$

where r_j is the per contract return for the jth call, put or straddle combination, 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, $D_{j,q}$ is a dummy variable that equals 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 that equals 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.

Asterisks (*) indicate significance at 5% level.
n is the number of observations.

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 – 12/31/2005

	Calls		Puts		Straddle	
	Parameter Estimates	t-ratio	Parameter Estimates	t-ratio	Parameter Estimates	t-ratio
Constant	124.91	0.32	12.91	0.06	-147.44	-0.48
Linear Trend	-0.18	-0.03	-5.74	-1.15	-2.99	-0.47
Quadratic Trend	0.02	0.55	0.02	0.85	0.04	0.91
Q2	-384.88	-1.00	-33.86	-0.22	-355.33	-1.09
Q3	-737.46*	-2.04	525.4	1.57	-95.31	-0.27
Q4	-381.35	-1.36	61.25	0.39	-275.82	-1.05
Ann	-88.17	-0.38	308.58	1.7	202.97	0.88
R^2	4.86		9.05		3.09	
n	686		705		196	

The regression model is,

$$r_j = a + b\ x_j + b2\ x_j^2 + \sum_{q=2}^{4} c_q\ D_{j,q} + d\ Ann_j + \epsilon_j$$

where r_j is the per contract return for the jth call, put or straddle combination, 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, $D_{j,q}$ is a dummy variable that equals 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 that equals 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.

Asterisks (*) indicate significance at 5% level.
n is the number of observations.

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 – 12/31/2005

	Calls		Puts		Straddle	
	Parameter Estimates	t-ratio	Parameter Estimates	t-ratio	Parameter Estimates	t-ratio
Constant	-161.03	-1.15	-195.65	-1.75	-380.83*	-2.11
Linear Trend	4.83	0.91	6.79*	1.96	18.68	1.97
Quadratic Trend	-0.05	-1.26	-0.04	-1.48	-0.18*	-2.20
Q2	204.23	0.81	312.34*	2.21	366.10	1.55
Q3	196.06	0.69	34.53	0.16	143.77	0.91
Q4	-131.57	-0.89	30.41	0.27	-32.73	-0.19
Ann	-214.22	-0.63	-116.21	-0.53	-124.37	-0.80
R^2	3.76		5.17		10.52	
n	587		583		127	

The regression model is,

$$r_j = a + b\, x_j + b2\, x_j^2 + \sum_{q=2}^{4} c_q\, D_{j,q} + d\, Ann_j + \epsilon_j$$

where r_j is the per contract return for the jth call, put or straddle combination, 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, $D_{j,q}$ is a dummy variable that equals 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 that equals 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.

Asterisks (*) indicate significance at 5% level.
n is the number of observations.

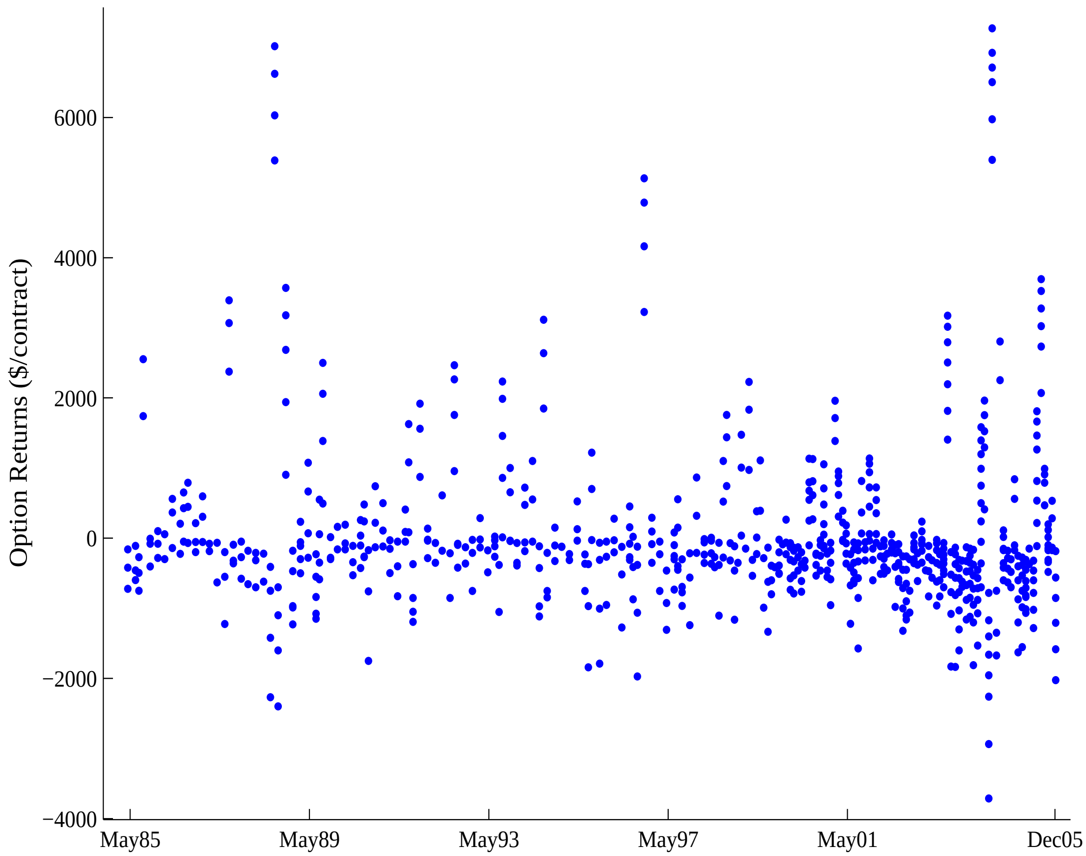

Figure 1: Dolar returns for 30-day soybean puts, 2/19/1985 – 12/31/2005

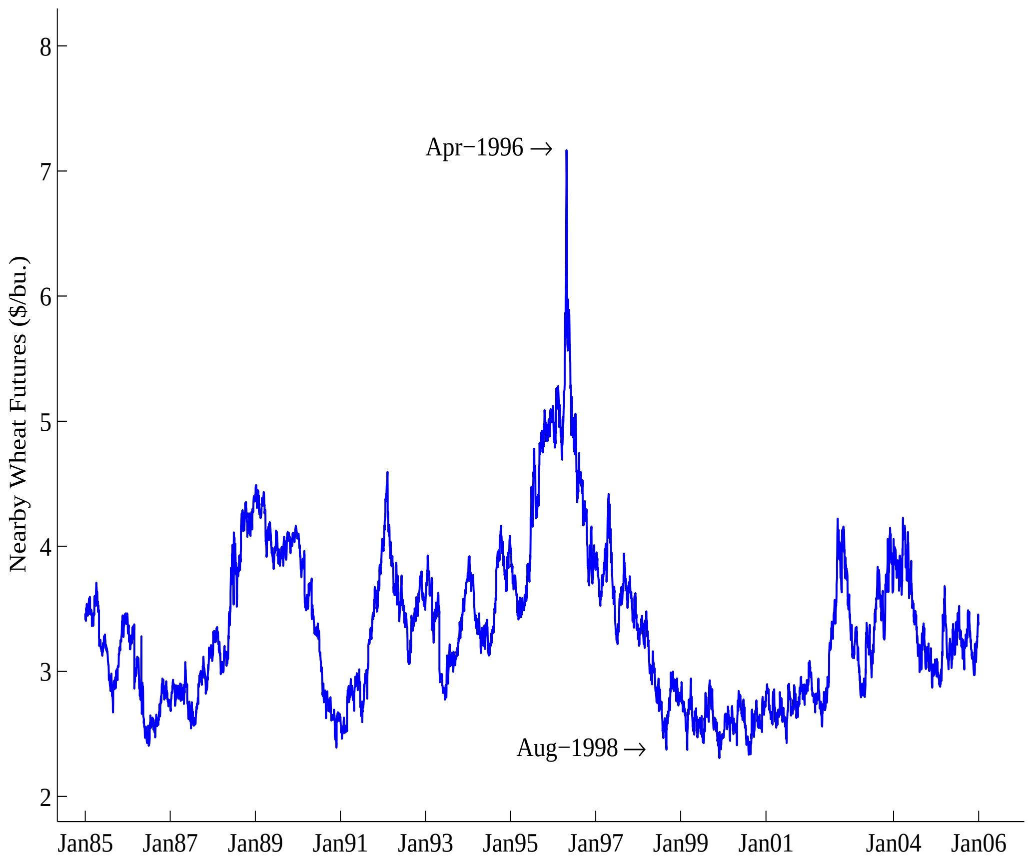

Figure 2: Nearby Wheat Futures, Jan-1985 — Dic-2005