ESSAYS ON ROLLOVER HEDGING, VALUE OF INCREASING KERNEL UNIFORMITY, AND MARKET INVERSION IN COMMODITY FUTURES PRICES

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ABSTRACT

Both market advisors and researchers have often suggested rollover hedging as a way to increase producer returns. This study determines whether rollover hedging can increase expected returns for producers. For rollover hedging to increase expected returns, futures prices must follow a mean-reverting process. To test for the existence of mean reversion in agricultural commodity prices, this study uses a longer set of price data and a wider range of test procedures than past research. Using both the return predictability test based on long-horizon regression and the variance ratio test, we find that mean reversion does not exist in futures prices for corn, wheat, soybeans, soybean oil and soybean meal. The findings are consistent with the weak form of market efficiency. Simulated trading results for three-year rollover hedges provide additional evidence that the expected returns to the rollover hedging strategies are not statistically different from the expected returns to routine annual hedges and cash sale at harvest. The results of the study imply that rollover hedging should not be seriously considered as a marketing alternative.

Key Words: rollover hedging, mean reversion, random walk, market efficiency

CAN ROLLOVER HEDGING INCREASE MEAN RETURNS?

Introduction

When agricultural commodity prices are unusually high, producers are tempted to try to lock in prices for several years of production at the high levels. Some have argued that producers can capture the benefits of higher prices over an extended period of time by rollover hedging (Gardner, 1989; Kenyon and Beckman, 1997). Rollover hedging recommendations were also made in the popular press and extension literature when crop prices were high as recently as 1996. For example, *Farm Journal* economist, Bob Utterback, recommended the following strategy (p. 7, *Farm Journal*, 1996).

> The trigger for selling multiple years' crops is a close in the lead-month futures below the 18-day moving average; we'll buy September put options two strikes in the money. My plan is to price 100% of expected 1997 production when the trigger is tripped, and the '98 and '99 crops if the trigger occurs above $4. Then we'll convert the put options to futures when weather scares are past, and just keep rolling them forward.

The price changes of agricultural commodities in recent years have been dramatic and major crops recorded historical highs in mid-1996 and prices are now quite low. The price variability of agricultural commodities is expected to increase since the 1996 farm bill is more market-oriented and removes target prices for wheat, feedgrains, and cotton. With larger price volatility, the interest in rollover hedging is likely to increase.

The available empirical literature (Gardner, 1989; Huang, Turner, and Houston, 1994; Kenyon and Beckman, 1997; Conley and Almonte-Alvarez, 1998) suggests that rollover hedging is poorly understood. This literature has used sample sizes that are too small to be conclusive and also generally fails to recognize the connections between rollover hedging, market efficiency, and the underlying stochastic process.

A recent survey of extension marketing economists found that a majority of extension economists did not disagree with the statement that rollover hedging can increase expected returns (Brorsen and Anderson, 1999). Given the widespread failure of hedge-to-arrive contracts, the survey result is surprising. Lence and Hayenga (1998) argue that it is infeasible for hedge-to arrive contracts involving interyear rollover hedging to lock in high current prices for crops to be harvested one or more years in the future. Yet, their results still leave open the possibility of a small increase in returns.

Rollover hedging is different from standard hedging in that it involves continuously switching from a nearby futures contract to a more distant futures contract. In rollover hedging, the hedger first opens a position in a nearby futures contract and later closes it while simultaneously opening the same position using a more distant futures contract.

For rollover hedging to increase expected returns, futures price movements should follow a mean reversion process, where price gradually moves toward its underlying fundamental value whenever it deviates from the underlying value (Ross, 1997). A mean reversion price process violates the efficient market hypothesis that is associated with the assertion that futures price changes are unpredictable. Cash prices should be mean reverting as long-run adjustments in supply and demand force cash prices back to their long-term equilibrium. In an efficient market, the mean reversion of cash prices would have been foreseen by futures traders, and there would be no mean reversion in individual futures contracts.

This paper primarily aims to determine whether rollover hedging can be used to increase mean returns for producers. Specifically, this study will determine if cash and futures prices are mean reverting in corn, soybeans, and wheat markets using two different statistical tests. Futures prices must be mean reverting for rollover hedging to increase expected returns. In addition, simulations will be conducted to provide additional evidence about whether rollover hedging can increase expected returns. Past simulation studies had too few observations to have any confidence in them. This study uses more commodities and longer time series than past research. Further, while Irwin, Zulauf, and Jackson (1996) have examined mean reversion for a subset of the dataset used here, past studies have not included both mean reversion tests and simulation studies, which makes it difficult to determine if differences in results are due to differences in techniques or differences in data.

Theories of Mean Reversion

Since Fama's (1970) discussion of efficient capital markets, the efficient market hypothesis (EMH) has become the dominant paradigm used by economists to understand and investigate the behavior of financial and commodity markets. The efficient market hypothesis holds that the market adjusts so quickly to new information that there exist no trading rules that consistently outperform the market in terms of expected returns. Even if there are inefficiencies, they are expected to be either too small or too short-lived to be exploited by investors. Thus, it is best for investors in the stock market to buy and hold a diversified market portfolio rather than attempt to time investments to beat the market. The implication of market efficiency for agricultural marketing strategies is that any sophisticated marketing strategy is no better than a naive cash sale at harvest.

However, in contrast to the efficient market hypothesis, a substantial number of anomalies in asset prices have been documented by financial researchers. Some have found mean reversion in asset prices and further suggested that asset prices are somewhat predictable. The literature explaining market inefficiencies and mean reversion in asset prices focuses on investor irrationality (noise) and temporary deviations of market price from its fundamental value. On the other hand, the mean reversion in stock prices perhaps should have been expected and it may not represent an inefficiency. A stock price has more in common with a commodity cash price than with a futures price.

Biases of Judgment and Decision Making

Various literature on cognitive psychology and behavioral finance has documented systematic biases in the way people use information and make decisions. There are many systematic errors of judgment and decision making that are relevant for investor behavior in financial and commodity markets.

Kahneman, et al. (1982), and Kahneman and Riepe (1998) argue that first, investors tend to be overconfident or overoptimistic in their own abilities, which makes them bear more risk or attribute their investment success to skill rather than luck. Second, when only a few observations are available, investors tend to place too much weight on the available data and thus make erroneous inferences (fallacy of small numbers). Third, investors tend to think backward and consistently exaggerate what they knew in foresight (hindsight bias). They not only tend to view what has happened as having been inevitable but also to view it as having appeared relatively inevitable before it happened. Thus, hindsight is an important element of investor overconfidence and a cause of regret (or myopic loss aversion). Fourth, investors put too little weight on background information and too much weight on new information in making inferences, which might lead them to overreact to news. Finally, investors tend to extrapolate recent trends into the future that are at odds with long-run averages and statistical odds, which can lead them to chase trends. When their naive extrapolation of the past time series is not warranted by fundamentals, prices reverse toward their long-run mean.

Behavioral finance offers some theoretical support for mean reversion in futures prices. However, previous research on rollover hedging (Gardner, 1989; Huang, Turner, and Houston, 1994; Kenyon and Beckman, 1997; Conley and Almonte-Alvarez, 1998) may be tainted by the fallacy of small numbers or hindsight bias.

Overreaction or Overshooting

Using evidence from cognitive psychology, De Bondt and Thaler (1985, 1987) argue that the stock market systematically overreacts to news about fundamentals. Rausser and Walraven (1990) also argue that agricultural commodity markets overreact to a disturbance (e.g., droughts and other weather-related phenomena) and therefore, prices of agricultural commodities overshoot their final equilibrium levels.

As a consequence of investor overreaction, asset prices may temporarily depart from their underlying fundamental values. When pricing errors due to overreaction bias are eventually corrected, asset prices revert to their long-term mean. This investor overreaction hypothesis suggests that, on average, assets that have performed poorly (well) in one period will earn above-average (below-average) returns in the next period. Thus, a contrarian strategy of buying past losers and selling past winners should yield abnormal returns.

Fads or Speculative Bubbles

Shiller (1981), and Poterba and Summers (1988) argue that asset prices are heavily affected by fads or waves of optimistic or pessimistic market psychology. The fashions and fads in investor attitudes often drive the market price from its fundamental value and induce excess volatility. When the fads end, the prices revert to their mean (or negative autocorrelations in returns) and therefore, the speed of mean reversion depends on how quickly fads die out.

Similarly, Summers (1986), West (1988), and McQueen and Thorley (1994) explain anomalies in asset prices by a speculative bubble. A bubble process is characterized by a long run-up in price (or a long run of many small positive abnormal returns) followed by a dramatic price drop or crash (relatively few large negative abnormal returns). When an explosive or consistently cumulative deviation of an asset price from its fundamental value finally ends, price reverts back to its fundamental value. According to these explanations, mean reversion in asset prices occurs during the process in which transitory pricing errors induced by fads or speculative bubbles are corrected.

Time-Varying Risk Premium

For speculators who act as insurers to be induced to trade, they must be paid risk premium for bearing the risks hedgers wish to transfer. This implies that speculators receive positive returns as compensation for risk, while hedgers pay to reduce their risks. The compensation to the speculator is made by the difference between the current futures price and the expected future spot price.

Hartzmark (1987), and Fama and French (1987, 1988) argue that since the amount of risk that speculators must bear varies through the passage of time, asset prices exhibit mean reverting behavior. Time-varying risk premium causes asset prices to vary even in the absence of new information regarding fundamental values. Kolb (1992) finds that futures markets for grains such as wheat, corn and oats do not consistently exhibit a risk premium. But, there is still the possibility of a risk premium existing only during times of high prices.

While the dominant theory is still efficient markets, there are alternative theories that can explain temporary deviations of asset prices from their equilibrium. In financial literature, judgment biases, investor overreaction, fads or bubbles, and time-varying risk premia are cited as a source of market inefficiencies. However, if such inefficiencies existed in the past, by making them known, the actions of traders could cause them to disappear and so there is a good reason to be cautious in recommending such strategies capitalizing on market inefficiencies to farmers.

Data

The agricultural commodities chosen for the analysis of mean reversion in futures prices are corn, wheat, soybeans, soybean oil, and soybean meal. Futures prices from the Chicago Board of Trade are obtained from the Annual Report of the Board of Trade of the City of Chicago and from a computer database compiled by Technical Tools, Inc. The sample period extends from January 1891 through December 1999 for corn and wheat, from January 1951 through December 1999 for soybeans, and from January 1959 through December 1999 for soybean oil and soybean meal.[1] This is the longest set of futures price data ever used to study rollover hedging. A long data set increases the power of the statistical tests, but it is open to the criticism of not considering the possibility of structural change.

To test for mean reversion in agricultural futures prices, return horizons of 1, 3, and 6 months are examined. For each return horizon, the beginning price and ending price are taken to calculate the *k*-month returns. The futures contract used to calculate the *k*-month returns is defined as the nearby futures contract that has enough days to maturity to cover the *k*-month period. The beginning price is the closing price for a given futures contract on the first trading day of each calendar month, and the ending price is the closing price for the corresponding futures contract on the first trading day of the coming month with *k*-month interval. For example, constructing a 3-month return horizon for corn in January, the beginning price is the closing price of May futures observed on the

[1] This study planned to extend the data period of each commodity to the launch date of each futures contract. But, in early years after the introduction of futures contracts, the trading volume was extremely low and prices of only a few nearby contracts were irregularly reported. These years might be considered as a learning period during which markets learn how to price new contracts, and thus, were excluded from the price series. The launch dates of futures contracts are as follows: corn and wheat, January 2, 1877; soybeans, October 5, 1936; soybean oil, July 17, 1950; soybean meal, August 19, 1951.

first trading day in January, and the ending price is the closing price for the same May futures contract observed on the first trading day in April. The k-month returns are defined as the natural logarithmic difference between the beginning price and the ending price of the k-month horizon.

The agricultural commodities chosen for the analysis of mean reversion in cash prices are corn, soybeans, and wheat. For cash grain prices, monthly data from 1908 to 1999 were obtained from National Agricultural Statistics Service (NASS) of the U.S. Department of Agriculture. The cash prices are U.S. average prices received by farmers and denoted in dollars per bushel. Return horizons of 1, 3, 6, 12, 24, and 36 months are examined.

In order to test for mean reversion, the underlying mean value of the commodities must be estimated. In this study, 5-year moving averages are used to estimate the mean value of each commodity. A 5-year moving average is often used in the literature as a reasonable proxy for underlying value since it averages prices across a variety of supply and demand conditions and thus smooths out the effect of weather on yield in any one crop year. The futures prices used to calculate the 5-year moving averages are closing prices for the futures contract nearest to maturity on the first trading day of each calendar month. For example, the 5-year moving average for January 1999 is the sum of the nearby closing futures prices on the first trading day of each month from January 1994 through December 1998 divided by sixty.

Procedures

In previous studies, three general approaches are used to test for mean reversion. The first approach uses autocorrelation coefficients and involves regressing multiperiod returns on lagged multiperiod returns (Fama and French, 1988; Kim, Nelson, and Startz, 1991). That is, the cumulative return from time t to time t + T is regressed on the return from t - T to t. If prices are a random walk, then the slope coefficient in the regression should be zero. If prices are mean reverting, then the regression slope should be negative.

The second approach is a return predictability test using information on fundamentals (Cutler, Poterba, and Summers, 1991; Irwin, Zulauf, and Jackson, 1996). This approach regresses observed market price movements over various return horizons on the deviation of current price from an estimate of fundamental value. A positive, significant regression slope coefficient is considered evidence of return predictability, and implies mean reverting price behavior.

The third approach uses variance ratios (Poterba and Summers, 1988; Cochrane, 1988; Lo and Mackinlay, 1988; Kim, Nelson, and Startz, 1991). This approach exploits the fact that if the logarithm of prices follows a random walk, then the return variance of a random walk is a linear function of the length of the time interval. The variance ratios are scaled so that if returns are uncorrelated through time, the ratios converge to 1 (random walk). While a variance ratio of less than one implies negative serial correlation (mean reversion), a ratio greater than one implies positive serial correlation.

The variance ratio test is closely related to the regression test based on estimated autocorrelations. Lo and Mackinlay (1988) show that the variance ratio is equal to a linear combination of autocorrelation coefficients. Poterba and Summers (1988) show that the variance ratio tests are more powerful than regression tests based on autocorrelation coefficients. Therefore, this study uses the return predictability test and the variance ratio test for mean reversion.

Return Predictability Test

The return predictability test examines whether the deviation of current market prices from estimates of underlying mean value can help predict returns over various horizons. We study returns over different horizons by estimating the following regression equations:

$$(1) \qquad (\ln P_{t+k} - \ln P_t) = \alpha_k + \beta_k (\ln M_t - \ln P_t) + \varepsilon_{t+k} ,$$

where P_{t+k} is the market price (cash, futures) at the end of the return horizon, P_t is the market price (cash, futures) at the beginning of the return horizon, and M_t is an estimated mean value at the beginning of the return horizon. The logarithmic price relative $(\ln P_{t+k} - \ln P_t)$ is the continuously compounded return over k months.

The estimated coefficient β_k is the rate of mean reversion, meaning the fraction of the price deviation from the underlying mean value that is adjusted over a k-month horizon. If the current price is one percent below (above) the mean value, then returns will be increased (decreased) by 0.01β over the next k months. A finding that β_k is significantly greater than zero is evidence in favor of a mean reversion process.

Overlapping sample periods are used. Ordinary least squares (OLS) can produce consistent parameter estimates in this case, but the usual standard errors estimated are biased due to serial correlation in the error terms (Harri and Brorsen, 1998). In this study, the standard errors of regression coefficients are bias-adjusted using Newey-West (1987) correction method. The Newey-West method is consistent, but tends to underestimate standard errors in small samples.[2] It is possible to correct the standard errors with Monte Carlo methods, but there is no need to here since the null hypothesis is not rejected even with standard errors that are underestimated.

Another caution is that since the underlying mean value of commodities is estimated imprecisely by using proxy variables, that is, 5-year moving averages, measurement error may be present. This measurement error causes a bias towards zero in the estimate of the regression coefficient β_k.

In estimating equation (1) using cash prices, the seasonal factors in cash prices may affect the slope coefficient of the regression. The seasonality is removed by including a set of monthly dummies as regressors.

Variance Ratio Test

The variance ratio approach of Lo and MacKinlay (1988) uses the fact that if the natural logarithm of a price series P_t follows a random walk process, then the variance of k-period returns should equal k times the variance of one-period returns. The general k-period variance ratio statistic VR(k) is defined as:

$$VR(k) = \frac{Var[r_t(k)]}{k \cdot Var[r_t(1)]} = \frac{\sigma^2(k)}{k \cdot \sigma^2(1)} = 1 + 2\sum_{t=1}^{k-1}\left(1 - \frac{t}{k}\right)\rho(t), \tag{2}$$

where $r_t(k) = r_t + r_{t-1} + \cdots r_{t-k+1}$, that is, k-period continuously compounded return, $r_t(1)$ is

[2] Harri and Brorsen (1998) showed that when dealing with the overlapping data problem, generalized least squares (GLS) is often superior to the conventional Newey-West estimator. But, since lagged dependent variables are used as explanatory variables, GLS is not the preferred estimator here.

a one-period return, and $\rho(t)$ is the tth-order autocorrelation coefficient of return series r_t. Equation (2) shows that VR(k) is a particular linear combination of the first t-1 autocorrelation coefficients of return series r_t, with linearly declining weights.

Lo and MacKinlay show that the variance ratio estimator can be calculated as follows:

(3) $$\sigma^2(k) = \frac{1}{m}\sum_{t=k}^{nk}\left(P_t - P_{t-k} - k\hat{\mu}\right)^2,$$

where $$m = k(nk - k + 1)\left(1 - \frac{k}{nk}\right).$$

and

(4) $$\sigma^2(1) = \frac{1}{(nk-1)}\sum_{t=1}^{nk}\left(P_t - P_{t-1} - \hat{\mu}\right)$$

in which $$\hat{\mu} = \frac{1}{nk}\sum_{t=1}^{nk}\left(P_t - P_{t-1}\right) = \frac{1}{nk}\left(P_{nk} - P_0\right),$$

where P_0 and P_{nk} are the first and last observation of the price series. The asymptotic variance of the variance ratio under homoskedasticity, $\psi(k)$, is:

(5) $$\psi(k) = \frac{2(2k-1)(k-1)}{3k(nk)}.$$

The standard Z test statistic under the assumption of homoskedasticity, $Z(k)$, is:

(6) $$Z(k) = \frac{VR(k) - 1}{\left[\psi(k)\right]^{\frac{1}{2}}} \overset{a}{\rightarrow} N(0,1),$$

where $\overset{a}{\rightarrow}$ indicates that the standardized test statistic is asymptotically normally distributed. A variance ratio equal to one implies that futures price follows a random walk process, while a variance ratio of less than one implies a mean reversion process.

Simulations

Testing the returns obtained by simulated trading strategies is a more direct test of the effectiveness of rollover hedging than statistical tests. The disadvantage of simulations is that few signals may be generated and so tests may have low power. The objective of the simulation is to determine whether a multiyear rollover hedge can increase the hedger's average returns compared to marketing alternatives. The marketing alternatives considered are routine annual hedges and cash sale at harvest.

A basic assumption in the multiyear rollover hedge is that unusually high prices occur infrequently and that when they occur, hedgers should lock in these favorable prices for several years of production. To identify unusually favorable prices, the cumulative frequency distribution of the past sixty months (or five years) of futures prices is used. The futures prices used to calculate the 5-year moving frequency distribution of historical prices are closing prices for the new crop futures contract observed on the first trading day of each calendar month. Specifically, December futures prices for corn, July futures prices for wheat, and November futures prices for soybeans are used to construct the frequency distribution. The futures price series extends the period 1948 through 1999 for corn and wheat, and 1958 through 1999 for soybeans. Before the first year of the sample periods, only old crop futures contracts were reported for early months of the year. Therefore, we couldn't go back farther in time to construct the frequency distribution using new crop futures prices. At the beginning of each month, the frequency distribution of the historical futures prices is updated by adding the price of the most recent month and deleting the most distant month's price, thus keeping a constant sample size of 60 observations.

In this study, the trigger price levels to enter into a rollover hedge are set at the upper 5%, 10% and 15% of the frequency distribution, respectively. Three-year rollover hedging periods are used.

In choosing a method of rolling over futures contracts, the first decision to be made is the selection of contract months involved in rollovers. The previous studies (Gardner, 1989; Huang, Turner, and Houston, 1994; Kenyon and Beckman, 1997; and Conley and Almonte-Alvarez, 1998) simply chose to roll over from the maturing new crop futures contract to the next new crop futures contract. For example, December 1994 corn futures contract was switched by December 1995 corn futures contract at harvest time in 1994.

In this study, two different rollover methods are used. The first method is to continuously rollover from the maturing contract to the subsequent contract using every contract month ("continuous rollovers"). For example, a three-year rollover hedge for corn is initiated using the December contract of the first year, and when the December contract matures, it is rolled into the March contract of the second year, and then the maturing March contract is rolled into the subsequent contract. This process of rolling over contracts is continued until the rollover hedge is finally lifted.

The second method is to roll over from the maturing new crop futures contract to the next new crop contract in the following year, as done in the previous studies, but includes one intermediate contract month to serve as a bridge between the new crop futures contracts ("bridged rollovers"). Specifically, May futures contract for corn and soybean, and December futures contract for wheat is used as bridge contracts. Thus, for example, the maturing December futures contract for corn of the first year is rolled into the May contract of the second year, and when the May contract matures, it is rolled into the December contract of the second year, and so on.

The second decision to be made in the method of rolling over contracts is the selection of a point in time to roll over, i.e., when to switch from the maturing contract to the next contract. Ma, Mercer, and Walker (1992) suggest that the use of first notice day as rollover dates is a logical choice for most purposes as well as a popular choice for trading purposes. This study also uses the first notice day, i.e., the last business day of the month preceding the delivery month, as rollover dates to switch contracts and terminal dates to lift the hedge. The three-year rollover hedging rules used in the study are summarized as follows:

First, the producer is assumed to produce 5,000 bushels or one contract of corn, wheat, or soybeans each year. At the beginning of each calendar month, if a price equal to or exceeding the trigger price level is observed, the hedger will sell three contracts to execute a three-year rollover hedge. Once a three-year rollover hedge is executed in any year, no new additional positions are taken with other price signals within the same year since the 5,000 bushels of crop for each year are already priced. However, even when a rollover hedge is already in place for the production of the year, the hedger will sell additional contracts for the expected crop in the following years to a total of three contracts. For example, assume that a three-year rollover hedge is initiated for corn in May 1995. The producer would sell three December 1995 contracts. Even if another price above the trigger price level is observed in July 1995, the producer is not allowed to sell additional contracts. However, if a new price exceeding the trigger price level is observed in June 1996, the producer will sell one contract for the expected 1998 crop, besides the 1996 and 1997 crops already priced in May 1995.

Second, at rollover dates, the hedger will roll forward to next contract month by simultaneously closing the positions on all contracts and opening new positions on the remaining unhedged long-term production.

Trading futures contracts incurs transaction costs, which include brokerage fees and liquidity costs. It is assumed that brokerage fees are \$50 for a round-turn trade (that is, buying and selling) of a 5,000-bushel futures contract. Liquidity costs are payments earned by floor traders for the services of filling an order immediately at the market price. They are incurred each time a futures contract is traded. Liquidity costs for grain futures market is estimated to be one price tick (1/4 cent for bushel) for the more heavily traded nearby contracts and two price ticks for the more lightly traded contracts that are more than five months from delivery (Brorsen, 1989; Thompson and Waller, 1989). With the two components combined, transaction costs are at least \$75 (or 1.5 cents for bushel) for a round-turn futures trade.

The expected returns from the three-year rollover hedge can be calculated for each year separately. Denote the initial futures price at which a three-year rollover hedge is placed as F_i, and assume that crop size for each year is equal to one contract, then the producer's revenue for the first year is given by

(7) $$R_1 = F_i + B_1 - C,$$

where B_1 is the contemporaneous cash-futures basis at the time the cash sale is made in the first year, and C is the futures transaction costs. For corn, B_1 is the difference between the producer's cash price and the December futures price on the first notice date of the December contract in the first year.

The revenue for the second year is

$$R_2 = F_i + \sum_{k=1}^{N} S_k + B_2 - (N+1)C, \tag{8}$$

where S_k is the spread between the maturing futures contract and the next futures contract at a rollover date, B_2 is the contemporaneous cash-futures basis in the second year, N is the number of rollovers, and C is the futures transaction costs. For example, when continuous rollovers are used for corn, there are five rollover spreads involved in one crop year, i.e., the December-March spread, the March-May spread, the May-July spread, the July-September spread, and the September-December spread.

Finally, the revenue for the third year is

$$R_3 = F_i + \sum_{k=1}^{2N} S_k + B_3 - (2N+1)C, \tag{9}$$

where B_3 is the contemporaneous cash-futures basis in the third year.

Generalizing to an n-year rollover hedge for any commodity, the revenue in year t can be written as

$$R_t = F_i + \sum_{k=1}^{(t-1)N} S_k + B_t - [(t-1)N+1]C, \tag{10}$$

where F_i is the initial futures price at which an n-year rollover hedge is placed, $\sum_{k=1}^{(t-1)N} S_k$ is the sum of spreads at rollovers, B_t is the is the contemporaneous cash-futures basis at the time the cash sale is made in year t, N is the number of rollovers in one crop year, and

$[(t-1)N+1]C$ is the total futures transaction costs. The total revenue for the n-year rollover hedge is $\sum_{t=1}^{n} R_t$.

For routine annual hedges, the producer would hedge each year's crop by selling a new crop contract at or soon after planting. Specifically, December corn and November soybean contracts are sold on the first trading day of May, and July wheat contract is sold on the first trading day of December. The annual hedges are also lifted on the first notice day of each new crop futures contract.

For cash sales at harvest, the producer will sell each year's crop when harvested at the harvest-time cash price. In this study, U.S. monthly average prices at harvest for each commodity are used. Specifically, November average prices for corn, October average prices for soybean, and June average prices for wheat are used, since the first notice date for December corn futures contract, November soybean futures contract, and July wheat futures contract is the last business day in November, October, and June, respectively.

Results

In this section, the results of mean reversion tests on agricultural futures and cash prices, and the results of three-year rollover hedges are reported.

Return Predictability Test

The evidence on the forecast power of the difference between fundamental mean value and current futures price is presented in Table 1. The estimated β coefficients are not statistically significant at the 5 percent level except for corn with a one-month return horizon. But, the negative β coefficient of –0.02 suggests mean aversion rather than mean reversion. Overall, the regression R^2 values are extremely low. R^2 value represents the percentage of the observed change over the return horizon that is explained by the difference between futures price and the mean value at the beginning of the return horizon. Thus, the deviation of futures price from its estimated mean value explains at most 1.0 percent of the observed change in futures price.

As expected, cash prices do show some evidence of mean reversion in Table 2. The estimated β coefficients for all commodities over the 6-month return horizon are greater than zero at the 5 percent level. The β coefficient of corn for 6-month return horizon suggests that 11 percent of a price deviation from the mean value is adjusted over the subsequent 6 months. Studies in stock markets also tend to find more evidence of mean reversion at longer horizons (Fama and French, 1988; Porterba and Summers, 1988).

<u>Variance Ratio Test</u>

The variance ratio test results in Table 3 also find little evidence of mean reversion in futures prices. Except for corn with a 3-month return horizon, the variance ratios, $VR(k)$, are not significantly different than 1.0. The variance ratio for corn with a 3-month return horizon is 1.10, implying that there is positive serial correlation (mean aversion).

Table 4 presents the results of variance ratio tests for deseasonalized cash prices. The variance ratios for corn are all greater than 1.0, ranging from 1.62 with k=3 to 2.03 with k=12. The variance ratios for corn imply that there exists positive serial correlation in multiperiod returns. The variance ratios for wheat and soybeans show that multiperiod returns are uncorrelated when return horizons are over 24 months. The results provide little evidence for mean reversion in cash prices at these horizons. It may be that because of policy interventions during this period those prices were slow to respond. This may be especially true for periods of low prices.

Simulations

The results of simulations for corn, soybeans, and wheat marketing strategies are reported in Tables 5, 6, and 7. The expected prices from the three-year rollover hedges are higher than the expected prices from the routine annual hedges and cash sales at harvest across all three commodities. This result is mainly due to the selective nature of the three-year rollover hedges. The three-year rollover hedges are selective in that the producer only enters into a rollover hedge when current futures prices at the beginning of the month exceed a predetermined percent level of the five-year moving frequency distribution. However, the standard deviation of expected prices for the three-year rollover hedges are much larger than the routine annual hedges and cash sales at harvest. This suggests that three-year rollover hedges are very risky strategies.

The results for corn marketing strategies (Table 5) show that the expected prices for the three-year rollover hedges using a bridge contract are higher than those using every contract month continuously, since continuous rollovers involve higher transaction costs. Routine annual hedges and cash sales at harvest have almost identical means and standard deviations of expected prices.

The results for soybean marketing strategies (Table 6) show that three-year rollover hedges have the highest expected prices and also the largest standard deviations at all trigger price levels. The expected prices from the continuous rollover hedges are higher than the expected prices from the bridged rollover hedges, while the standard deviations of the bridged rollover hedges are larger than the standard deviations of the continuous rollover hedges. Thus, from the mean-variance (EV) criterion, the continuous rollover hedges dominate the bridged rollover hedges.

The results for wheat marketing strategies (Table 7) show that cash sale at harvest has the lowest price and lowest standard deviation. The expected prices from the continuous rollover hedges are higher than the expected prices from the bridged rollover hedges in spite of higher transaction costs. This is mainly due to the larger gains in rollover spreads.

To determine whether the expected prices from the three-year rollover hedges are equal to the expected prices from the marketing alternatives, paired-difference tests are used. Paired-difference tests use the pairwise differences (d_i) of the expected prices between two marketing strategies. The null hypothesis to be tested is that the mean of the paired differences of the expected prices from two marketing strategies is zero, in other words, the expected prices of the two marketing strategies are equal.

The results of the paired-difference tests for corn, soybeans, and wheat are presented in Tables 8, 9 and 10. The paired t-tests comparing the expected prices of the two marketing strategies are based on the following five pairs of strategies: (1) continuous rollover hedges vs. routine annual hedges (CRH-RAH); (2) continuous rollover hedges vs. cash sales at harvest (CRH-CSH); (3) bridged rollover hedges vs.

routine annual hedges (BRH-RAH); (4) bridged rollover hedges vs. cash sales at harvest (BRH-CSH); and (5) routine annual hedges vs. cash sale at harvest (RAH-CSH).

In Tables 8, 9 and 10, the *t*-ratios ranging from –0.03 to 1.81 indicate that all these pairs for each commodity are not statistically different from each other at the 5% level. This implies that the expected prices from the three-year rollover hedges are not different from the expected prices from the marketing alternatives across all commodities. The fact that even a \$0.50/bushel gain is not statistically significant illustrates the low power of the simulation approach even with our extensive dataset. While the returns to some of the rollover hedging strategies look enticing, they are not statistically significant. Thus, the simulation results are consistent with the results of the mean reversion tests.

Conclusions

Both market advisors and researchers have often suggested rollover hedging as a way to increase producer returns. This study determined whether rollover hedging could increase expected returns for producers. For rollover hedging to increase expected returns, futures prices must follow a mean-reverting process. To test for the existence of mean reversion in agricultural commodity prices, this study used a longer set of price data and a wider range of test procedures than past research. While rollover hedging increasing mean returns is inconsistent with the efficient market hypothesis, there are psychological theories that offer some support for rollover hedging being profitable.

Using both the return predictability test based on long-horizon regression and the variance ratio test, we found that mean reversion does not exist in futures prices for corn, wheat, soybeans, soybean oil and soybean meal. The findings on futures prices are consistent with the weak form of market efficiency suggested by Fama (1970).

The simulated trading results for three-year rollover hedges provided additional evidence that the expected returns to the rollover hedging strategies are not statistically different from the expected returns to routine annual hedges and cash sale at harvest. Because of the positive, but statistically insignificant returns to the simulation strategies, the results may not be sufficient enough to put the issue of rollover hedging to rest.

On the basis of this research, we can not recommend rollover hedging as a marketing strategy. It is a very risky strategy with returns that are not statistically significant. The lack of statistical significance is found across three diverse tests.

Table 1. Results of Return Predictability Tests Using Futures Prices

Commodity	Return Horizon (k months)	Data Period	Number Of Observation	β_k	t-statistic	R^2
Corn	1	1891-1999	1,200	-0.02	-2.06*	0.01
	3	1891-1999	1,198	-0.04	-1.65	0.01
	6	1948-1999	618	0.06	1.23	0.01
Wheat	1	1891-1999	1,193	-0.00	-0.34	0.00
	3	1891-1999	1,191	-0.01	-0.24	0.00
	6	1948-1999	618	0.06	0.93	0.01
Soybeans	1	1951-1999	526	0.02	0.81	0.00
	3	1951-1999	524	0.07	1.04	0.01
	6	1957-1999	509	0.07	0.88	0.01
Soybean Oil	1	1959-1999	431	-0.01	-0.26	0.00
	3	1959-1999	429	0.02	0.26	0.00
	6	1959-1999	426	0.08	0.80	0.01
Soybean Meal	1	1959-1999	431	0.02	0.56	0.00
	3	1959-1999	429	0.05	0.66	0.01
	6	1959-1999	426	0.06	0.56	0.00

Note: The estimated regression equation is $(\ln P_{t+k} - \ln P_t) = \alpha_k + \beta_k(\ln M_t - \ln P_t) + \varepsilon_{t+k}$ where $(\ln P_{t+k} - \ln P_t)$ is the continuously compounded return in futures prices from month t to month $t+k$, and $(\ln M_t - \ln P_t)$ is the natural logarithmic difference between the estimated mean value on the first trading day of month t and the closing futures price on the first trading day of month t. The t-statistics are bias-corrected using the Newey-West procedure. The test statistics marked with asterisks indicates that the corresponding regression coefficients are statistically significant at 5% level.

Table 2. Results of Return Predictability Tests Using Cash Prices

Commodity	Return Horizon (k months)	Data Period	Number Of Observation	β_k	t-statistic	R^2
Corn	1	1908-99	1,043	0.00	0.06	0.21
	3		1,041	0.03	1.43	0.23
	6		1,038	0.11	2.72*	0.20
	12		1,032	0.25	5.36*	0.07
	24		1,020	0.53	9.74*	0.17
	36		1,008	0.69	14.98*	0.23
Wheat	1	1908-99	1,043	-0.00	-0.28	0.07
	3		1,041	0.01	0.59	0.08
	6		1,038	0.04	2.12*	0.06
	12		1,032	0.11	2.55*	0.02
	24		1,020	0.33	5.82*	0.07
	36		1,008	0.52	9.96*	0.13
Soybeans	1	1924-99	851	0.01	0.55	0.11
	3		849	0.05	1.58	0.17
	6		846	0.12	2.50*	0.16
	12		840	0.24	4.08*	0.06
	24		828	0.38	6.39*	0.09
	36		816	0.37	7.39*	0.08

Note: The estimated regression equation is $(\ln P_{t+k} - \ln P_t) = \alpha_k + \beta_k(\ln M_t - \ln P_t) + \varepsilon_{t+k}$ where $(\ln P_{t+k} - \ln P_t)$ is the continuously compounded return in futures prices from month t to month $t+k$, and $(\ln M_t - \ln P_t)$ is the natural logarithmic difference between the estimated mean value on the first trading day of month t and the closing futures price on the first trading day of month t. The t-statistics are bias-corrected using the Newey-West procedure. The test statistics marked with asterisks indicates that the corresponding regression coefficients are statistically significant at 5% level.

Table 3. Results of Variance Ratio Tests Using Nearby Futures Price Series

Commodity	Return Horizon (k months)	Data Period	Number Of Observation	Variance Ratio [VR(k)]	Z-statistic
Corn	3	1891-1999	1,257	1.10	2.28*
	6		1,254	1.12	1.66
Wheat	3	1891-1999	1,250	1.06	1.45
	6		1,247	1.03	0.47
Soybeans	3	1951-1999	583	1.11	1.78
	6		580	1.04	0.41
Soybean Oil	3	1959-1999	488	0.98	-0.28
	6		485	0.96	-0.39
Soybean Meal	3	1959-1999	488	1.09	1.41
	6		485	1.04	0.34

Note: The variance ratio is $VR(k) = \dfrac{\sigma^2(k)}{k \cdot \sigma^2(1)}$ where $\sigma^2(k)$ is the variance of k-month returns and $\sigma^2(1)$ is the variance of one-month returns. The null hypothesis is that VR(k)=1, meaning that futures prices follow a random walk process. The Z-statistic marked with asterisk indicates that the corresponding variance ratio is statistically different from 1.0 at the 5% level of significance.

Table 4. Results of Variance Ratio Tests Using Deseasonalized Cash Prices

Commodity	Return Horizon (k months)	Data Period	Number Of Observation	Variance Ratio [VR(k)]	Z-statistic
	3	1908-99	1,101	1.62	13.73*
	6		1,098	1.92	12.40*
Corn	12		1,092	2.03	9.11*
	24		1,080	1.93	5.59*
	36		1,068	1.68	3.34*
	3	1908-99	1,101	1.35	6.86*
	6		1,098	1.36	4.29*
Wheat	12		1,092	1.48	3.69*
	24		1,080	1.32	1.70
	36		1,068	1.10	0.44
	3	1924-99	909	1.35	7.14*
	6		906	1.41	5.07*
Soybeans	12		900	1.37	2.98*
	24		888	1.19	1.07
	36		876	0.98	-0.09

Note: The variance ratio is $VR(k) = \frac{\sigma^2(k)}{k \cdot \sigma^2(1)}$ where $\sigma^2(k)$ is the variance of k-month returns and $\sigma^2(1)$ is the variance of one-month returns. The null hypothesis is that $VR(k)$=1, meaning that cash prices follow a random walk process. The Z-statistics marked with asterisks indicate that the corresponding variance ratios are different from 1.0 at the 5% level of significance.

Table 5. Expected Prices and Standard Deviations for Corn Marketing Strategies, 1948-1999

Trigger Price Level	No. Obs.	Statistics	1) Initial Futures Price	2) Cash-Futures Basis	3) Rollover Spread		4) Transaction Cost		5) Expected Returns (1+2+3+4)		Routine Annual Hedges	Cash Sale at Harvest
					Continuous Rollovers	Bridged Rollovers	Continuous Rollovers	Bridged Rollovers	Continuous Rollovers	Bridged Rollovers		
5%	29	Mean	235.68	-22.75	7.34	4.06	-11.85	-5.64	208.42	211.35	194.88	195.10
		Std. Dev.	95.01	15.69	48.92	40.88	5.81	2.33	109.77	104.97	74.56	72.45
10%	30	Mean	237.98	-23.53	10.78	7.87	-12.25	-5.80	212.97	216.51	195.93	196.16
		Std. Dev.	94.73	16.01	51.13	44.19	5.80	2.32	110.92	107.27	73.48	71.43
15%	34	Mean	245.64	-23.50	11.30	7.09	-12.75	-6.00	220.69	223.23	200.90	200.23
		Std. Dev.	93.20	15.29	50.60	43.47	5.30	2.12	106.54	102.67	71.20	68.29

Note: Continuous rollovers denote continuously rolling over from the maturing contract to the subsequent contract using every contract month, and bridged rollovers denote rolling over from the maturing new crop futures contract to the next new crop contract, with one intermediate contract month that serves as a bridge between the new crop futures contracts.

Table 6. Expected Prices and Standard Deviations for Soybean Marketing Strategies, 1958-1999

Trigger Price Level	No. Obs.	Statistics	1) Initial Futures Price	2) Cash-Futures Basis	3) Rollover Spread		4) Transaction Cost		5) Expected Returns (1+2+3+4)		Routine Annual Hedges	Cash Sale at Harvest
					Continuous Rollovers	Bridged Rollovers	Continuous Rollovers	Bridged Rollovers	Continuous Rollovers	Bridged Rollovers		
5%	29	Mean	577.50	-24.08	14.78	-8.64	-15.98	-5.64	552.22	539.14	496.25	492.86
		Std. Dev.	255.37	29.53	108.91	120.34	8.61	2.46	299.09	315.84	194.88	185.96
10%	32	Mean	572.40	-25.52	22.19	-12.95	-17.25	-6.00	551.81	527.93	495.17	494.72
		Std. Dev.	250.74	29.96	112.88	136.33	8.00	2.29	295.05	312.78	194.74	184.28
15%	34	Mean	564.77	-26.13	24.52	-8.63	-17.25	-6.00	545.91	524.01	500.12	499.32
		Std. Dev.	235.52	29.71	109.81	133.29	7.86	2.25	282.55	299.52	190.01	179.89

Note: Continuous rollovers denote continuously rolling over from the maturing contract to the subsequent contract using every contract month, and bridged rollovers denote rolling over from the maturing new crop futures contract to the next new crop contract, with one intermediate contract month that serves as a bridge between the new crop futures contracts.

Table 7. Expected Prices and Standard Deviations for Wheat Marketing Strategies, 1948-1999

Trigger Price Level	No. Obs.	Statistics	1) Initial Futures Price	2) Cash-Futures Basis	3) Rollover Spread		4) Transaction Cost		5) Expected Returns (1+2+3+4)		Routine Annual Hedges	Cash Sale At Harvest
					Continuous Rollovers	Bridged Rollovers	Continuous Rollovers	Bridged Rollovers	Continuous Rollovers	Bridged Rollovers		
5%	20	Mean	350.31	-11.70	29.03	10.11	-10.88	-5.25	356.76	343.47	327.96	302.95
		Std. Dev.	110.06	26.32	79.45	72.85	6.38	2.55	167.95	164.47	107.15	95.28
10%	24	Mean	361.16	-9.99	25.95	10.33	-11.50	-5.50	365.62	356.00	327.70	306.38
		Std. Dev.	105.11	24.37	80.48	69.92	6.12	2.45	161.32	156.70	97.44	87.57
15%	26	Mean	352.55	-10.99	26.47	13.45	-11.89	-5.65	356.14	349.36	319.77	301.27
		Std. Dev.	102.60	23.83	78.88	68.43	6.03	2.41	157.12	151.00	97.85	86.69

Note: Continuous rollovers denote continuously rolling over from the maturing contract to the subsequent contract using every contract month, and bridged rollovers denote rolling over from the maturing new crop futures contract to the next new crop contract, with one intermediate contract month that serves as a bridge between the new crop futures contracts.

Table 8. Results of Paired-Difference Tests for Corn Marketing Strategies, 1948-1999.

Trigger Price	No. Obs.	Statistics	CRH-RAH	CRH-CSH	BRH-RAH	BRH-CSH	RAH-CSH
		Mean	13.54	13.32	16.47	16.25	-0.22
5%	29	Std. Dev.	82.14	101.01	76.46	95.85	50.61
		t-Ratio	0.89	0.71	1.16	0.91	-0.02
		Mean	17.04	16.81	20.58	20.35	-0.23
10%	30	Std. Dev.	81.55	100.39	76.05	95.40	49.73
		t-Ratio	1.15	0.92	1.48	1.17	-0.03
		Mean	19.79	20.46	22.33	23.00	0.67
15%	34	Std. Dev.	77.52	95.46	72.07	90.36	47.71
		t-Ratio	1.49	1.25	1.81	1.48	0.08

Note: CRH-RAH denotes the paired difference of the expected price between the continuous rollover hedges and the routine annual hedges, CRH-CSH denotes the paired difference of the expected price between the continuous rollover hedges and the cash sales at harvest, BRH-RAH denotes the paired difference of the expected price between the bridged rollover hedges and the routine annual hedges, BRH-CSH denotes the paired difference of the expected price between the bridged rollover hedges and the cash sales at harvest , and RAH-CSH denotes the paired difference of the expected price between the routine annual hedges and the cash sale at harvest. The *t*-statistic is $t = \frac{\bar{d}-0}{\sqrt{s_D^2/n}}$, where $\bar{d}$ is the average of the paired differences (d_i) of the expected prices between two marketing strategies, n is the number of paired differences, and $s_D^2 = \frac{\sum_{i=1}^{n} d_i^2 - \frac{1}{n}\left(\sum_{i=1}^{n} d_i\right)^2}{n-1}$.

Table 9. Results of Paired-Difference Tests for Soybean Marketing Strategies, 1948-1999.

Trigger Price	No. Obs.	Statistics	CRH-RAH	CRH-CSH	BRH-RAH	BRH-CSH	RAH-CSH
		Mean	55.97	59.35	42.89	46.28	3.39
5%	29	Std. Dev.	193.80	239.50	231.78	277.46	112.34
		t-Ratio	1.56	1.34	1.00	0.90	0.16
		Mean	56.65	57.09	32.76	33.21	0.45
10%	32	Std. Dev.	186.08	229.00	228.10	272.89	109.35
		t-Ratio	1.72	1.41	0.81	0.69	0.02
		Mean	45.79	46.59	23.89	24.69	0.80
15%	34	Std. Dev.	184.26	223.07	222.47	264.14	107.70
		t-Ratio	1.45	1.22	0.63	0.55	0.04

Note: CRH-RAH denotes the paired difference of the expected price between the continuous rollover hedges and the routine annual hedges, CRH-CSH denotes the paired difference of the expected price between the continuous rollover hedges and the cash sales at harvest, BRH-RAH denotes the paired difference of the expected price between the bridged rollover hedges and the routine annual hedges, BRH-CSH denotes the paired difference of the expected price between the bridged rollover hedges and the cash sales at harvest , and RAH-CSH denotes the paired difference of the expected price between the routine annual hedges and the cash sale at harvest. The *t*-statistic is $t = \frac{\bar{d}-0}{\sqrt{s_D^2/n}}$, where $\bar{d}$ is the average of the paired differences (d_i) of the expected prices between two marketing strategies, n is the number of paired differences, and $s_D^2 = \frac{\sum_{i=1}^{n} d_i^2 - \frac{1}{n}\left(\sum_{i=1}^{n} d_i\right)^2}{n-1}$.

Table 10. Results of Paired-Difference Tests for Wheat Marketing Strategies, 1948-1999.

Trigger Price	No. Obs.	Statistics	CRH-RAH	CRH-CSH	BRH-RAH	BRH-CSH	RAH-CSH
		Mean	28.81	53.81	15.51	40.52	25.01
5%	20	Std. Dev.	155.73	168.29	167.34	173.03	67.29
		t-Ratio	0.83	1.43	0.42	1.05	1.66
		Mean	37.92	59.25	28.30	49.63	21.33
10%	24	Std. Dev.	150.16	158.38	158.61	161.31	62.56
		t-Ratio	1.24	1.83	0.87	1.51	1.67
		Mean	36.38	54.88	29.59	48.09	18.50
15%	26	Std. Dev.	146.31	153.98	154.98	157.19	60.98
		t-Ratio	1.27	1.82	0.97	1.56	1.55

Note: CRH-RAH denotes the paired difference of the expected price between the continuous rollover hedges and the routine annual hedges, CRH-CSH denotes the paired difference of the expected price between the continuous rollover hedges and the cash sales at harvest, BRH-RAH denotes the paired difference of the expected price between the bridged rollover hedges and the routine annual hedges, BRH-CSH denotes the paired difference of the expected price between the bridged rollover hedges and the cash sales at harvest , and RAH-CSH denotes the paired difference of the expected price between the routine annual hedges and the cash sale at harvest. The *t*-statistic is $t = \frac{\bar{d} - 0}{\sqrt{s_D^2 / n}}$, where $\bar{d}$ is the average of the paired differences (d_i) of the expected prices between two marketing strategies, n is the number of paired differences, and $s_D^2 = \frac{\sum_{i=1}^{n} d_i^2 - \frac{1}{n}\left(\sum_{i=1}^{n} d_i\right)^2}{n-1}$.

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Chapter II

VALUE OF INCREASING KERNEL UNIFORMITY

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ABSTRACT

This study develops grain sorting strategies for elevators to use to increase kernel size uniformity and determine the size of potential benefits from sorting. Kernel size uniformity is an important physical quality attribute in terms of processing efficiency, quality control, and milling yield. Cluster analysis and nonlinear optimization are used to sort loads to increase kernel size uniformity. Cluster analysis and nonlinear optimization increased the percent flour yield relative to no sorting by 0.13% and 0.32% respectively. Cluster analysis increased the daily milling income relative to no sorting by 104.99 dollars (5%), and nonlinear optimization increased the milling income by 265.90 dollars (13%). The results show that cluster analysis is vastly inferior to the nonlinear optimization. Future grain science research should address the benefits of milling efficiency and flour quality from increased kernel uniformity.

Key Words: kernel uniformity, sorting, cluster analysis, nonlinear optimization

Value of Increasing Kernel Uniformity

Introduction

While consumers demand diverse food products with higher quality, food processors require uniform raw materials with specific quality attributes. Virtually in all areas of food processing industry, processors desire uniform raw materials to improve the efficiency of production and product quality, and to save costs. Meanwhile, recent advances in quality testing and processing technology enable processors to meet their rigorous product requirements.

In the grain industry, the search for equitable, uniform measures of quality has established grades and grade requirements, but the appropriate grading factors and factor limits for designating numerical grades have been a persistent issue in grain markets (Hill, 1990). Moreover, Hill (1988) argues that grain grades lack economic rationale and fail to accurately evaluate the product and the value of different qualities.

Current U.S. standards for wheat determine grades based on test weight, total defects, and other material. However, these generic grades and standards are becoming less meaningful in effectively describing wheat, because processors are becoming more interested in and demanding such characteristics as greater kernel size and kernel size uniformity (Lyford et al., 1999).

For flour millers, kernel size uniformity is an important physical quality attribute in terms of processing efficiency, quality control, and milling yield. In the flour milling process, the tempered wheat is first ground on a series of rollermills to separate the endosperm (starch and protein) from the outer bran skins. When there is a wide variation in kernel size, small kernels pass through the rollermills unground or are only partially broken in the initial breaking process, thus requiring additional processing. This additional processing requires more milling time and energy costs, and further decreases the overall quality of the flour due to higher ash content (Li, 1989). However, with uniform wheat, the wheat kernels are ground more evenly in the milling process, which leads to higher extraction of flour with a lower ash content. Considering the fact that the wheat kernels must pass through five or more of the breaking rollermills before the bran is completely removed, the increased kernel size uniformity will significantly contribute to an increase in milling efficiency, extraction rate and flour quality.

However, it is not an easy task to achieve the benefits from increased kernel uniformity in the current grain marketing system. Since wheat kernel size uniformity is not among the grade determining factors and the increased kernel size uniformity is not properly rewarded, grain elevators are not strongly encouraged to develop and implement various strategies to increase kernel size uniformity. The kernel size uniformity can be increased by sorting rather than blending various truckloads of wheat with different kernel sizes when wheat is delivered to grain elevators.

The previous studies on grain sorting (Johnson and Wilson, 1993; Adam, Kenkel, and Anderson, 1994; Hennessy and Wahl, 1997) were largely motivated by the concerns about declining U.S. export market share and foreign buyer complaints about poor quality grain. These studies focus on the costs and benefits of cleaning wheat to reduce dockage levels.

This study takes a different direction from past research. The primary objective of this study is to develop grain sorting strategies for elevators to use to increase kernel size uniformity and determine the size of potential benefits from sorting.

First, graphical models are presented to illustrate the importance of concavity and convexity in making optimal blending and sorting decisions. Cluster analysis and nonlinear optimization are used to sort loads to increase kernel size uniformity. To evaluate the performance of cluster analysis and nonlinear optimization, percent flour yields from cluster analysis and nonlinear optimization are compared to percent flour yield from the whole sample without sorting. Finally, to measure the monetary value of increasing kernel uniformity, the percent flour yields obtained from cluster analysis and nonlinear optimization are evaluated using a daily milling income equation.

Theory

When elevators receive grain, they can blend the grain by mixing the incoming loads, resulting in average quality, or they can segregate and sort the loads into different quality levels. In this section, graphical models are established to analyze the economics of blending and sorting using the framework in Hennessy (1996), and Hennessy and Wahl (1997).

Blending

Consider two loads of wheat that are different in quality, one is of low quality and the other is of high quality. Let low quality wheat be denoted by quality index q_L and high quality wheat by q_H. Then, any mixture of low quality and high quality wheat can be expressed as a convex combination of q_L and q_H, i.e., $\lambda q_L + (1-\lambda)q_H$, where $0 < \lambda < 1$. The yield associated with low quality and high quality wheat is given by $Y(q_L)$ and $Y(q_H)$ respectively. The weighted average of the yields $Y(q_L)$ and $Y(q_H)$ from distinct qualities q_L and q_H can be expressed by $\lambda Y(q_L) + (1-\lambda)Y(q_H)$. On the other hand, the yield from mixed wheat, i.e., a linear combination of low quality and high quality wheat, can be expressed by $Y(\lambda q_L + (1-\lambda)q_H)$, with λ varying from 0 to 1.

Figure 1 illustrates a globally concave yield-quality function. The yield from a convex combination of low quality and high quality wheat, i.e., $Y(\lambda q_L + (1-\lambda)q_H)$, is higher than the weighted average of yield $Y(q_L)$ and $Y(q_H)$, i.e., $\lambda Y(q_L) + (1-\lambda)Y(q_H)$. This suggests that when the yield-quality function is concave, the yield produced from blended wheat with average quality exceeds the average of yields from unhandled wheat with different qualities. Thus, in the concave region, the market provides the elevator with an incentive to completely blend wheat and sell only loads of wheat with equal, mean levels of quality.

Sorting

Consider a globally convex yield-quality function as depicted in Figure 2. As opposed to the result of a globally concave yield-quality function, the weighted average of two yields $Y(q_L)$ and $Y(q_H)$, i.e., $\lambda Y(q_L) + (1-\lambda)Y(q_H)$, is higher than the yield from a convex combination of low quality and high quality wheat, i.e., $Y(\lambda q_L + (1-\lambda)q_H)$, with λ varying from 0 to 1. This suggests that when the yield-quality function is convex, the average of yields produced from sorted wheat with distinct qualities exceeds the yield from mixed wheat with average quality. Thus, in the convex region, the market provides the elevator with an incentive to sort high quality wheat from low quality.

The elevator's decisions on blending and sorting are dependent upon the curvature attributes of the yield-quality schedule. Generally, the concavity of yield-quality schedule is associated with blending and the convexity with sorting. On the contrary, Hennessy and Wahl (1997) used the discount schedules for dockage in their analysis, and thus the convexity of the dockage schedule led to blending and the concavity led to sorting. For kernel uniformity to have a value and cause yield to increase from sorting, the property of convex function is necessary. The linear function is a concave function as well as a convex function; therefore it is hypothesized that linearity of a yield-quality schedule is essentially neutral and can lead to either blending or sorting.

Data

Data used in this study were collected over a four-year time period and span all major U.S. hard red winter wheat producing areas. From 1995 through 1998, hard red winter wheat samples were collected during the Hard Red Winter Wheat (HRW) Crop Survey. HRW samples were provided from 22 survey districts when wheat was delivered to elevators during harvest. Texas and Oklahoma were covered by 4 districts, Kansas was represented by 9 districts, eastern Colorado by 2 districts, Nebraska by 5 districts, and South Dakota and Montana were treated as one district for each state. From each district, 7 samples on average were randomly collected over 4 years, resulting in a total of 609 wheat samples.

Each HRW sample collected was tested using the Single Kernel Characterization System (Perten SKCS 4100) in the Grain Science & Industry Department at Kansas State University. The Single Kernel Characterization System (SKCS) measures a variety of physical characteristics of wheat kernels by individually selecting and analyzing 300 kernels per sample. This device completes a test in about 3 minutes, and simultaneously reports mean and standard deviation data for single kernel weight, single kernel diameter (size), single kernel hardness, and single kernel moisture. Besides the single kernel characteristics, test weight was measured as a basic wheat quality attribute.

After initial SKCS tests on the individual survey samples, each sample was tempered to 16% moisture for 18 hours. The tempered samples were milled using fixed roll settings from the Buhler laboratory mill (MLU-202). Milling performance, reported as percent flour yield (PFY), was calculated as the percentage of flour out of total product recovered from the Buhler laboratory mill.

Table 1 presents summary statistics for wheat quality characteristics and average percent flour yields. The percent flour yields data used here are from fixed roll settings and thus may underestimate the value of kernel uniformity. In practice, flour millers can increase the milling yield by optimally adjusting the space of rollermills to different kernel sizes. The wheat samples from 22 districts across 7 states may result in an overestimation of the variability of kernel size when they are combined. The kernel size of wheat from several different regions may be more variable than that from a single region or geographically close regions. This study would have benefited from the measurements of ash content during the milling process to accurately evaluate the value of kernel uniformity in reducing ash content.

Procedures

The first step to develop and evaluate wheat sorting strategies is to estimate an equation that relates the percent flour yield (extraction) to the single kernel characteristics and test weight. The data on wheat quality characteristics and percent flour yield consist of 609 observations on the 22 cross-sections of districts over the 4-year time period. This study pools the time-series and cross-sectional data using the following error components model[1]:

(1) $$PFY_{it} = \beta_0 + \beta_1 KD_{it} + \beta_2 KDS_{it} + \beta_3 KH_{it} + \beta_4 KHS_{it} + \beta_5 TW_{it} + \mu_i + \varepsilon_{it},$$

where i represents the districts ($i = 1, 2, \ldots, 22$), t represents the years (t = 1995, 1996, 1996, and 1998), PFY_{it} is the percent flour yield (%), KD_{it} is the average single kernel diameter (mm), KDS_{it} is the standard deviation of single kernel diameter, KH_{it} is the average single kernel hardness (hardness index), KHS_{it} is the standard deviation of single kernel hardness, and TW_{it} is the test weight (lb/bu). The βs are the fixed-effects coefficients, the μ_i are the random-effects parameters assumed to be independent and identically distributed with $E[\mu_i] = 0$ and $E[\mu_i^2] = \sigma_\mu^2$, and the ε_{it} are independent and

[1] The single kernel diameter (*KD*) and single kernel weight (*KW*) may be considered as alternative measures of kernel size. To avoid the multicollinearity problem that arises from including two measures of the same thing, the following model was estimated separately:

$$PFY_{it} = \beta_0 + \beta_1 KW_{it} + \beta_2 KWS_{it} + \beta_3 KH_{it} + \beta_4 KHS_{it} + \beta_5 TW_{it} + \mu_i + \varepsilon_{it},$$

where KW_{it} is the average single kernel weight (mg), KWS_{it} is the standard deviation of single kernel weight. However, the results of t-tests showed that the estimated coefficients β_1 *and* β_2 are not statistically significant at the 5% level.

identically distributed random variables with $E[\varepsilon_{it}]=0$, $E[\varepsilon_{it}^2]=\sigma_\varepsilon^2$, and uncorrelated with the μ_i. That is, $E[\mu_i\varepsilon_{it}]=0$.

The model was fit using PROC NLMIXED in SAS version 8.0. The data are assumed normally distributed and the mean (expected value) of the data is linear in terms of a set of explanatory variables and the random-effects parameters, i.e.,

$$(2) \qquad E[PFY_{it}]=\beta_0+\beta_1 KD_{it}+\beta_2 KDS_{it}+\beta_3 KH_{it}+\beta_4 KHS_{it}+\beta_5 TW_{it}+\mu_i.$$

The random-effects parameters μ_i enter the model linearly. This study also considered average single kernel moisture (*KM*) and standard deviation of single kernel moisture (*KMS*), but dropped them because they were not statistically significant. Further, the standard deviation of single kernel moisture (*KMS*) should not matter since each sample is tempered to 16% moisture. The ordinary least squares (OLS) estimates of the coefficients were used as the starting values for the coefficients of the mean model. The variance and covariance of the data is an exponential function of a linear combination of explanatory variables, i.e.,

$$(3) \qquad \sigma_\varepsilon^2=\exp[\alpha_0+\alpha_1 KD_{it}+\alpha_2 KDS_{it}+\alpha_3 KH_{it}+\alpha_4 KHS_{it}+\alpha_5 TW_{it}].$$

Finally, the estimated percent flour yield equation is

$$(4) \qquad \begin{array}{l} PFY = 48.24 + 1.32KD - 2.25KDS - 0.07KH - 0.04KHS + 0.44TW \\ \qquad\quad (29.58) \quad (3.19) \quad (-2.30) \quad (-7.95) \quad (-1.84) \quad (13.14) \end{array}$$

where *PFY* is the percent flour yield (%), *KD* is the average single kernel diameter (mm), *KDS* is the standard deviation of single kernel diameter, *KH* is the average single kernel hardness (hardness index), *KHS* is the standard deviation of single kernel hardness, and *TW* is the test weight (lb/bu). The *t*-statistics of the coefficients are presented in parentheses.

The percent flour yield equation is linear with respect to all quality variables. The negative coefficients on the standard deviation terms (*KDS*, *KHS*) in equation (4) yield a convex function, which will lead to sorting being optimal.

Equation (4) shows that flour yield is expected to increase with increases in single kernel diameter (*KD*) and test weight (*TW*), but decrease with increases in single kernel hardness (*KH*), standard deviation of single kernel diameter (*KDS*), and standard deviation of single kernel hardness (*KHS*).[2] The elasticity of percent flour yield with respect to the standard deviation of single kernel diameter (*KDS*), i.e., -2.25, is much bigger in absolute value than that with respect to the standard deviation of single kernel hardness (*KHS*), i.e., -0.04.

This study also evaluated other yield equations that are available in past research. One is the dough factor equation estimated by Baker (1998) at Kansas State University. The dough factor equation relating the amount of dough to wheat quality attributes is expressed as:

$$\begin{aligned} DF = 22.45 + 2.94KW - 6.87KWS + 6.81PT - 0.07KW^2 \\ - 0.23PT^2 + 0.19KW \cdot KWS + 0.37TW, \end{aligned} \tag{5}$$

where *DF* represents the amount of flour-water dough that can be produced from a given quantity of wheat, *KW* denotes kernel weight (mg), *KWS* denotes standard deviation of kernel weight, *PT* denotes protein (%), and *TW* denotes test weight (lb/bu). Since the dough factor equation is strictly concave with respect to kernel weight (*KW*) and protein

[2] Milling yield increases when wheat becomes softer in hard wheat. However, milling yield increases as hardness increases in soft wheat.

(PT), i.e., $\frac{\partial^2 DF}{\partial KW^2} < 0$ and $\frac{\partial^2 DF}{\partial PT^2} < 0$, the model resulted in a perfect blending of all loads.

The other is the percent flour yield equation estimated by Lyford (2000) at Oklahoma State University. The percent flour yield equation is expressed as:

$$\begin{aligned}(6)\qquad PFY = 37.01 + 0.39TW + 1.44KW - 0.03KW^2 - 0.05KH - 1.51KWS \\ + 0.05KW \cdot KWS,\end{aligned}$$

where PFY denotes percent flour yield, TW denotes test weight (lb/bu), KW denotes kernel weight (mg), KH denotes kernel hardness (hardness index), and KWS denotes kernel weight standard deviation. The percent flour yield equation is not convex over the entire data range, which also lead to blending being optimal. Since the primary interest of the study lies in sorting rather than blending, these two models were not used.

Cluster Analysis

Cluster analysis is commonly used to group observations into clusters such that each cluster is as homogeneous as possible with respect to certain characteristics. The clusters formed should be highly internally homogeneous, i.e., observations in each cluster are similar to each other, and highly externally heterogeneous, i.e., observations of one cluster should be different from the observations of other clusters.

Cluster analysis is a useful technique for sorting grain. It can be used to group a large number of grain loads into a desired number of clusters in which each load is similar to one another with respect to kernel size. Since the loads in any cluster are homogeneous with respect to kernel size, the variability of kernel size among individual loads is minimal. This suggests that the variation of kernel size between loads can be reduced by forming homogeneous groups or clusters, and further implies that the overall variation of kernel size can be reduced when various loads of grain are mixed in the bin.

This study employs a two-stage clustering procedure suggested by Punj and Stewart (1983). Two-stage clustering procedure is characterized by the complementary use of hierarchical and nonhierarchical clustering techniques. In other words, in a two-stage clustering procedure, nonhierarchical clustering is used to refine the clustering solution obtained from the hierarchical method. A two-stage cluster analysis is based on the results of simulation studies showing that nonhierarchical clustering techniques are quite sensitive to the selection of the initial seeds, i.e., local optima can be numerous. However, their performance is much superior when the results from hierarchical clustering methods are used to form the initial or starting seeds.

In the first stage, one of the hierarchical clustering methods that has demonstrated superior performance in terms of within-standard deviation and R^2 is used to obtain k initial cluster centroids or seeds. In this study five primary hierarchical clustering methods are evaluated: (1) centroid method, (2) single-linkage or nearest-neighbor method, (3) complete-linkage or farthest-neighbor method, (4) average-linkage method, and (5) Ward's or minimum variance method.

For hierarchical clustering, PROC CLUSTER in SAS 8.0 is used. After the data are first subjected to hierarchical clustering, the PROC TREE is used to specify the number of clusters desired (k). Then, the PROC MEANS is used to compute the means of each clustering variable for each cluster. The k cluster means or centroids for each clustering variable is used as the initial or starting seeds.

In the second stage, the *k* initial cluster centroids or seeds obtained from the hierarchical clustering are submitted to the nonhierarchical clustering technique for refinement of the clusters. In the nonhierarchical clustering, each observation is initially assigned to the cluster to which it is the closest. In the next iterative procedure, the observation is reassigned or reallocated to one of the *k* clusters until the convergence criterion is satisfied. Since this nonhierarchical clustering algorithm uses *k* initial cluster centroids or seeds as starting points and produces exactly *k* different clusters of greatest possible distinction, it is commonly referred to as *k*-means clustering method. For nonhierarchical clustering, PROC FASTCLUS in SAS 8.0 is used.

Since the primary interest of the study lies in the kernel size uniformity, loads for each year are clustered with respect to the average single kernel diameter (*KD*). Three cluster solutions are used because kernel size can be simply classified into three categories, i.e., small, medium, and large kernels.

Nonlinear Optimization

The basic function of grain elevators is to store grain delivered from farmers and then sell it to processors or other merchandisers. The elevators often rearrange grain by blending and/or sorting high-quality grain with or from low-quality grain to take advantage of profit opportunities. The elevator is assumed to have a prior knowledge of the distribution of wheat quality characteristics before the loads of wheat are delivered to the elevator. The elevator allocates truckloads of wheat with different quality attributes into a number of storage bins such that total flour yield from all wheat stored in the bins is maximized. This optimization problem is solved using a mathematical programming approach.

For a mathematical programming model, truckloads are indexed by i ($i = 1, 2, \ldots, N$), each containing wheat with different levels of quality attributes. Storage bins are indexed by j. Considering the fact that grain grades can be simply classified into three categories, i.e., low, medium, and high quality, three storage bins ($j = 1, 2, 3$) are used. Total quantity of wheat in bin j is denoted by QTY_j.

The objective is to maximize the total flour yield from all wheat contained in the bins, and the objective function is defined as:

$$
\begin{aligned}
(7) \quad & \underset{QTY}{Max} \sum_j PFY(KD_j, KDS_j, KH_j, KHS_j, TW_j)QTY_j \\
& = \underset{QTY}{Max} \sum_j (48.24 + 1.32KD_j - 2.25KDS_j - 0.07KH_j - 0.04KHS_j + 0.44TW_j)QTY_j,
\end{aligned}
$$

where KD_j is the average single kernel diameter for wheat in bin j, KDS_j is the standard deviation of single kernel diameter in bin j, KH_j is the average single kernel hardness for wheat in bin j, KHS_j is the standard deviation of single kernel hardness in bin j, and TW_j is the test weight for wheat in bin j.

The maximization problem is subject to a number of constraints concerning wheat allocation and quality attributes. Let X_{ij} denote the quantity of wheat allocated from load i to bin j, then the total quantity of wheat available in bin j is:

$$(8) \qquad QTY_j = \sum_i X_{ij}.$$

For simplicity, each truckload is treated as one unit and then the proportion of load i allocated into bin j is summed to 1. That is, $\sum_j X_{ij} = 1$. The model allows a load to be partially allocated into different bins to avoid the extra complexity of integer programming.

One of the useful properties of grains of different quality is that they can be readily mixed, and for many quality characteristics the effects of mixing can be easily computed. These quality attributes include kernel diameter, kernel hardness, and test weight. This ability to compute the physical quality characteristics of mixed grain arises from the linear homogeneity attributes of mixing. Denote the proportion of load i allocated into bin j by p_{ij}, and let the average single kernel diameter for wheat in load i be KD_i, then the average single kernel diameter for wheat in bin j is given by

(9) $$KD_j = \sum_i p_{ij} KD_i \text{ where } p_{ij} = \frac{X_{ij}}{\sum_i X_{ij}}.$$

Similarly, the average single kernel hardness for wheat in bin j is given by

(10) $$KH_j = \sum_i p_{ij} KH_i \text{ where } p_{ij} = \frac{X_{ij}}{\sum_i X_{ij}}.$$

Finally, the average test weight for wheat in bin j is given by

(11) $$TW_j = \sum_i p_{ij} TW_i \text{ where } p_{ij} = \frac{X_{ij}}{\sum_i X_{ij}}.$$

When grain from separate truckloads that differ in kernel size is combined in the bin, the variation of kernel size in bin j results from two sources. One is the within-load variation and the other is the between-load variation. Within-load variation means the variation of kernel size within a load, i.e., the difference between each kernel size and its load mean, and between-load variation means the variation of kernel size across loads, i.e., the difference between the mean kernel size of each load and the overall mean kernel size of the bin. Thus, the total variation of kernel size in the bin is calculated as the sum of the variation within each load and the variation between loads.

The within-load variation is inherent to each load in the sense that it can not be altered by rearranging the loads and so it does not influence the optimal solution. However, the between-load variation can be reduced by combining the loads of similar kernel size when truckloads are allocated into the bins. The smaller between-load variation in turn means the smaller total variation of kernel size in the bin.

In equation (7), the standard deviation of single kernel diameter (KDS_j) reflects the variation of kernel size in bin j. There are two methods that can be used to estimate the standard deviation of kernel diameter for wheat in bin j. The first method estimates the standard deviation of kernel diameter using a similar procedure with the analysis of variance. The second method approximates the standard deviation of kernel diameter using mean absolute deviations.

In the first method, the total variation of kernel size is calculated as the sum of within-load variation and between-load variation. The total variation of kernel diameter about its overall mean for wheat in bin j is measured by

$$(12) \qquad \sum_{i=1}\sum_{k=1} p_{ij}(KD_{ik} - KD_j)^2 = \sum_{i=1}\sum_{k=1} p_{ij}(KD_{ik} - KD_i)^2 + \sum_{i=1} 300 p_{ij}(KD_i - KD_j)^2,$$

where p_{ij} is the proportion of load i allocated into bin j, i.e., $p_{ij} = \dfrac{X_{ij}}{\sum_{i=1} X_{ij}}$, KD_{ik} denotes the single kernel diameter of the kth kernel in the ith load ($k = 1, \ldots, 300$; $i = 1, \ldots, N$), KD_i is the mean of single kernel diameter in the load i, KD_j is the overall mean of single kernel diameter in the bin j.

With the appropriate degrees of freedom associated, the variance of kernel diameter in the bin j is calculated as

$$(13)\quad \sum_{i=1}\sum_{k=1}\frac{p_{ij}(KD_{ik}-KD_j)^2}{(300N-1)}=\sum_{i=1}\sum_{k=1}\frac{p_{ij}(KD_{ik}-KD_i)^2}{N(300-1)}+\sum_{i=1}300\frac{p_{ij}(KD_i-KD_j)^2}{(N-1)}.$$

Since the standard deviation of kernel diameter in load i, i.e., $KDS_i=\sqrt{\sum_{k=1}\frac{(KD_{ik}-KD_i)^2}{(300-1)}}$,

we obtain

$$(14)\quad \sum_{i=1}\sum_{k=1}\frac{p_{ij}(KD_{ik}-KD_j)^2}{(300N-1)}=\sum_{i=1}\frac{p_{ij}KDS_i^2}{N}+\sum_{i=1}300\frac{p_{ij}(KD_i-KD_j)^2}{(N-1)}.$$

Taking the square root of the equation (14), we finally obtain the standard deviation of single kernel diameter in bin j

$$(15)\quad KDS_j=\sqrt{\sum_{i=1}\frac{p_{ij}KDS_i^2}{N}+\sum_{i=1}300\frac{p_{ij}(KD_i-KD_j)^2}{(N-1)}}.$$

In the alternative procedure to approximate the standard deviation of kernel diameter, the within-load standard deviation of kernel diameter for wheat in bin j is approximated by mean absolute deviation estimator. This is based on the theoretical results by Taylor (pp.98-99, 1986). Taylor presented that the expected value of absolute deviation is equal to $1/1.25$ times the expected value of the standard deviation. Since the standard deviation of single kernel diameter in load i is readily available, we can obtain the mean absolute deviation estimator as an approximation to the within-load standard deviation of kernel diameter.

On the other hand, the between-load standard deviation of kernel diameter for wheat in bin j is estimated by the expected absolute deviation of the load average kernel diameter from the bin average kernel diameter. Let the deviation of the average single kernel diameter for wheat in load i from the average single kernel diameter for wheat in bin j, or $KD_i - KD_j$, be denoted by u_{ij}^+ if it is positive, and by u_{ij}^- if it is negative. Then, $\sum_i (u_{ij}^+ + u_{ij}^-)$ measures the sum of the absolute deviations for average single kernel diameter. Taking the expected value of $\sum_i (u_{ij}^+ + u_{ij}^-)$, we can obtain the mean absolute deviation estimator as an approximation to the between-load standard deviation of kernel diameter.

With the within-load standard deviation and the between-load standard deviation combined together, the average standard deviation of kernel diameter for wheat in bin j is

$$\begin{aligned} KDS_j &= \sum_i p_{ij} \frac{KDS_i}{1.25} + \sum_i p_{ij}(u_{ij}^+ + u_{ij}^-) \\ &= \sum_i p_{ij} \left[\frac{KDS_i}{1.25} + \left(u_{ij}^+ + u_{ij}^-\right) \right], \; where \; p_{ij} = \frac{X_{ij}}{\sum_i X_{ij}}. \end{aligned} \tag{16}$$

Similarly, the average standard deviation of kernel hardness for wheat in bin j is estimated by

$$\begin{aligned} KHS_j &= \sum_i p_{ij} \frac{KHS_i}{1.25} + \sum_i p_{ij}(u_{ij}^+ + u_{ij}^-) \\ &= \sum_i p_{ij} \left[\frac{KHS_i}{1.25} + \left(u_{ij}^+ + u_{ij}^-\right) \right], \; where \; p_{ij} = \frac{X_{ij}}{\sum_i X_{ij}}. \end{aligned} \tag{17}$$

The elevator's maximization problem is solved using the MINOS5 solver in GAMS, a general nonlinear optimizer. Nonlinearities occur in several constraints and the feasible region for the problem is not convex. Due to the non-convexity, there is no guarantee that a local optimum found is actually global.

To deal with this problem, a global optimization approach is required. A global optimization method solves the non-convex model with numerous different starting values for a selected variable (Brooke, Kendrick, Meerhaus, and Raman, p. 154). In this study, the global solution was tracked by randomizing the starting values up to 1000 times. Specifically, the starting values for variable X_{ij}, i.e., amount of load allocated, were varied by random numbers generated from uniform distribution, within a range of 0.0001 and 1/3. The model was repetitively solved and the solution that gave the largest objective value was selected as a global maximum.

Since the global optimization method using random restarts searches for a global optimum from a large number of starting values, the computer time is really a matter of concern. The problem with the first method of estimating the standard deviation is that it imposes heavy nonlinear constraints and thus it is very slow to converge. This study uses the alternative method that approximates the standard deviation using the mean absolute deviation estimator since it is considerably faster to converge. Even with the alternative method, it took more than 35 hours to solve the model using a personal computer equipped with an Intel Pentium III processor at 450 MHz in the computer lab at the Department of Agricultural Economics at Oklahoma State University.

Cluster analysis and nonlinear optimization are evaluated by how much they increase the percent flour yield relative to the whole sample without sorting. In addition, to measure the monetary value of increasing kernel uniformity, the percent flour yields obtained from cluster analysis and nonlinear optimization are evaluated by the following milling income equation (Lyford, 2000):

$$\begin{aligned} MI = 15{,}500 * \{&[TW * PFY * 1.018 * (1-(DK+TD)) * FP/100] \\ &+ [TW * (DK+TD) * (MP/2000)] + [(1-PFY) * (MP/2000)] \\ &- [WP + 0.636 + 0.120 * PFY]\}, \end{aligned} \tag{18}$$

where *MI* is the milling income per day, denoted in dollars, *TW* is the test weight, *PFY* is the percent flour yield, *DK* is the dockage level, *TD* is the total defects, *FP* is the flour price, and *MP* is the mill feed price. The estimated milling income equation is based on the daily throughput of 15,500 bushels of wheat, represented by a medium-sized mill. It is assumed that flour price (FP) is $9.20/cwt, wheat price (WP) $3.10/bushel, dockage (DK) 0.5%, total defects (TD) 2.5%, and mill feed price $56/ton.

Results

The quality characteristics and flour yield assuming all loads for each year are blended are presented in Table 2. The standard deviation of single kernel diameter (*KDS*) and standard deviation of single kernel hardness (*KHS*) are larger than the average values reported in Table 1. This is because the standard deviation of the two variables in Table 2 reflects the between-load standard deviation as well as the within-load standard deviation. The percent flour yield (*PFY*) predicted by equation (4) is lowest in 1996 with 70.52 and highest in 1998 with 71.66. The predicted average percent flour yields are generally lower than the actual average percent flour yields presented in Table 1, since they are based on the increased standard deviation of single kernel diameter and single kernel hardness.

<u>Cluster Analysis</u>

The cluster solutions from 1995 to 1998 are reported in Tables 3 and 4. The first column of Table 3 indicates the hierarchical clustering algorithm that gave the best solution in the first stage of two-stage clustering. There were only slight differences in the solutions obtained when the centroids from the single-linkage, complete-linkage, centroid, average-linkage, and Ward's methods were used as initial seeds or starting points. The R^2s ranging from 0.76 to 0.85 are quite large, suggesting that the clusters are quite homogeneous and well separated. The low values of within standard deviation ranging from 0.05 to 0.06 further confirm this conclusion.

The cluster solution can be labeled using the cluster means of each cluster. For example, considering 1995 sample in Table 4, cluster 1 consists of loads that have medium kernels and therefore this cluster can be labeled as medium-kernel cluster. Similarly, cluster 2 can be labeled as small-kernel cluster, and cluster 3 as large-kernel cluster.

Table 5 exhibits the average wheat quality attributes of the clusters in each year and the estimated percent flour yield. The overall mean of the percent flour yield is 71.13 for 1995, 70.69 for 1996, 71.46 for 1997, and 71.74 for 1998. The percent flour yields obtained from clustering are higher than those without sorting across the board. This result is from the fact that by sorting the loads for each year into homogeneous clusters, the between-load variations of single kernel diameter and single kernel hardness are decreased, and in turn the average standard deviations of single kernel diameter and single kernel hardness are decreased.

Nonlinear Optimization

Table 6 shows the results of the nonlinear optimization. A small number of loads were partially allocated into the bins, and thus the total quantities of loads allocated into each bin are not round numbers. The average percent flour yield is 71.33 for 1995, 70.89 for 1996, 71.67 for 1997, and 71.91 for 1998. The yields are higher than those from cluster analysis as well as whole sample without sorting.

Table 7 summarizes the results in Tables 2, 5 and 6. The results show slight increases in percent flour yield from two sorting methods. Specifically, the cluster analysis and nonlinear optimization increase the percent flour yield relative to the whole sample without sorting by 0.13% and 0.32% respectively. This implies that when one million bushels of wheat are milled, the cluster analysis will increase flour yield by 1,300 bushels, and the nonlinear optimization will increase flour yield by 3,200 bushels.

Table 8 reports the milling incomes per day from whole sample without sorting, cluster analysis, and nonlinear optimization. Cluster analysis increases the milling income relative to the whole sample without sorting by 104.99 dollars (5%) on average, and nonlinear optimization increases the milling income relative to whole sample without sorting by 265.90 dollars (13%) on average.

Conclusions

This study developed grain sorting strategies for elevators to use to increase kernel uniformity and determined the size of potential benefits from sorting. Kernel size uniformity is an important physical quality attribute in terms of processing efficiency, quality control, and milling yield.

Cluster analysis and nonlinear optimization were used to sort loads to increase kernel size uniformity. Cluster analysis and nonlinear optimization increased the percent flour yield relative to no sorting by 0.13% and 0.32% respectively. Cluster analysis increased the daily milling income relative to no sorting by 104.99 dollars (5%), and nonlinear optimization increased the milling income by 265.90 dollars (13%). The results show that cluster analysis is vastly inferior to nonlinear optimization.

This study was unable to include all the potential values of kernel uniformity. The milling yield data used here are from fixed roll settings. In practice, flour millers can optimally adjust the space of rollermills to take advantage of the kernel size uniformity. Future grain science research needs to look at the possibility of optimally adjusting roller settings. There is also the possibility of improving flour quality (reduced ash content) from increased kernel uniformity. Future grain science research should also address flour quality. These additional benefits of kernel uniformity may need to be considered before firms would adopt sorting strategies to increase kernel uniformity.

Table 1. Summary Statistics for Wheat Quality Characteristics and Actual Percent Flour Yield, 1995–1998

		Single Kernel Characteristics									
Year		KW	KWS	KD	KDS	KH	KHS	KM	KMS	TW	PFY
	Mean	27.87	7.74	2.29	0.42	67.56	17.34	10.70	0.64	59.41	71.75
	StDev	2.59	0.81	0.12	0.04	4.28	1.35	0.80	0.19	2.09	1.48
1995	Min	22.75	5.89	2.03	0.33	56.98	13.66	8.33	0.37	54.00	67.10
	Max	35.53	10.79	2.66	0.55	78.95	21.60	12.57	1.72	63.00	75.07
	Obs	148	148	148	148	148	148	148	148	148	148
	Mean	28.21	8.00	2.23	0.46	70.81	17.18	13.00	0.51	59.40	70.74
	StDev	2.91	0.79	0.14	0.04	6.11	1.37	0.86	0.08	1.38	1.50
1996	Min	22.19	6.31	1.89	0.38	57.67	13.24	9.46	0.32	55.65	66.01
	Max	34.99	10.24	2.59	0.57	85.09	21.85	14.96	0.78	63.18	73.77
	Obs	156	156	156	156	156	156	156	156	156	156
	Mean	30.23	8.53	2.31	0.47	69.36	17.47	12.58	0.48	60.71	71.29
	StDev	2.82	0.90	0.14	0.04	5.84	1.98	1.05	0.12	1.37	0.93
1997	Min	22.37	6.77	1.95	0.38	49.24	13.19	9.82	0.33	56.07	67.77
	Max	37.35	11.61	2.65	0.58	81.43	27.00	15.16	1.31	63.42	73.07
	Obs	136	136	136	136	136	136	136	136	136	136
	Mean	30.16	7.67	2.31	0.42	72.78	15.86	12.12	0.47	61.56	71.80
	StDev	1.94	0.47	0.10	0.03	6.70	1.89	0.89	0.09	1.21	1.29
1998	Min	23.44	6.50	1.93	0.35	50.67	12.21	9.87	0.32	58.30	67.65
	Max	36.99	9.24	2.64	0.48	82.92	27.23	14.09	0.86	63.78	74.65
	Obs	169	169	169	169	169	169	169	169	169	169

Notes: *KW* is the average single kernel weight (mg), *KWS* is the standard deviation of single kernel weight, *KD* is the average single kernel diameter (mm), *KDS* is the standard deviation of single kernel diameter, *KH* is the average single kernel hardness (hardness index), *KHS* is the standard deviation of single kernel hardness, *KM* is the average single kernel moisture (%), *KMS* is the standard deviation of single kernel moisture, *TW* is the test weight (lb/bu), and *PFY* is the percent flour yield (%).

Table 2. Average Wheat Quality Attributes and Predicted Percent Flour Yield from Whole Sample without Sorting, 1995–1998

Year	Obs	KD	KDS	KH	KHS	TW	PFY
1995	148	2.29	0.43	67.56	17.22	59.41	71.01
1996	156	2.23	0.48	70.81	18.80	59.40	70.52
1997	136	2.31	0.48	69.36	18.56	60.71	71.32
1998	169	2.31	0.41	72.78	17.89	61.56	71.66

Notes: *Obs* is the number of observations, *KD* is the average single kernel diameter (mm), *KDS* is the standard deviation of single kernel diameter, *KH* is the average single kernel hardness (hardness index), *KHS* is the standard deviation of single kernel hardness, and *TW* is the test weight (lb/bu), and *PFY* is the percent flour yield (%). *KDS* and *KHS* are calculated by combining the within-load standard deviation and between-load standard deviation.

Table 3. Summary Statistics for Two-Stage Cluster Analysis, 1995 – 1998

Year	Hierarchical Clustering Method	Total Standard Deviation	Within Standard Deviation	R-Squared
1995	Single-Linkage	0.12	0.05	0.81
1996	Single-Linkage	0.14	0.06	0.85
1997	Complete-Linkage	0.14	0.06	0.82
1998	Centroid	0.10	0.05	0.76

Note: Loads are clustered with respect to average single kernel diameter (KD) in each cluster.

Table 4. Cluster Means and Standard Deviation, 1995 – 1998

Year	No. of Clusters	No. of Loads	Cluster Mean	Cluster Std. Dev.
1995	1	62	2.29	0.04
	2	54	2.17	0.05
	3	32	2.46	0.08
1996	1	78	2.24	0.05
	2	42	2.04	0.06
	3	36	2.42	0.06
1997	1	27	2.10	0.07
	2	75	2.31	0.05
	3	34	2.48	0.06
1998	1	88	2.31	0.03
	2	46	2.42	0.06
	3	35	2.17	0.07

Note: Loads are clustered with respect to average single kernel diameter (KD) in each cluster.

Table 5. Clusters, Average Quality Attributes and Percent Flour Yield, 1995-1998

Year	Cluster	Obs	KD	KDS	KH	KHS	TW	PFY	Mean PFY
	1	62	2.29	0.37	68.63	17.41	59.66	71.19	
1995	2	54	2.17	0.37	66.05	17.13	57.98	70.48	71.13
	3	32	2.46	0.42	68.02	16.78	61.36	72.12	
	1	78	2.24	0.41	68.89	18.45	59.52	70.89	
1996	2	42	2.04	0.39	73.78	18.87	58.33	69.81	70.69
	3	36	2.42	0.45	71.50	17.43	60.37	71.28	
	1	27	2.10	0.43	69.80	18.91	59.06	70.39	
1997	2	75	2.31	0.42	70.43	18.18	60.94	71.50	71.46
	3	34	2.48	0.42	66.63	18.60	61.51	72.22	
	1	88	2.31	0.36	72.14	18.97	61.58	71.76	
1998	2	46	2.42	0.37	72.43	16.57	62.24	72.26	71.74
	3	35	2.17	0.38	74.81	17.00	60.62	71.00	

Notes: *Obs* is the number of observations, *KD* is the average single kernel diameter (mm), *KDS* is the standard deviation of single kernel diameter, *KH* is the average single kernel hardness (hardness index), *KHS* is the standard deviation of single kernel hardness, and *TW* is the test weight (lb/bu), *PFY* is the percent flour yield (%), and *Mean PFY* is the average PFY of the clusters.

Table 6. Results of Nonlinear Optimization, 1995-1998

Year	Variables	Bin Number		
		1	2	3
1995	Quantity	70.92	32.34	44.74
	KD	2.28	2.45	2.17
	KDS	0.20	0.42	0.37
	KH	69.71	66.84	64.67
	KHS	16.71	16.86	16.56
	TW	59.79	61.07	57.62
	Average PFY		71.33	
1996	Quantity	69.02	45.00	41.98
	KD	2.23	2.39	2.04
	KDS	0.41	0.46	0.39
	KH	67.26	72.38	74.98
	KHS	17.87	17.06	18.25
	TW	59.30	60.38	58.50
	Average PFY		70.89	
1997	Quantity	58.54	33.89	43.57
	KD	2.41	2.13	2.33
	KDS	0.44	0.45	0.30
	KH	66.54	68.82	73.53
	KHS	17.47	18.95	16.86
	TW	61.18	59.33	61.16
	Average PFY		71.67	
1998	Quantity	35.85	52.46	80.69
	KD	2.31	2.23	2.37
	KDS	0.39	0.20	0.38
	KH	62.51	75.48	75.57
	KHS	17.98	15.69	15.09
	TW	60.44	61.28	62.25
	Average PFY		71.91	

Notes: *Quantity* is the total number of loads allocated into the bin, *KD* is the average single kernel diameter (mm), *KDS* is the standard deviation of single kernel diameter, *KH* is the average single kernel hardness (hardness index), *KHS* is the standard deviation of single kernel hardness, and *TW* is the test weight (lb/bu), and *PFY* is the percent flour yield (%).

Table 7. Predicted Average Percent Flour Yield from Whole Sample without Sorting, Cluster Analysis, and Nonlinear Optimization, 1995-1998

Year	Whole Sample Without Sorting	Cluster Analysis		Nonlinear Optimization	
		PFY	Increase	PFY	Increase
1995	71.01	71.13	0.12	71.33	0.32
1996	70.52	70.69	0.17	70.89	0.37
1997	71.32	71.46	0.14	71.67	0.35
1998	71.66	71.74	0.08	71.91	0.25
Average	71.13	71.26	0.13	71.45	0.32

Note: PFY represents the percent flour yield and increases in PFY are calculated relative to the PFY from whole sample without sorting.

Table 8. Milling Incomes per Day from Whole Sample without Sorting, Cluster Analysis, and Nonlinear Optimization, 1995-1998

(Unit: Dollars)

Year	Whole Sample without Sorting	Cluster Analysis			Nonlinear Optimization		
		Milling Income	Dollar Increase	Percent Increase	Milling Income	Dollar Increase	Percent Increase
1995	1,079.58	1,177.23	97.65	9%	1,339.97	260.39	24%
1996	670.80	809.11	138.31	21%	971.82	301.02	45%
1997	2,654.47	2,770.96	116.48	4%	2,945.68	291.21	11%
1998	3,806.23	3,873.75	67.52	2%	4,017.23	211.00	6%
Average	2,052.77	2,157.76	104.99	5%	2,318.68	265.90	13%

Note: Dollar increases and percent increases are calculated relative to the milling income from whole sample without sorting.

Figure 1.: Concave Yield-Quality Schedule

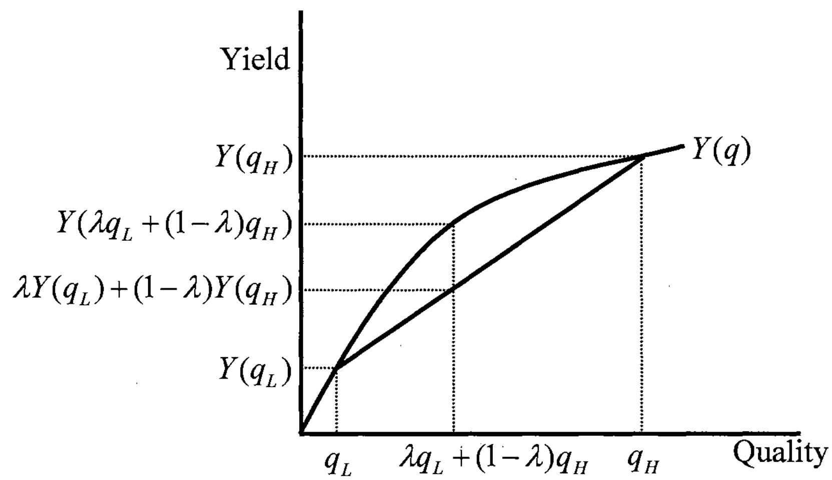
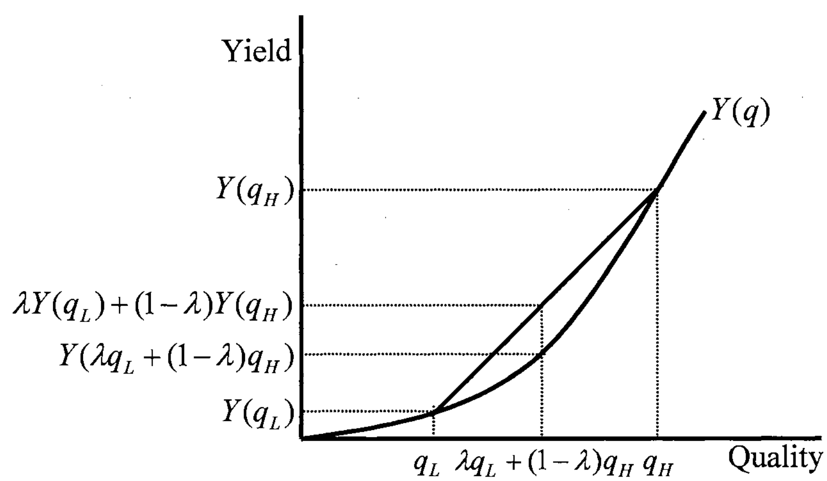


Figure 2.: Convex Yield-Quality Schedule



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Chapter III

MARKET INVERSION IN COMMODITY FUTURES PRICES

MARKET INVERSION IN COMMODITY FUTURES PRICES

ABSTRACT

As opposed to a normal market, an inverted market has a negative price of storage or spread. Market inversions in nearby spreads rarely occur during early months of the crop year since stocks are usually abundant after harvest. However, market inversions become more pronounced when the spreads are observed across crop years at the end of the crop year or just before new harvest. The regressions of spreads on the logarithm of U.S. quarterly stocks show that there exists a positive relationship between the spread and the level of stocks, and further implies that when stocks are scarce, markets will be inverted. Simulations are conducted to determine whether a market inversion is a signal to sell the stocks. The results of the paired-difference tests reveal that as the crop cycle advances towards the end of the crop year, market inversions clearly reflect the market's signal to release stocks in anticipation of new crop supplies. The regressions of actual returns to storage on predicted returns to storage clearly show that a market inversion is a signal to sell. The results support the behavioral finance hypothesis that producers are choosing to hold excess stocks because of some type of biased expectations.

Key Words: market inversion, negative price of storage, cost of carry, risk premium, convenience yield

MARKET INVERSION IN COMMODITY FUTURES PRICES

Introduction

A principal theory of futures markets tells that futures prices for storable commodities should be higher than spot prices by the carrying charges. Carrying charges represent the cost of storage, primarily warehousing and insurance cost plus interest foregone. If the spot price is too low relative to the futures price, a cash-and-carry arbitrage opportunity arises and the trader who engages in arbitrage reaps a riskless profit. Thus, in a normal market, a futures price spread is limited by arbitrage to the full cost of carry.

However, this theory is not always supported by empirical evidence. A puzzling phenomenon in actual commodity markets is that processors and merchandisers routinely hold inventories in the face of inverse carrying charges. In an inverted market, a commodity's price for future delivery is below the price for immediate delivery and intertemporal arbitrage conditions fail to apply. Under market inversion, since the price spread in futures markets fails to cover commodity-holding costs, stockholders apparently gain negative returns to storage.

This aspect of commodity markets was first noticed by Working (1934), while studying the price relationships between old and new-crop wheat futures at Chicago. He observes that nationwide wheat stocks are held even when the intertemporal spread (price of storage) is inverted, and argues that the price of storage is dependent upon the aggregate level of stocks. Later, Working's findings were represented by the supply-of-storage curve, which shows that the farther the spot/futures spreads are below full carrying charges, the less amount of stocks are held.

Traditionally, there were two major, but contradictory, theories explaining the phenomenon of market inversion. The risk premium theory of Keynes (1930) holds that speculators must be compensated for their risk taking by hedgers in the form of a risk premium. In markets where speculators are predominantly short, the futures price is biased downward relative to the expected future spot price by the amount of a risk premium. In contrast, the convenience yield theory, first employed by Kaldor (1939), maintains that when processors and merchandisers hold stocks readily available at hand, they receive some non-monetary benefits that do not accrue to the holders of futures contracts.

Recently, alternative explanations for market inversions have been suggested, notably in articles by Wright and Williams; Benirschka and Binkley; and Brennan, Williams, and Wright. According to their view, the apparent relationship between market inversions and return to storage is caused by mismeasurement. Wright and Williams (1989), and Brennan, Williams, and Wright (1997) argue that market inversions may occur when the stocks of very similar but economically distinct commodities in terms of grade or location are aggregated into a composite while the prices for the commodities are represented by a single price. Brennan, Williams, and Wright also suggest that the market inversion may be caused by the probability of a stock out. Benirschka and Binkley (1995) argue that "storage at a loss" illusion exists because the opportunity costs of storage are overestimated by using grain prices at the central market, not at the storage locations. Frechette and Fackler (1999) examined Benirschka and Binkley's proposition, that is, the location of stocks matters in the intertemporal price relationships of storable commodities, for the U.S. corn market and found mixed empirical support.

A market inversion appears to be a situation where the market is begging producers to sell, yet many continue to store their stocks. Behavioral finance (Kahneman, et al., 1982; Kahneman and Riepe, 1998) offers an alternative explanation that producers are choosing to hold excess stocks because of some type of biased expectations. Hurt (1987), for example, argues that a market inversion is a signal to sell.

The studies cited above rationalize the market inversion well, but have not provided measurements of the frequency of market inversions or evaluated marketing strategies based on market inversions. The primary objective of the study is to determine the optimal marketing strategy when agricultural commodity futures markets are inverted. First, the frequency of market inversions in corn, soybeans, and wheat markets will be determined by comparing nearby futures price spreads with the contemporaneous costs-of-carry. Then, regression analysis will be used to determine the situations in which the market inversions occur. Finally, simulations will be conducted to determine the optimal marketing strategy when markets are inverted.

Theory

Market inversion is commonly known as backwardation in British terms.[1] It

[1] The term "backwardation" used here has a different meaning than "normal backwardation." The theory of normal backwardation originated with Keynes (1930) and holds that the futures price is less than the expected future spot price due to a risk premium, and that the futures price should rise over time to equal the expected future spot price at expiration. As opposed to normal backwardation, "contango" refers to a price process in which the futures price falls over the life of the contract.

describes a market situation in which the spot price exceeds the futures price or a nearby futures price exceeds a distant futures price.

The theory of the price of storage that explains intertemporal price relationships between spot and futures with respect to the cost of carrying a commodity was first proposed by Kaldor (1939). Following Kaldor, Working (1948, 1949), Brennan (1958, 1991), Telser (1959), Fama and French (1987, 1988), and Heaney (1998) have elaborated on the theory of storage.

The theory of the price of storage explains the price difference between spot and futures in terms of interest foregone in storing a commodity (the opportunity cost of storage), physical storage costs, risk premium, and convenience yield for holding stocks. Let $F(t, T)$ be the futures price at time t for delivery of a commodity at time T, $S(t)$ the spot price at time t, $S(t)R(t, T)$ the interest forgone during storage, $W(t, T)$ the physical storage costs, $P(t, T)$ the risk premium, and $C(t, T)$ the convenience yield, then the price of storage (basis), $F(t, T) - S(t)$, is defined as:

$$(1) \qquad F(t,T) - S(t) = S(t)R(t,T) + W(t,T) + P(t,T) - C(t,T).$$

The price of storage or basis, $F(t, T) - S(t)$, can be interpreted as the return to storage from time period t to T ($t < T$), i.e., the return from purchasing the commodity at t and selling it for delivery at T. The interest forgone, $S(t)R(t, T)$, is the opportunity cost of holding stocks, i.e., the opportunity cost of investing cash in the commodity stock now rather than using a futures contract. The physical cost of storage, $W(t, T)$, is the sum of rent for storage space, handling or in-and-out charges, insurance, transport, etc. As the quantity of stocks held by a firm increases, the physical cost of storage increases. However, the marginal physical cost of storage for an additional unit of stocks is approximately constant for a wide range of stocks less than total storage capacity. Beyond the level at which the total storage capacity is almost fully utilized, the marginal physical cost of storage will rise sharply because of the large fixed costs required to construct additional storage facilities.

The risk premium, *P(t, T)*, is the compensation for the risk of monetary loss on the stocks held. Brennan (1958) incorporated the risk premium originated with Keynes and Hicks into the components of the cost of storage. He argues that the market must offer a risk premium to encourage firms to hold stocks because the risk of loss of inventory value constitutes the net cost of storage. When stock levels are low, the risk of a commodity losing its value is small. However, as stock levels increase, the risk of loss of inventory value also increases, potentially up to the critical point at which a firm's credit position is seriously endangered. The higher the level of stocks, the more risky the investment in stocks, and the greater the compensation required for holding the stocks. Thus, the risk premium (or risk aversion factor denoted by Brennan (1958)) is assumed to be an increasing function of stocks. It rises with increases in stocks at an increasing rate; $\frac{\partial P}{\partial X} > 0$ and $\frac{\partial^2 P}{\partial^2 X} > 0$, where X is the amount of stocks held.

The convenience yield, *C(t, T)*, refers to a stream of implicit benefits that accrues to the owner of a physical stock but not to the owner of a contract for future delivery. Stockholders earn the convenience yield because stocks on hand allow them to respond more flexibly and efficiently to unexpected supply and demand shocks. Where stocks are held, regular customer demands can be met, and sudden and unexpected increases in demand can be accommodated without disrupting production schedules. The convenience yield may be thought of as a negative price of storage in that it reflects the benefits rather than the cost of stockholding. These benefits are most significant when stocks are scarce. When stocks are abundant, the convenience yield approaches zero because the scarcity value of stocks is minimal. Empirical evidence presented by Working (1949, 1949), Telser (1958), Fama and French (1987, 1988), and Brennan (1991) also suggest that the convenience yield is a decreasing (convex) function of stocks. It declines with increases in stocks but at a decreasing rate; $\frac{\partial C}{\partial X} < 0$ and $\frac{\partial^2 C}{\partial^2 X} > 0$, where *X* is the amount of stocks held.

The theory of the price of storage also applies to the relationships between two futures contracts of different delivery months. The price of storage or spread between the nearby and distant futures contracts is defined as:

(2) $$F(t,D) - F(t,N) = F(t,N)R(N,D) + W(N,D) + P(N,D) - C(N,D), \quad D > N,$$

where *F(t, D)* is a distant futures price quoted at time *t*, maturing at time *D*, *F(t, N)* is a nearby futures price quoted at time *t*, maturing at time *N (D > N)*. Thus, *F(t, D) – F(t, N)* is the market spread or the return to storage from time period *N* to *D*. *F(t, N)R(N, D)* is the opportunity cost of holding stocks for the period *N* to *D*. *W(N, D)* is the physical costs of storage from time *N* to *D*. *P(N, D)* is the risk premium for holding stocks for the period *N* to *D*. *C(N, D)* is the convenience yield arising from stockholding from time *N* to *D*.

In equations (1) and (2), two of the components that determine the price of storage, i.e., risk premium and convenience yield, are not directly observable. When stocks are sufficiently low, the theory of the price of storage predicts a negative price of storage (negative spread) or market inversion since the convenience yield overwhelms the sum of interest forgone, storage costs and risk premium. On the other hand, if the stock levels are sufficiently high, the convenience yield is negligible and the price of storage (spread) is essentially the sum of interest forgone, storage costs and risk premium. Here, one testable hypothesis generated by the theory of the price of storage is that markets will be inverted when stocks are low.

When markets are inverted, a negative price of storage (negative spread) can be interpreted as a market signal that encourages firms to release their stocks into consumption channels. Under market inversion, it is best for stockholders to sell their stocks now since storage only occurs at a very high opportunity cost. Another testable hypothesis from this argument is that producers will receive highest expected returns by selling stocks rather than storing when markets are inverted.

Data

The agricultural commodities selected for the analysis of market inversion in futures prices are corn, soybeans, and wheat. Futures prices from the Chicago Board of Trade are obtained from the Annual Report of the Board of Trade of the City of Chicago and from a computer database compiled by Technical Tools, Inc. Futures price is the closing price of the corresponding contract month observed on the first trading day of each calendar month. The sample period extends from 1957 through 1999 for corn, and from 1958 through 1999 for wheat and soybeans. A long time series is needed because market inversions occur infrequently. However, before the first year of the sample periods, only nearby futures contracts were reported and a lot of observations, for example, March futures prices, were missing. Thus, this study could not go back farther in time.

For the same periods with the futures price series, monthly cash grain prices are obtained from National Agricultural Statistics Service (NASS) of the U.S. Department of Agriculture. The cash prices are U.S. monthly average prices received by farmers and denoted in dollars per bushel. The average price is the open-market price resulted from dividing the total dollars received by all farmers by the total quantity sold. U.S. monthly average prices are computed by weighting monthly prices by the estimated percentage of monthly sales during the month by State. U.S. quarterly grain stocks, and grain supply and demand data are also from National Agricultural Statistics Service of the U.S. Department of Agriculture.

The cost-of-carry or carrying charge from the perspective of off-farm, commercial storage consists of two components: physical storage costs charged by elevators and the interest opportunity cost. Commercial grain storage rates over the 1970-1999 period, characterized as variable cost only, were obtained from Oklahoma Cooperative Extension Service at Oklahoma State University. The prevailing commercial grain storage rates in recent years are commonly cited as 2.5 to 2.6 cents per bushel per month (Jackson, Irwin, and Good, 1997; Kastens and Dhuyvetter, 1999). To create a historical time series of storage costs for the period 1957 through 1969, the average commercial grain storage cost of 2.55 cents per bushel per month is deflated using the producer price index (PPI) from Bureau of Labor Statistics. The U.S. prime loan rates from the Federal Reserve Bank of St. Louis are used to calculate the opportunity or interest costs for stored grain.

Procedures

The market spread, defined as the difference between two futures prices can be constructed within and across crop years. The spread between futures prices for nearby and distant delivery dates is defined by

$$S(t) = F(t,D) - F(t,N), \tag{3}$$

where $S(t)$ represents the spread between two futures prices observed at time t, $F(t, D)$ represents the futures price of a distant delivery month at time t, and $F(t, N)$ represents the futures price of a nearby delivery month at time t. For corn, the December-March spread in December, the March-May spread in January, February, and March, the May-July spread in April and May, and the July-September spread in June and July are examined. In futures contract months for corn, December represents harvest, March represents preplanting, May represents planting, July represents the middle of the growing season, and September represents the late growing season or early harvest. For soybeans, the November-January spread in November, the January-March spread in December and January, the March-May spread in February and March, the May-July spread in April and May, the July-August spread in June and July, and the August-September spread in August are examined. For wheat, the July-September spread in July, the September-December spread in August and September, the December-March spread in October, November, and December, and the Mar-May spread in January, February, and March are examined.

The cost of carry or carrying charge necessary to carry the commodity from the nearby delivery date to the distant delivery date is defined by

$$CC(t,(N,D)) = F(t,N)[e^{r(N,D)} - 1] + W(N,D), \tag{4}$$

where *CC(t, (N, D))* is the carrying charges from *N* to *D* at time *t*, *F(t, N)* is a nearby futures price quoted at time *t*, $e^{r(N,D)}$ is continuously compounded rate of return for the period *N* to *D*, and *W(N, D)* is the physical cost of storage from time *N* to *D*.

Using equations (3) and (4), this study measures the extent to which the market spread between futures prices for nearby and distant delivery dates falls below full carrying charges. The degree of being below full carry is classified into six categories based on the percentage of market spread to the cost of carry or carrying charge. The frequency of market inversions is identified using information on the percentage of market spread to the cost of carry.

An empirically testable hypothesis drawn from the equations (1) and (2) is that when stocks are low, the price of storage (basis or spread) becomes negative and markets will be inverted. To test the hypothesis, the relationship between the spread and the level of stocks is determined using a regression analysis[2].

In this study, two regressions are estimated to examine the spread-stock relationship. First, market spreads are regressed on the logarithm of U.S. quarterly stocks:

$$Spread_t = \beta_0 + \beta_1 \ln(QS_t) + \varepsilon_t, \tag{5}$$

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[2] Extensive literature deals with the relationship between the price of storage (spread) and the level of stocks. With the difficulty in defining and accurately measuring the relevant inventory, a major difference among the studies lies in the measurement of the level of stocks. Telser (1958) showed that the price of storage is determined by the total marketable stocks rather than the total level of existing stocks. Weymar (1966) stressed that the expected level of stocks between two futures' time periods is more important than the current level of stock for the determination of the price of storage for two distant futures contracts. Gray and Peck (1981) demonstrated that the price of storage is determined by the current stocks readily available for delivery, rather than by the total level of current stocks.

where $\ln(QS_t)$ is the natural logarithm of U.S. quarterly stocks and ε_t is the error term. Each quarterly stock estimate is analyzed with respect to the spread corresponding to the nearest futures contract. For example, December stocks for corn are compared to December-March spreads on December 1, March stocks are compared to Mar-May spreads on March 1, and June stocks are compared to July-September spreads on June 1. Since the quarterly grain stocks estimates are based on the stock levels as of the first day of December, March, June, and September, the spread-stock relationships are synchronous. A similar regression was also used in coffee and cocoa futures markets (Thompson, 1986), and energy futures markets (Cho and McDougall, 1990). The major weakness of this regression is that the two variables included in the regression have time trends and show some degree of autocorrelation. Spreads tend to grow due to inflation and U.S. quarterly stocks tend to increase due to increases in crop production over the years. Regressing one trending variable against another trending variable may result in a too high estimated regression coefficient.

Second, the percentage of market spread to the cost of carry is regressed on the stocks-to-use ratio:

$$\%Carry_t = \beta_0 + \beta_1 SUR_t + \varepsilon_t, \qquad (6)$$

where $\%Carry_t$ is the percentage of market spread to the cost of carry, SUR_t is the stocks to use ratio, and ε_t is the error term. The stocks-to-use ratio is calculated as a percent of end-of-crop-year stocks (ending stocks) to the five-year moving average of total use. The five-year moving average of total use is used to smooth out the effect of sudden increases in demand in any one crop year. Asynchronicity may be a problem with this regression.

Since the ending stock figures are used, the market may not be aware of exact stock availability at the point that the percent of spread to cost-of-carry ($\%Carry_t$) is computed.

When markets are inverted, stockholders apparently gain negative returns to storage due to inverse carrying charges. Thus, the recommended strategy is 'sell the stocks'. To determine whether a market inversion is a signal to sell stocks, simulations are conducted.

Simulation strategies considered are cash sale, unhedged storage, and hedged storage. To compare the results of three strategies, net returns to each strategy are evaluated at a future date, i.e., when the hedge for a hedged storage is lifted. The hedge is lifted on the first trading day of the delivery month for the distant futures contract. For example, in the Dec-Mar spread for corn observed on December 1, the hedge initiated on December 1 is finally lifted on March 1. For this study, the producer is assumed to produce 5,000 bushels of corn, soybeans, or wheat. The simulation strategies are summarized as follows:

1. Cash sale: At the beginning of each calendar month, if the percentage of a nearby spread to the cost of carry falls below zero or a predetermined level, e.g., 0.25%, the producer will sell 5,000 bushels of grain. The cash price examined in this study is U.S. average prices received by farmers during the month the cash commodity is sold. Interest is accrued to the proceeds from the cash sale at a continuously compounding rate. Thus, net returns to cash sale is calculated as the sum of cash price sold and the accrued interest.

2. Unhedged storage: This strategy involves storing the cash commodity without using any hedging instrument. Returns to unhedged storage are determined by the levels

of cash prices. This strategy is used as the benchmark against which cash sale and hedged storage are evaluated.

3. Hedged storage: At the beginning of each calendar month, if the percentage of a nearby spread to the cost of carry falls below zero or a predetermined level, e.g., 0.25%, the producer will sell one lot (5,000 bushels) of distant futures contract. On the first trading day of the delivery month for the distant futures contract, the hedge is lifted and the cash commodity is sold. Returns to hedged storage are dependent upon changes in the cash price relative to changes in the futures price. Futures transaction costs including brokerage fees and liquidity costs are assumed to be 1.5 cents per bushel or 75 dollars per contract.

To compare the net returns to three marketing strategies, paired-differences tests are conducted. The paired *t*-tests are based on the following three pairs of strategies: (1) cash sale vs. unhedged storage (CS-US); (2) cash sale vs. hedged storage (CS-HS); and (3) unhedged storage vs. hedged storage (US-HS).

As with all simulations, an adequate number of observations to fully specify the distribution of net returns to each strategy are a real matter of concern. Since the true market inversions with negative spreads are expected to rarely occur during early months of the crop year, the number of observations in this study may not be large enough to meet the desired number of observations from statistical sampling theory. Thus, this study relaxes the decision rule for market inversion such that market spread as a percent of the cost-of-carry below 0.25 is considered as a market inversion.

As another way to deal with a small sample problem for the monthly observations, this study pools the monthly observations by commodity. With the aggregated data, this study regresses the actual returns to storage (unhedged and hedged) on the predicted returns to storage and a set of dummies representing the distance to harvest. The actual returns to unhedged (hedged) storage are computed by subtracting the returns to cash sale from the returns to unhedged (hedged) storage, and the predicted returns to storage are the corresponding futures price spreads.

Results

Table 1 reports summary statistics for the market spreads of three commodities. Since the length of spreads is not of equal time intervals, they are standardized to reflect equal spread length of one month. To calculate the mean value of spreads per month, spreads are adjusted by dividing by the number of months between the near and distant futures. For example, the mean of Dec-Mar spread for corn is adjusted by dividing by the spread interval of three months. To measure the volatility of the spreads per month, spreads are adjusted by dividing by the square root of the spread length and subsequently computing the standard deviation of the adjusted spreads.

From Table 1, it can be observed that there is a seasonal pattern in the mean of spreads for all three commodities. In general, the mean value of the spreads declines from the beginning of the crop year to the end of the crop year. Mean spreads are greatest after harvest or during early months of the crop year, then decrease to minimums and even go negative on average during the growing season or just before the new harvest. Negative spreads or inverse carrying charges are consistently observed in the July-September spread for corn, the July-August and August-September spreads for soybeans, and the

March-May spread for wheat. For corn and soybeans, the July futures contract is the last consistently old crop contract. The September futures contract may be a new crop contract if harvest starts early enough and thus is often treated as a transitional contract between old and new crop. The results confirm that in grain markets, market inversions are most frequent between the last of the old-crop delivery months and the first of the new crop delivery months, i.e., across crop years. Contrary to the behavior of mean spreads, the volatility of the spreads has a tendency to increase from harvest to the full growing season of the crop year. For example, the standard deviation of the Dec-Mar spread for corn in December is 2.42, while the standard deviation of the Jul-Sep spread for corn in July is 15.00.

Table 2 presents summary statistics for spreads as a percent of contemporaneous costs-of-carry. The mean of the spread to cost-of-carry ratio falls below one for all spreads, indicating that grain markets on average are below full carry. The highest ratio is 0.96 in the September-December wheat futures spread observed in September. Figures 1, 2, and 3 present the graphs for selected spreads as a percent of contemporaneous costs-of-carry for corn, soybeans, and wheat respectively.

Table 3 exhibits the occurrences of spreads as a percent of contemporaneous costs-of-carry at various levels. Market inversions in nearby spreads rarely occur during early months of the crop year. During 3 months after harvest, market inversions occur only 2 to 7% of the time. The theory of the price of storage also predicts that negative spreads between two new crop futures contracts are less likely to occur because stocks are usually plentiful after harvest, and thus convenience yields are small. On the contrary, the number of observations with the percent of cost-of-carry greater than one, i.e., above full carry, is relatively large. This implies that there exist substantial cash-and-carry arbitrage opportunities because the cost of carry is too low relative to the market spread. One reason for being above full carry is that the fixed cost component of grain storage costs is missed in calculating the cost-of-carry, and thus the cost-of-carry is underestimated. Another possible reason is that market spreads may reflect risk premia with buildup in stocks after new-crop harvest or during early months of the crop year.

Table 4 reports the regression results for spreads against U.S. quarterly grain stocks. The R^2 values are very low, ranging from 0.01 in the Mar-May spread for wheat to 0.20 in the Sep-Dec spread for wheat. The slope terms for the first two spreads in corn and soybeans are statistically significant at the 5% level. The slope term for the Sep-Dec spread in wheat is statistically significant at the 5% level and that for the Dec-Mar spread is significant at the 10% level. There is a tendency for regressions during early months of the crop year to fit better than the regressions towards the end of the crop year, suggesting that the spread-stock relationship is more pronounced when stocks are abundant. Overall, the results support that there is a positive relationship between the spread and the level of stocks, and thus when the stocks are scarce, the spread becomes negative and markets are inverted.

Table 5 summarizes the regressions of the percentage of spread to cost-of-carry on the stocks-to-use ratio. The results show that none of the regressions for corn and soybeans are statistically significant at the 5% level. Three regressions for wheat are statistically significant at the 5% level, yet their overall explanatory power is low since R^2 values are extremely small. The findings suggest that the market spreads do not closely approximate the price of storage relationships when regressed on the ending stocks.

Tables 6, 7, and 8 report the results of simulations when markets are inverted, and Tables 9, 10, and 11 report the results for the corresponding paired-differences tests. Across three commodities, net returns to cash sale becomes higher than net returns to unhedged storage and hedged storage with the approach of new harvest.

The results of paired-differences tests for corn (Table 9) show that net returns to cash sale are greater than that of unhedged storage or hedged storage after May. For the Jul-Sep spread in July, returns to cash sale are higher than returns to both unhedged storage and hedged storage. For the Jul-Sep corn spread in July, returns to cash sale are higher than returns to unhedged storage and hedged storage by 14.07 cents and 10.72 cents respectively.

The results of paired-differences tests for soybeans (Table 10) show that returns to cash sale are consistently higher than returns to unhedged storage after June. For the Aug-Sep soybeans spread in August, returns to cash sale are higher than returns to unhedged storage and hedged storage by 32.34 cents and 20.38 cents respectively. Given the fact that the full cost-of-carry was not covered on average, the results were expected.

The results of paired-differences tests for wheat (Table 11) show that returns to cash sale are consistently higher than returns to hedged storage after October. One reason that net returns to hedged storage should be lower than the returns to cash sale is the costs associated with trading futures contracts.

The results from simulations when markets are inverted show that as the crop cycle advances towards the end of the crop year, market inversions clearly reflect the market's signal to release stocks in anticipation of new crop supplies. However, it is not conclusive whether a market inversion is a signal to sell during early months of the crop year due to the low frequency of market inversions.

Tables 12, 13, and 14 report the results of simulations when markets are not inverted, and Tables 15, 16, and 17 report the results for the corresponding paired-differences tests. For all three commodities, returns to cash sale are lower than returns to hedged storage right after harvest. The results of paired-differences tests for wheat without market inversion (Table 17) show that returns to hedged storage (HS) are higher than that for unhedged storage (US) after October. This is consistent with the findings of Zulauf and Irwin (1998), and Kastens and Dhuyvetter (1999) that when using the basis or spread to guide storage decisions, only returns to hedged storage are improved, but not to unhedged storage.

Table 18 presents the regression results for actual returns to storage against predicted returns to storage. There exists a positive relationship between actual returns to storage and predicted returns to storage except the unhedged storage for wheat. The result for wheat may come from the difference in crop variety. While the wheat futures contract traded on the Chicago Board of Trade is based on soft red winter wheat, U.S. monthly cash prices aggregate all varieties and qualities. The results suggest that as predicted returns to storage, i.e., spreads, get smaller or even go negative, the actual returns to storage decreases, and thus support the argument that a market inversion is a signal to sell.

Conclusions

As opposed to a normal market, an inverted market has a negative price of storage or spread. Futures price spreads for corn, soybeans, and wheat exhibit a seasonal pattern. In general, mean spreads gradually decline from the start of the crop year and even go negative on average at the end of the crop year or just before the new harvest. In contrast, the volatility of spreads measured by the standard deviation of spreads has a tendency to increase from harvest to the full growing season of the crop year. The spreads as percent of contemporaneous costs of carry are less than one on average, indicating that grain markets on average are below full carry.

Market inversions in nearby spreads rarely occur during early months of the crop year since stocks are usually abundant after harvest. During 3 months after harvest, market inversions occur only 2 to 7% of the time. However, market inversions become pronounced when the spreads are observed across crop years at the end of the crop year or just before the new harvest. The regressions of spreads on the logarithm of U.S. quarterly stocks show that there exists a positive relationship between the spread and the level of stocks, and further implies that when stocks are scarce, markets will be inverted.

A market inversion appears to be a situation where the market encourages producers to release their stocks, yet many continue to store their grain. The simulations were conducted to determine whether a market inversion is a signal to sell the stocks. The results of the paired-differences tests reveal that as the crop cycle advances towards the end of the crop year, market inversions clearly reflect the market's signal to release stocks in anticipation of new crop supplies. The regressions of actual returns to storage on predicted returns to storage clearly show that a market inversion is a signal to sell. The results support the behavioral finance hypothesis that producers are choosing to hold excess stocks because of some type of biased expectations.

Table 1: Summary Statistics for Futures Price Spreads, 1957-1999

Commodity	Month	Spread	No. Obs.	Mean	Standard Deviation	Minimum	Maximum
Corn	December	Dec-Mar	43	2.24	2.42	-0.75	18.25
	January	Mar-May	43	2.34	1.91	-2.00	12.25
	February	Mar-May	43	2.27	2.64	-9.88	13.00
	March	Mar-May	43	2.47	2.94	-6.50	14.75
	April	May-Jul	43	1.39	2.94	-12.75	12.25
	May	May-Jul	43	0.96	3.80	-21.75	11.50
	June	Jul-Sep	43	-2.84	10.42	-77.25	9.25
	July	Jul-Sep	43	-2.29	15.00	-122.75	31.25
Soybeans	November	Nov-Jan	42	4.10	4.77	-3.00	29.50
	December	Jan-Mar	42	3.74	4.69	-4.75	33.25
	January	Jan-Mar	42	3.79	4.48	-4.13	27.50
	February	Mar-May	42	3.15	5.52	-23.13	26.00
	March	Mar-May	42	3.37	6.38	-37.00	24.75
	April	May-Jul	42	2.50	5.40	-22.25	25.50
	May	May-Jul	42	1.42	11.14	-80.88	23.75
	June	Jul-Aug	37	-5.43	18.47	-98.50	7.25
	July	Jul-Aug	37	-1.57	11.13	-51.00	15.00
	August	Aug-Sep	37	-11.01	24.80	-128.00	10.00
Wheat	July	Jul-Sep	42	2.63	3.35	-6.00	19.50
	August	Sep-Dec	42	3.14	4.15	-14.25	31.00
	September	Sep-Dec	42	3.38	4.26	-6.00	29.50
	October	Dec-Mar	42	2.13	4.46	-15.00	25.25
	November	Dec-Mar	42	1.90	5.31	-18.50	25.25
	December	Dec-Mar	42	1.75	5.74	-16.00	30.75
	January	Mar-May	42	-2.34	7.66	-29.50	10.50
	February	Mar-May	42	-2.20	8.44	-37.50	15.25
	March	Mar-May	42	-0.99	9.07	-44.25	13.50

Table 2: Summary Statistics for Spreads as a Percent of Contemporaneous Costs-of-Carry, 1957-1999

Commodity	Month	Spread	No. Obs.	Mean	Standard Deviation	Minimum	Maximum
Corn	December	Dec-Mar	43	0.77	0.32	-0.06	1.60
	January	Mar-May	43	0.79	0.38	-0.51	1.54
	February	Mar-May	43	0.76	0.64	-2.46	1.73
	March	Mar-May	43	0.86	0.58	-0.96	1.91
	April	May-Jul	43	0.53	0.57	-1.17	1.71
	May	May-Jul	43	0.40	0.72	-1.83	1.80
	June	Jul-Sep	43	-0.71	1.55	-6.69	1.10
	July	Jul-Sep	43	-0.53	2.02	-9.78	3.72
Soybeans	November	Nov-Jan	42	0.81	0.43	-0.26	1.66
	December	Jan-Mar	42	0.71	0.39	-0.38	1.44
	January	Jan-Mar	42	0.70	0.41	-0.90	1.41
	February	Mar-May	42	0.54	0.68	-3.12	1.14
	March	Mar-May	42	0.64	0.81	-3.97	1.47
	April	May-Jul	42	0.39	0.63	-2.64	1.08
	May	May-Jul	42	0.23	1.34	-7.25	1.10
	June	Jul-Aug	37	-0.87	2.31	-12.22	0.77
	July	Jul-Aug	37	-0.45	1.73	-6.58	2.04
	August	Aug-Sep	37	-2.22	3.65	-15.03	1.05
Wheat	July	Jul-Sep	42	0.73	0.49	-0.70	1.45
	August	Sep-Dec	42	0.91	0.48	-1.16	1.47
	September	Sep-Dec	42	0.96	0.47	-0.42	1.54
	October	Dec-Mar	42	0.61	0.52	-0.90	1.32
	November	Dec-Mar	42	0.53	0.66	-1.41	1.27
	December	Dec-Mar	42	0.47	0.74	-1.97	1.37
	January	Mar-May	42	-0.57	1.19	-2.60	1.20
	February	Mar-May	42	-0.51	1.34	-3.66	1.27
	March	Mar-May	42	-0.17	1.42	-4.35	1.86

Table 3: Occurrences of Spreads as a Percent of Contemporaneous Costs-of-Carry, 1957-1999

Month	Spread	No. Obs.	Percent(%) of Market Spread to Cost-of-Carry					
			0 < %	0 < % < 0.25	0.25 < % < 0.50	0.50 < % < 0.75	0.75 < % < 1.0	% > 1.0
Commodity: Corn								
Dec	Dec-Mar	43	2	1	3	13	14	10
Jan	Mar-May	43	1	1	8	6	17	10
Feb	Mar-May	43	2	1	6	11	12	11
Mar	Mar-May	43	4	1	2	8	6	22
Apr	May-Jul	43	7	4	8	9	9	6
May	May-Jul	43	10	7	8	6	5	7
Jun	Jul-Sep	43	25	2	7	5	3	1
Jul	Jul-Sep	43	21	4	2	9	5	2
Commodity: Soybeans								
Nov	Nov-Jan	42	2	3	5	10	9	13
Dec	Jan-Mar	42	2	2	6	13	12	7
Jan	Jan-Mar	42	3	2	4	10	14	9
Feb	Mar-May	42	4	2	6	14	12	4
Mar	Mar-May	42	3	3	3	10	13	10
Apr	May-Jul	42	3	9	9	10	9	2
May	May-Jul	42	8	4	7	8	11	4
Jun	Jul-Aug	37	21	4	4	7	1	0
Jul	Jul-Aug	37	17	3	6	3	7	1
Aug	Aug-Sep	37	24	4	2	5	1	1
Commodity: Wheat								
Jul	Jul-Sep	42	3	4	6	5	9	15
Aug	Sep-Dec	42	1	3	1	6	9	22
Sep	Sep-Dec	42	3	0	3	4	11	21
Oct	Dec-Mar	42	5	2	9	5	11	10
Nov	Dec-Mar	42	8	4	4	5	10	11
Dec	Dec-Mar	42	10	6	2	3	8	13
Jan	Mar-May	42	26	2	1	6	5	2
Feb	Mar-May	42	23	2	5	2	4	6
Mar	Mar-May	42	19	1	5	2	6	9

Table 4: Regressions of Spreads on U.S. Quarterly Grain Stocks, 1957-1999

Commodity	Date	Spread	Quarterly Stocks	No. Obs.	β_0	β_1	R^2
	Dec 1	Dec-Mar	December	43	-41.10	5.56	0.16
					(-2.36)**	(2.74)**	
Corn	Mar 1	Mar-May	March	43	-36.07	4.96	0.14
					(-2.24)**	(2.54)**	
	Jun 1	Jul-Sep	June	43	-65.87	7.66	0.04
					(-1.35)	(1.23)	
	Dec 1	Nov-Jan	December	42	-28.07	5.07	0.15
					(-2.13)**	(2.71)**	
Soybeans	Mar 1	Mar-May	March	42	-35.91	6.47	0.14
					(-2.10)**	(2.50)**	
	Jun 1	Jul-Aug	June	42	-64.14	9.64	0.09
					(-1.99)**	(1.83)*	
	Sep 1	Sep-Dec	September	42	-113.22	16.12	0.20
					(-2.87)**	(3.13)**	
Wheat	Dec 1	Dec-Mar	December	42	-74.67	10.79	0.07
					(-1.63)	(1.74)*	
	Mar 1	Mar-May	March	42	-26.18	3.41	0.01
					(-0.58)	(0.54)	

Note: The estimated regression equation is $Spread_t = \beta_0 + \beta_1 \ln(QS_t) + \varepsilon_t$, where $ln(QS_t)$ is the natural logarithm of U.S. quarterly stocks and ε_t is the error term. The figures in parentheses are *t*-statistics with ** indicating statistical significance at the 5% level, and * statistical significance at the 10% level.

Table 5: Regressions of Percent of Spreads to Costs-of-Carry on Stocks-to-Use Ratio, 1957-1999

Commodity	Month	Spread	No. Obs.	β_0	β_1	R^2
	December	Dec-Mar	43	0.654	0.004	0.05
				(6.93)*	(1.41)	
	March	Mar-May	43	0.640	0.008	0.05
Corn				(3.72)*	(1.48)	
	May	May-Jul	43	0.230	0.006	0.02
				(1.05)	(0.88)	
	July	Jul-Sep	43	-0.660	0.005	0.00
				(-1.07)	(0.25)	
	November	Nov-Jan	42	0.860	-0.004	0.00
				(5.73)*	(-0.41)	
	March	Mar-May	42	0.667	-0.002	0.00
Soybeans				(2.36)*	(-0.10)	
	May	May-Jul	42	0.158	0.005	0.00
				(0.34)	(0.18)	
	July	Jul-Aug	37	-0.869	0.029	0.01
				(-1.33)	(0.72)	
	July	Jul-Sep	42	0.407	0.006	0.16
				(2.95)*	(2.74)*	
	September	Sep-Dec	42	0.620	0.006	0.19
Wheat				(4.78)*	(3.04)*	
	December	Dec-Mar	42	0.050	0.007	0.11
				(0.23)	(2.28)*	
	March	Mar-May	42	-0.342	0.003	0.01
				(-0.78)	(0.46)	

Note: The estimated regression equation is $\%Carry_t = \beta_0 + \beta_1 SUR_t + \varepsilon_t$, where $\%Carry_t$ is the percentage of market spread to the cost of carry, SUR_t is the stocks to use ratio, and ε_t is the error term. The stocks-to-use ratio is calculated as the ratio of end-of-crop-year stocks (ending stocks) to the five-year moving average of total use. The figures in parentheses are t-statistics with * indicating statistical significance at the 5% level.

Table 6: Simulation Results for Corn, 1957-1999

Month	Spread	Strategy	No. Obs.	Mean	Standard Deviation
December	Dec-Mar	Cash Sale	3	275.59	45.06
		Unhedged Storage	3	276.33	46.06
		Hedged Storage	3	271.08	51.25
January	Mar-May	Cash Sale	2	229.87	124.54
		Unhedged Storage	2	213.50	74.25
		Hedged Storage	2	236.38	142.31
February	Mar-May	Cash Sale	3	215.05	69.53
		Unhedged Storage	3	223.00	55.75
		Hedged Storage	3	206.33	60.91
March	Mar-May	Cash Sale	5	267.35	85.80
		Unhedged Storage	5	283.40	95.89
		Hedged Storage	5	256.83	70.23
April	May-Jul	Cash Sale	11	242.20	87.67
		Unhedged Storage	11	244.73	93.11
		Hedged Storage	11	235.22	80.00
May	May-Jul	Cash Sale	17	228.93	89.91
		Unhedged Storage	17	227.82	91.46
		Hedged Storage	17	219.55	85.63
June	Jul-Sep	Cash Sale	27	214.76	85.15
		Unhedged Storage	27	197.89	77.64
		Hedged Storage	27	209.05	90.97
July	Jul-Sep	Cash Sale	25	207.83	92.70
		Unhedged Storage	25	193.76	82.89
		Hedged Storage	25	197.11	84.32

Table 7: Simulation Results for Soybeans, 1958-1999

Month	Spread	Strategy	No. Obs.	Mean	Standard Deviation
		Cash Sale	5	514.89	129.46
November	Nov-Jan	Unhedged Storage	5	547.80	115.87
		Hedged Storage	5	519.15	121.66
		Cash Sale	4	586.21	200.59
December	Jan-Mar	Unhedged Storage	4	623.50	243.56
		Hedged Storage	4	588.75	206.93
		Cash Sale	5	503.35	166.16
January	Jan-Mar	Unhedged Storage	5	540.60	192.27
		Hedged Storage	5	481.88	164.27
		Cash Sale	6	549.83	165.63
February	Mar-May	Unhedged Storage	6	610.50	212.35
		Hedged Storage	6	532.67	148.87
		Cash Sale	6	493.70	208.43
March	Mar-May	Unhedged Storage	6	536.17	260.29
		Hedged Storage	6	492.65	208.03
		Cash Sale	12	496.85	192.72
April	May-Jul	Unhedged Storage	12	484.58	183.14
		Hedged Storage	12	471.72	215.97
		Cash Sale	12	578.15	246.08
May	May-Jul	Unhedged Storage	12	525.17	191.26
		Hedged Storage	12	542.22	241.05
		Cash Sale	25	525.91	235.37
June	Jul-Aug	Unhedged Storage	25	484.04	195.83
		Hedged Storage	25	516.69	238.28
		Cash Sale	20	474.75	197.56
July	Jul-Aug	Unhedged Storage	20	453.20	182.62
		Hedged Storage	20	472.86	199.06
		Cash Sale	28	518.66	199.82
August	Aug-Sep	Unhedged Storage	28	486.32	177.21
		Hedged Storage	28	498.29	193.56

Table 8: Simulation Results for Wheat, 1958-1999

Month	Spread	Strategy	No. Obs.	Mean	Standard Deviation
July	Jul-Sep	Cash Sale	7	249.79	98.85
		Unhedged Storage	7	293.29	129.76
		Hedged Storage	7	259.20	112.44
August	Sep-Dec	Cash Sale	4	364.20	118.27
		Unhedged Storage	4	358.50	103.01
		Hedged Storage	4	316.25	111.83
September	Sep-Dec	Cash Sale	3	406.11	93.91
		Unhedged Storage	3	395.00	89.01
		Hedged Storage	3	395.50	118.65
October	Dec-Mar	Cash Sale	7	325.06	110.82
		Unhedged Storage	7	322.14	112.73
		Hedged Storage	7	296.84	104.53
November	Dec-Mar	Cash Sale	12	305.60	101.00
		Unhedged Storage	12	304.92	108.74
		Hedged Storage	12	282.49	87.54
December	Dec-Mar	Cash Sale	16	321.82	114.55
		Unhedged Storage	16	315.63	117.40
		Hedged Storage	16	302.80	106.28
January	Mar-May	Cash Sale	28	289.38	118.43
		Unhedged Storage	28	275.43	109.04
		Hedged Storage	28	277.84	110.42
February	Mar-May	Cash Sale	25	294.04	120.00
		Unhedged Storage	25	281.24	108.58
		Hedged Storage	25	281.46	108.15
March	Mar-May	Cash Sale	20	291.41	116.34
		Unhedged Storage	20	284.10	111.36
		Hedged Storage	25	283.12	112.72

Table 9: Results of the Paired-differences Tests for Corn, 1957-1999

Month	Spread	Paired Difference	No. Obs.	Mean	Standard Deviation	t-Ratio
December	Dec-Mar	CS-US	3	-0.74	8.57	-0.15
		CS-HS	3	4.51	20.34	0.38
		US-HS	3	5.25	28.87	0.31
January	Mar-May	CS-US	2	16.37	50.29	0.46
		CS-HS	2	-6.50	17.76	-0.52
		US-HS	2	-22.88	68.06	-0.48
February	Mar-May	CS-US	3	-7.95	13.94	-0.99
		CS-HS	3	8.71	22.66	0.67
		US-HS	3	16.67	21.31	1.35
March	Mar-May	CS-US	5	-16.05	26.85	-1.34
		CS-HS	5	10.53	20.84	1.13
		US-HS	5	26.58	42.90	1.39
April	May-Jul	CS-US	11	-2.53	34.08	-0.25
		CS-HS	11	6.99	29.24	0.79
		US-HS	11	9.51	54.77	0.58
May	May-Jul	CS-US	17	1.11	21.74	0.21
		CS-HS	17	9.38	15.24	2.54*
		US-HS	17	8.27	27.90	1.22
June	Jul-Sep	CS-US	27	16.87	32.34	2.71*
		CS-HS	27	5.72	48.89	0.61
		US-HS	27	-11.16	55.05	-1.05
July	Jul-Sep	CS-US	25	14.07	26.85	2.62*
		CS-HS	25	10.72	16.62	3.23*
		US-HS	25	-3.35	28.69	-0.58

Note: CS-US denotes the paired difference of net returns between the cash sale (CS) and unhedged storage (US), CS-HS denotes the paired difference of net returns between the cash sale (CS) and hedged storage (HS), and US-HS denotes the paired difference of net returns between the unhedged storage (US) and hedged storage (HS). The t-ratio is $t = \frac{\bar{d} - 0}{\sqrt{s_D^2/n}}$, where $\bar{d}$ is the average of the paired differences (d_i) of the net returns between two marketing strategies, n is the number of paired differences, and $s_D^2 = \frac{\sum_{i=1}^{n} d_i^2 - \frac{1}{n}\left(\sum_{i=1}^{n} d_i\right)^2}{n-1}$.

Table 10: Results of the Paired-differences Tests for Soybeans, 1958-1999

Month	Spread	Paired Difference	No. Obs.	Mean	Standard Deviation	t-Ratio
		CS-US	5	-32.91	31.92	-2.31*
November	Nov-Jan	CS-HS	5	-4.26	15.37	-0.62
		US-HS	5	28.65	30.62	2.09*
		CS-US	4	-37.29	78.85	-0.95
December	Jan-Mar	CS-HS	4	-2.54	17.61	-0.29
		US-HS	4	34.75	87.21	0.80
		CS-US	5	-37.25	100.47	-0.83
January	Jan-Mar	CS-HS	5	21.47	24.41	1.97*
		US-HS	5	58.73	123.65	1.06
		CS-US	6	-60.67	111.61	-1.33
February	Mar-May	CS-HS	6	17.17	24.83	1.69
		US-HS	6	77.83	125.31	1.52
		CS-US	6	-42.46	88.74	-1.17
March	Mar-May	CS-HS	6	1.06	35.63	0.07
		US-HS	6	43.52	63.10	1.69
		CS-US	12	12.27	47.80	0.89
April	May-Jul	CS-HS	12	25.13	118.02	0.74
		US-HS	12	12.86	137.88	0.32
		CS-US	12	52.98	95.43	1.92
May	May-Jul	CS-HS	12	35.93	126.05	0.99
		US-HS	12	-17.05	127.09	-0.46
		CS-US	25	41.87	77.36	2.71*
June	Jul-Aug	CS-HS	25	9.23	38.70	1.19
		US-HS	25	-32.65	99.54	-1.64
		CS-US	20	21.55	36.51	2.64*
July	Jul-Aug	CS-HS	20	1.89	36.83	0.23
		US-HS	20	-19.66	58.65	-1.50
		CS-US	28	32.34	60.42	2.83*
August	Aug-Sep	CS-HS	28	20.38	45.57	2.37*
		US-HS	28	-11.96	50.75	-1.25

Note: CS-US denotes the paired difference of net returns between the cash sale (CS) and unhedged storage (US), CS-HS denotes the paired difference of net returns between the cash sale (CS) and hedged storage (HS), and US-HS denotes the paired difference of net returns between the unhedged storage (US) and hedged storage (HS). The t-ratio is $t = \frac{\bar{d} - 0}{\sqrt{s_D^2/n}}$, where $\bar{d}$ is the average of the paired differences (d_i) of the net returns between two marketing strategies, n is the number of paired differences, and $s_D^2 = \frac{\sum_{i=1}^{n} d_i^2 - \frac{1}{n}\left(\sum_{i=1}^{n} d_i\right)^2}{n-1}$.

Table 11: Results of the Paired-differences Tests for Wheat, 1958-1999

Month	Spread	Paired Difference	No. Obs.	Mean	Standard Deviation	t-Ratio
July	Jul-Sep	CS-US	7	-43.49	76.53	-1.50
		CS-HS	7	-9.40	20.63	-1.21
		US-HS	7	34.09	79.67	1.13
August	Sep-Dec	CS-US	4	5.70	39.28	0.29
		CS-HS	4	47.95	48.18	1.99*
		US-HS	4	42.25	77.55	1.09
September	Sep-Dec	CS-US	3	11.11	25.14	0.77
		CS-HS	3	10.61	28.90	0.64
		US-HS	3	-0.50	51.45	-0.02
October	Dec-Mar	CS-US	7	2.92	34.36	0.22
		CS-HS	7	28.22	28.47	2.62*
		US-HS	7	25.30	54.31	1.23
November	Dec-Mar	CS-US	12	0.68	28.42	0.08
		CS-HS	12	23.11	33.57	2.38*
		US-HS	12	22.43	52.65	1.48
December	Dec-Mar	CS-US	16	6.20	15.79	1.57
		CS-HS	16	19.02	26.16	2.91*
		US-HS	16	12.82	30.00	1.71
January	Mar-May	CS-US	28	13.95	43.57	1.69
		CS-HS	28	11.54	29.77	2.05*
		US-HS	28	-2.41	58.17	-0.22
February	Mar-May	CS-US	25	12.80	47.10	1.36
		CS-HS	25	12.58	31.43	2.00*
		US-HS	25	-0.22	58.19	-0.02
March	Mar-May	CS-US	20	7.31	38.67	0.85
		CS-HS	20	8.30	18.75	1.98*
		US-HS	20	0.98	63.79	0.07

Note: CS-US denotes the paired difference of net returns between the cash sale (CS) and unhedged storage (US), CS-HS denotes the paired difference of net returns between the cash sale (CS) and hedged storage (HS), and US-HS denotes the paired difference of net returns between the unhedged storage (US) and hedged storage (HS). The t-ratio is $t = \frac{\bar{d}-0}{\sqrt{s_D^2/n}}$, where $\bar{d}$ is the average of the paired differences (d_i) of the net returns between two marketing strategies, n is the number of paired differences, and $s_D^2 = \frac{\sum_{i=1}^{n} d_i^2 - \frac{1}{n}\left(\sum_{i=1}^{n} d_i\right)^2}{n-1}$.

Table 12: Simulation Results for Corn without Market Inversion, 1957-1999

Month	Spread	Strategy	No. Obs.	Mean	Standard Deviation
December	Dec-Mar	Cash Sale	40	186.30	73.05
		Unhedged Storage	40	189.65	73.55
		Hedged Storage	40	191.07	78.26
January	Mar-May	Cash Sale	41	196.12	75.56
		Unhedged Storage	41	200.76	78.37
		Hedged Storage	41	195.45	73.09
February	Mar-May	Cash Sale	40	196.28	77.65
		Unhedged Storage	40	199.73	79.06
		Hedged Storage	40	197.16	75.48
March	Mar-May	Cash Sale	38	189.53	71.90
		Unhedged Storage	38	190.55	69.09
		Hedged Storage	38	189.64	71.33
April	May-Jul	Cash Sale	32	188.77	72.37
		Unhedged Storage	32	188.34	71.68
		Hedged Storage	32	184.88	73.02
May	May-Jul	Cash Sale	26	188.26	68.46
		Unhedged Storage	26	186.38	69.42
		Hedged Storage	26	184.01	69.67
June	Jul-Sep	Cash Sale	16	196.70	72.40
		Unhedged Storage	16	184.38	69.64
		Hedged Storage	16	190.30	65.48
July	Jul-Sep	Cash Sale	18	202.97	67.89
		Unhedged Storage	18	191.61	62.47
		Hedged Storage	18	219.72	96.41

Table 13: Simulation Results for Soybeans without Market Inversion, 1958-1999

Month	Spread	Strategy	No. Obs.	Mean	Standard Deviation
November	Nov-Jan	Cash Sale	37	467.53	205.52
		Unhedged Storage	37	467.54	197.65
		Hedged Storage	37	478.40	212.60
December	Jan-Mar	Cash Sale	38	470.71	196.84
		Unhedged Storage	38	472.39	185.06
		Hedged Storage	38	482.88	213.75
January	Jan-Mar	Cash Sale	37	481.83	200.57
		Unhedged Storage	37	479.51	194.61
		Hedged Storage	37	486.01	211.10
February	Mar-May	Cash Sale	36	478.91	196.63
		Unhedged Storage	36	485.58	207.54
		Hedged Storage	36	475.22	193.89
March	Mar-May	Cash Sale	36	494.05	198.45
		Unhedged Storage	36	497.97	204.73
		Hedged Storage	36	484.38	191.05
April	May-Jul	Cash Sale	30	507.73	214.09
		Unhedged Storage	30	502.17	203.93
		Hedged Storage	30	495.27	208.72
May	May-Jul	Cash Sale	30	484.03	198.67
		Unhedged Storage	30	485.93	200.18
		Hedged Storage	30	477.54	197.69
June	Jul-Aug	Cash Sale	12	612.51	97.99
		Unhedged Storage	12	638.67	114.05
		Hedged Storage	12	589.69	106.83
July	Jul-Aug	Cash Sale	17	614.17	122.98
		Unhedged Storage	17	629.47	145.37
		Hedged Storage	17	611.53	161.96
August	Aug-Sep	Cash Sale	9	599.36	142.14
		Unhedged Storage	9	603.56	157.84
		Hedged Storage	9	588.83	133.96

Table 14: Simulation Results for Wheat without Market Inversion, 1958-1999

Month	Spread	Strategy	No. Obs.	Mean	Standard Deviation
July	Jul-Sep	Cash Sale	35	261.18	101.38
		Unhedged Storage	35	266.26	102.45
		Hedged Storage	35	267.01	104.21
August	Sep-Dec	Cash Sale	38	262.88	104.23
		Unhedged Storage	38	271.29	105.35
		Hedged Storage	38	264.80	108.34
September	Sep-Dec	Cash Sale	39	266.89	105.47
		Unhedged Storage	39	270.72	104.01
		Hedged Storage	39	265.08	107.12
October	Dec-Mar	Cash Sale	35	278.45	114.42
		Unhedged Storage	35	268.14	102.79
		Hedged Storage	35	281.27	121.59
November	Dec-Mar	Cash Sale	30	278.87	116.83
		Unhedged Storage	30	266.03	103.30
		Hedged Storage	30	284.84	128.08
December	Dec-Mar	Cash Sale	26	263.79	104.65
		Unhedged Storage	26	253.46	91.10
		Hedged Storage	26	272.70	116.19
January	Mar-May	Cash Sale	14	284.37	103.62
		Unhedged Storage	14	270.36	92.22
		Hedged Storage	14	290.44	108.31
February	Mar-May	Cash Sale	17	271.55	102.66
		Unhedged Storage	17	262.71	95.32
		Hedged Storage	17	278.34	110.33
March	Mar-May	Cash Sale	22	271.94	100.46
		Unhedged Storage	22	264.32	95.64
		Hedged Storage	22	273.18	101.00

Table 15: Results of the Paired-differences Tests for Corn without Market Inversion, 1957-1999

Month	Spread	Paired Difference	No. Obs.	Mean	Standard Deviation	t-Ratio
		CS-US	40	-3.35	15.29	-1.39
December	Dec-Mar	CS-HS	40	-4.77	14.86	-2.03*
		US-HS	40	-1.42	26.47	-0.34
		CS-US	41	-2.29	15.01	-0.98
January	Mar-May	CS-HS	41	0.25	11.12	0.14
		US-HS	41	2.54	19.20	0.85
		CS-US	40	-3.45	18.24	-1.20
February	Mar-May	CS-HS	40	-0.89	11.37	-0.49
		US-HS	40	2.56	25.55	0.63
		CS-US	38	-1.03	11.06	-0.57
March	Mar-May	CS-HS	38	-0.12	9.61	-0.07
		US-HS	38	0.91	16.75	0.34
		CS-US	32	0.43	23.78	0.10
April	May-Jul	CS-HS	32	3.89	13.42	1.64
		US-HS	32	3.46	30.61	0.64
		CS-US	26	1.87	22.49	0.42
May	May-Jul	CS-HS	26	4.25	13.29	1.63
		US-HS	26	2.38	30.93	0.39
		CS-US	16	12.33	30.41	1.62
June	Jul-Sep	CS-HS	16	6.40	16.43	1.56
		US-HS	16	-5.92	39.43	-0.60
		CS-US	18	11.36	20.59	2.34*
July	Jul-Sep	CS-HS	18	-16.76	64.17	-1.11
		US-HS	18	-28.11	65.61	-1.82

Note: CS-US denotes the paired difference of net returns between the cash sale (CS) and unhedged storage (US), CS-HS denotes the paired difference of net returns between the cash sale (CS) and hedged storage (HS), and US-HS denotes the paired difference of net returns between the unhedged storage (US) and hedged storage (HS). The t-ratio is $t = \frac{\bar{d} - 0}{\sqrt{s_D^2/n}}$, where $\bar{d}$ is the average of the paired differences (d_i) of the net returns between two marketing strategies, n is the number of paired differences, and $s_D^2 = \frac{\sum_{i=1}^{n} d_i^2 - \frac{1}{n}\left(\sum_{i=1}^{n} d_i\right)^2}{n-1}$.

Table 16: Results of the Paired-differences Tests for Soybeans without Market Inversion, 1958-1999

Month	Spread	Paired Difference	No. Obs.	Mean	Standard Deviation	t-Ratio
		CS-US	37	-0.01	29.54	0.00
November	Nov-Jan	CS-HS	37	-10.87	24.50	-2.70*
		US-HS	37	-10.86	42.69	-1.55
		CS-US	38	-1.69	53.52	-0.19
December	Jan-Mar	CS-HS	38	-12.18	36.48	-2.06*
		US-HS	38	-10.49	82.15	-0.79
		CS-US	37	2.31	33.00	0.43
January	Jan-Mar	CS-HS	37	-4.19	29.25	-0.87
		US-HS	37	-6.50	50.80	-0.78
		CS-US	36	-6.67	54.53	-0.73
February	Mar-May	CS-HS	36	3.70	26.22	0.85
		US-HS	36	10.37	69.33	0.90
		CS-US	36	-3.92	38.23	-0.62
March	Mar-May	CS-HS	36	9.67	33.36	1.74
		US-HS	36	13.59	54.88	1.49
		CS-US	30	5.57	85.47	0.36
April	May-Jul	CS-HS	30	12.46	34.95	1.95
		US-HS	30	6.90	88.78	0.43
		CS-US	30	-1.90	59.87	-0.17
May	May-Jul	CS-HS	30	6.49	37.18	0.96
		US-HS	30	8.40	75.22	0.61
		CS-US	12	-26.15	92.37	-0.98
June	Jul-Aug	CS-HS	12	22.82	39.15	2.02*
		US-HS	12	48.98	111.67	1.52
		CS-US	17	-15.30	77.96	-0.81
July	Jul-Aug	CS-HS	17	2.64	78.11	0.14
		US-HS	17	17.94	98.27	0.75
		CS-US	9	-4.20	42.95	-0.29
August	Aug-Sep	CS-HS	9	10.52	33.05	0.96
		US-HS	9	14.72	62.72	0.70

Note: CS-US denotes the paired difference of net returns between the cash sale (CS) and unhedged storage (US), CS-HS denotes the paired difference of net returns between the cash sale (CS) and hedged storage (HS), and US-HS denotes the paired difference of net returns between the unhedged storage (US) and hedged storage (HS). The t-ratio is $t = \frac{\bar{d} - 0}{\sqrt{s_D^2/n}}$, where $\bar{d}$ is the average of the paired differences (d_i) of the net returns between two marketing strategies, n is the number of paired differences, and $s_D^2 = \frac{\sum_{i=1}^{n} d_i^2 - \frac{1}{n}\left(\sum_{i=1}^{n} d_i\right)^2}{n-1}$.

Table 17: Results of the Paired-differences Tests for Wheat without Market Inversion, 1958-1999

Month	Spread	Paired Difference	No. Obs.	Mean	Standard Deviation	t-Ratio
July	Jul-Sep	CS-US	35	-5.07	23.18	-1.29
		CS-HS	35	-5.83	17.05	-2.02*
		US-HS	35	-0.75	32.66	-0.14
August	Sep-Dec	CS-US	38	-8.41	30.44	-1.70
		CS-HS	38	-1.92	14.76	-0.80
		US-HS	38	6.49	33.29	1.20
September	Sep-Dec	CS-US	39	-3.83	25.88	-0.92
		CS-HS	39	1.81	15.96	0.71
		US-HS	39	5.64	31.62	1.11
October	Dec-Mar	CS-US	34	12.21	31.60	2.25*
		CS-HS	34	-3.22	18.18	-1.03
		US-HS	34	-15.44	37.71	-2.39*
November	Dec-Mar	CS-US	30	12.83	29.70	2.37*
		CS-HS	30	-5.98	24.74	-1.32
		US-HS	30	-18.81	45.68	-2.26*
December	Dec-Mar	CS-US	26	10.33	24.98	2.11*
		CS-HS	26	-8.91	18.64	-2.44*
		US-HS	26	-19.24	37.04	-2.65*
January	Mar-May	CS-US	14	14.01	23.41	2.24*
		CS-HS	14	-6.07	14.77	-1.54
		US-HS	14	-20.08	30.99	-2.42*
February	Mar-May	CS-US	17	8.85	19.68	1.85
		CS-HS	17	-6.79	19.41	-1.44
		US-HS	17	-15.63	30.36	-2.12*
March	Mar-May	CS-US	22	7.62	15.03	2.38*
		CS-HS	22	-1.24	22.05	-0.26
		US-HS	22	-8.86	21.09	-1.97*

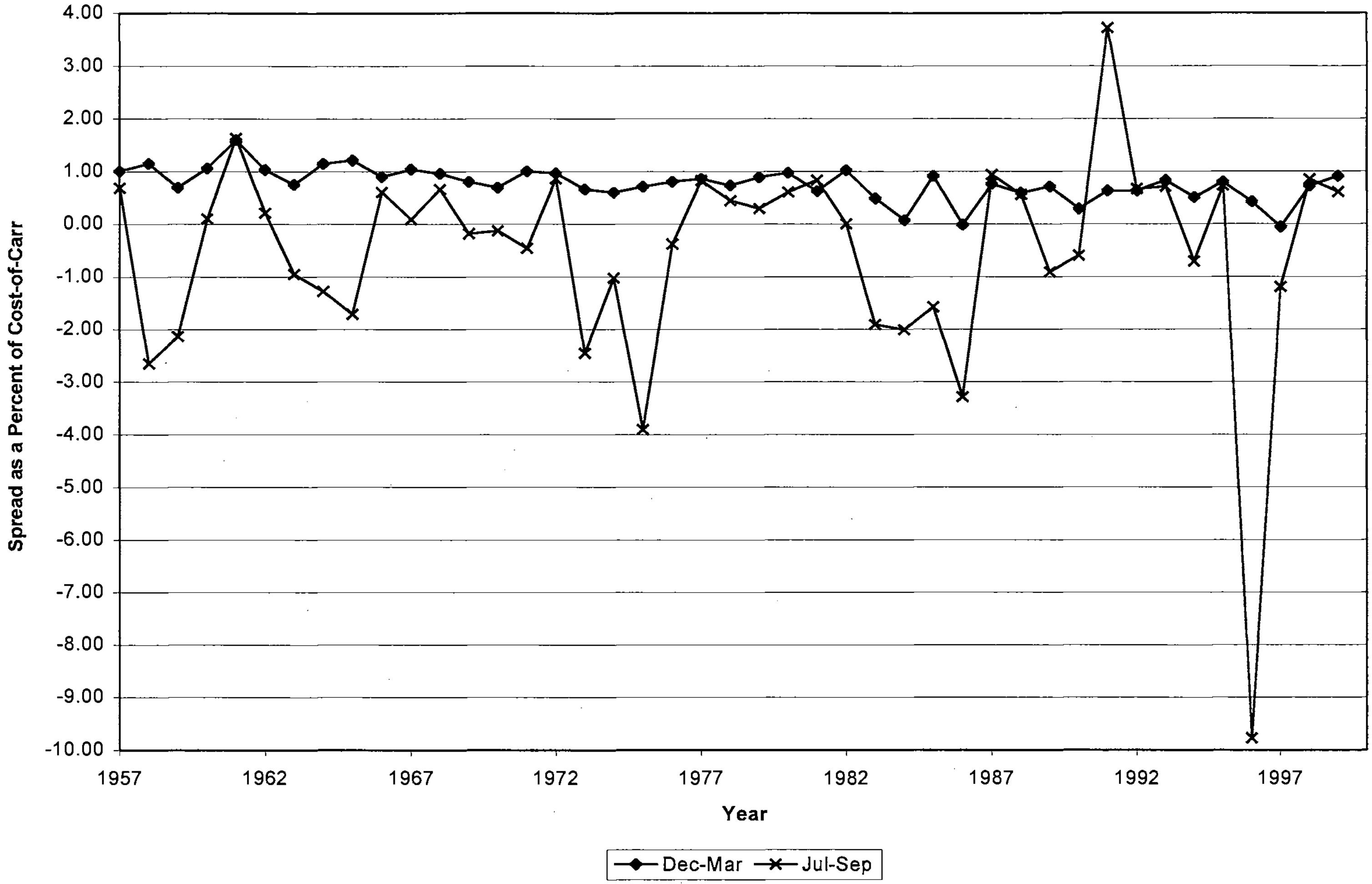
Note: CS-US denotes the paired difference of net returns between the cash sale (CS) and unhedged storage (US), CS-HS denotes the paired difference of net returns between the cash sale (CS) and hedged storage (HS), and US-HS denotes the paired difference of net returns between the unhedged storage (US) and hedged storage (HS). The t-ratio is $t = \frac{\bar{d} - 0}{\sqrt{s_D^2/n}}$, where $\bar{d}$ is the average of the paired differences (d_i) of the net returns between two marketing strategies, n is the number of paired differences, and $s_D^2 = \frac{\sum_{i=1}^{n} d_i^2 - \frac{1}{n}\left(\sum_{i=1}^{n} d_i\right)^2}{n-1}$.

Table 18: Regressions of Actual Returns to Storage on the Predicted Returns to Storage, 1957-1999

Commodity	Returns to Storage	No. Obs.	β_0	β_1	R^2
Corn	Unhedged	93	5.49	0.68	0.25
	(US-CS)		(0.95)	(3.80)*	
	Hedged	93	4.16	0.52	0.08
	(HS-CS)		(0.63)	(2.52)*	
Soybeans	Unhedged	123	14.10	1.13	0.27
	(US-CS)		(1.02)	(3.41)*	
	Hedged	123	6.24	1.66	0.27
	(HS-CS)		(0.55)	(6.00)*	
Wheat	Unhedged	122	2.92	0.40	0.10
	(US-CS)		(0.28)	(0.96)	
	Hedged	122	9.59	1.64	
	(HS-CS)		(1.42)	(5.99)*	0.32

Note: US-CS denotes the difference of net returns between unhedged storage (US) and cash sale (CS), i.e., actual returns to unhedged storage, and HS-CS denotes the difference of net returns between hedged storage (HS) and cash sale (CS), i.e., actual returns to hedged storage.

Figure 1. Spread As a Percent of Cost-of-Carry for Corn, 1957-1999

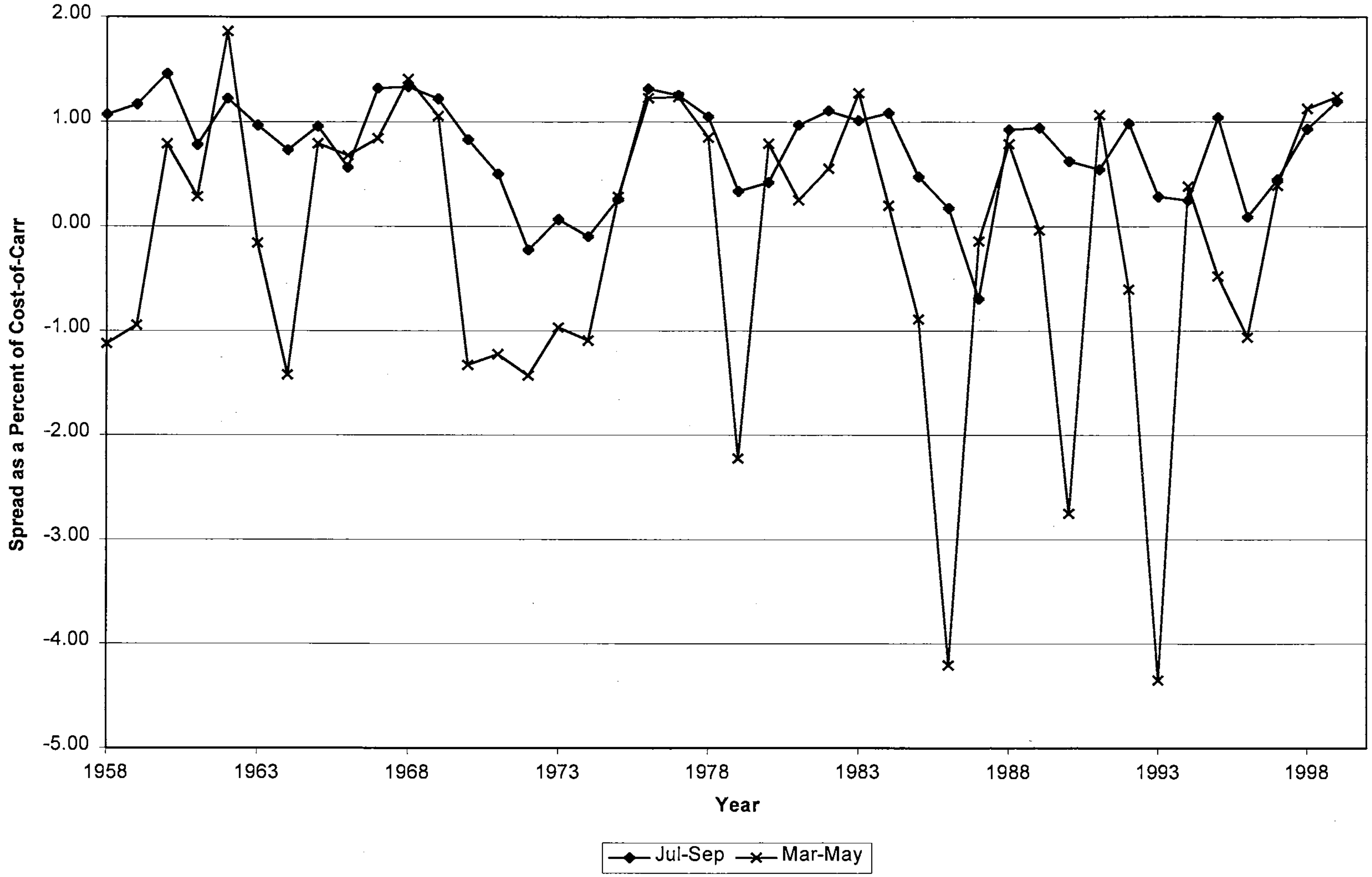


Note: The Dec-Mar spread is observed on December 1, and the Jul-Sep Spread is observed on July 1.

Figure 2. Spread As a Percent of Cost-of-Carry for Soybeans, 1958-1999

Note: The Nov-Jan spread is observed on November 1, and the Jul-Aug spread is observed on July 1.

Figure 3. Spread As a Percent of Cost-of-Carry for Wheat, 1958-1999



Note: The Jul-Sep spread is observed on July 1, and the Mar-May spread is observed on March 1.

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APPENDIXES

Appendix A

ROLLOVER HEDGING SIGNALS AND INITIAL FUTURES PRICES

Figure 1. Rollover Hedging Signals and Initial Futures Prices at the 5% Entry Level for Corn, 1948-1999

(Unit: Cents)

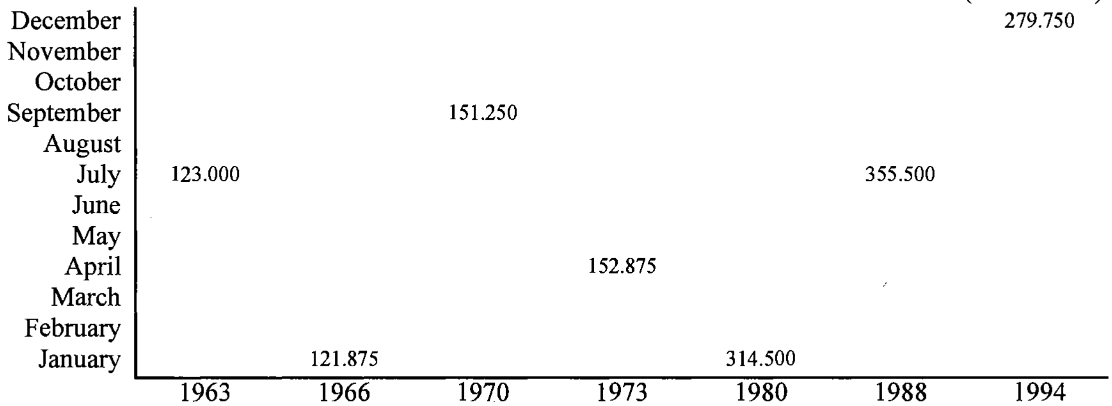


Figure 2. Rollover Hedging Signals and Initial Futures Prices at the 10% Entry Level for Corn, 1948-1999

(Unit: Cents)

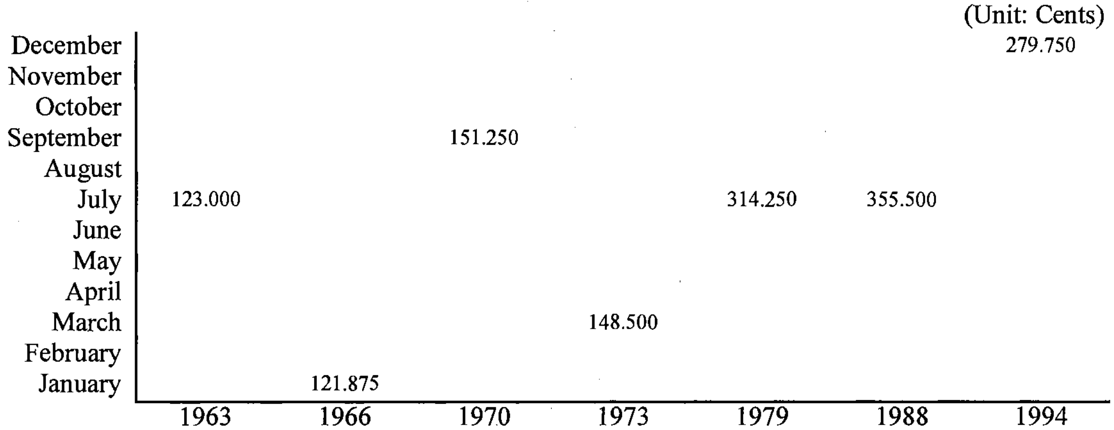


Figure 3. Rollover Hedging Signals and Initial Futures Prices at the 15% Entry Level for Corn, 1948-1999

(Unit: Cents)

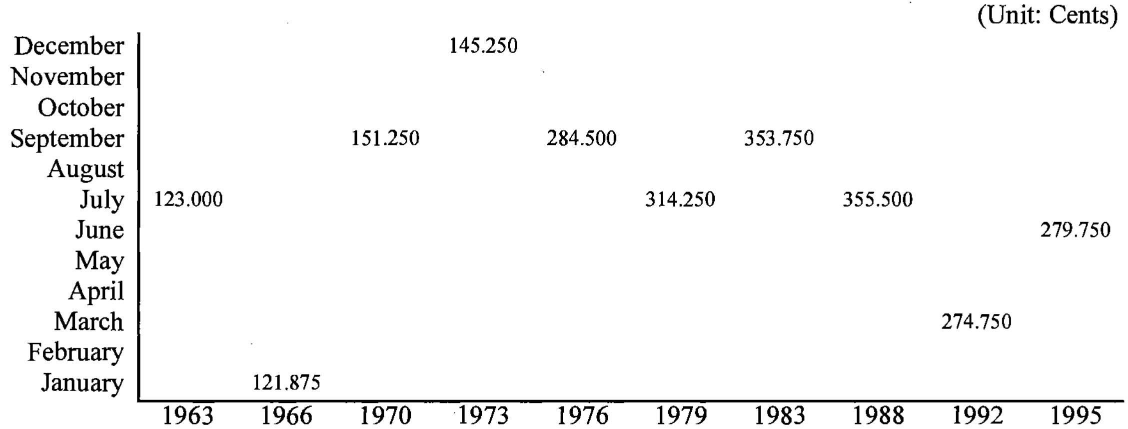


Figure 4. Rollover Hedging Signals and Initial Futures Prices at the 5% Entry Level for Soybeans, 1958-1999

(Unit: Cents)

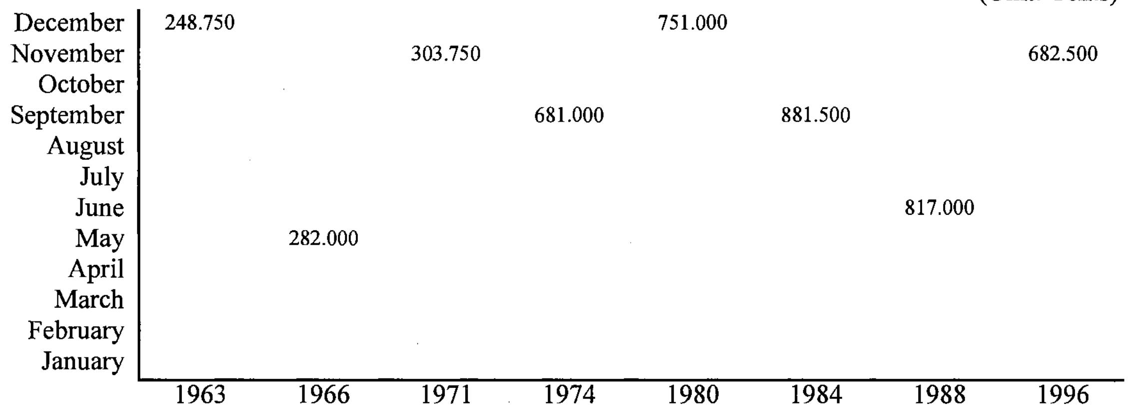


Figure 5. Rollover Hedging Signals and Initial Futures Prices at the 10% Entry Level for Soybeans, 1958-1999

(Unit: Cents)

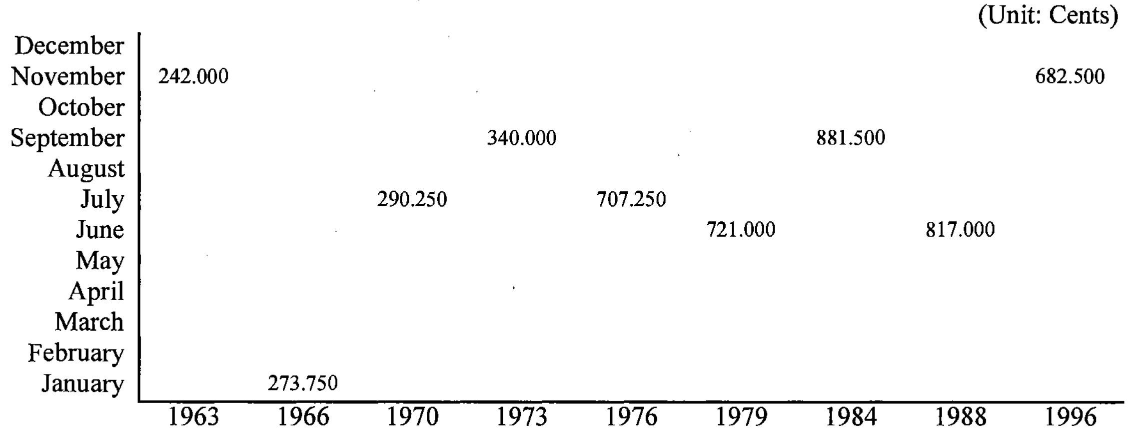


Figure 6. Rollover Hedging Signals and Initial Futures Prices at the 15% Entry Level for Soybeans, 1958-1999

(Unit: Cents)

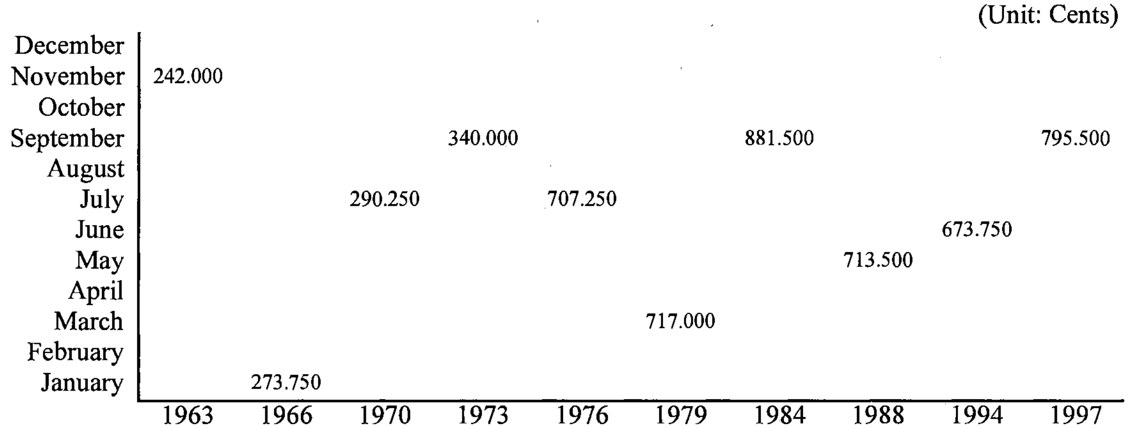


Figure 7. Rollover Hedging Signals and Initial Futures Prices at the 5% Entry Level for Wheat, 1948-1999

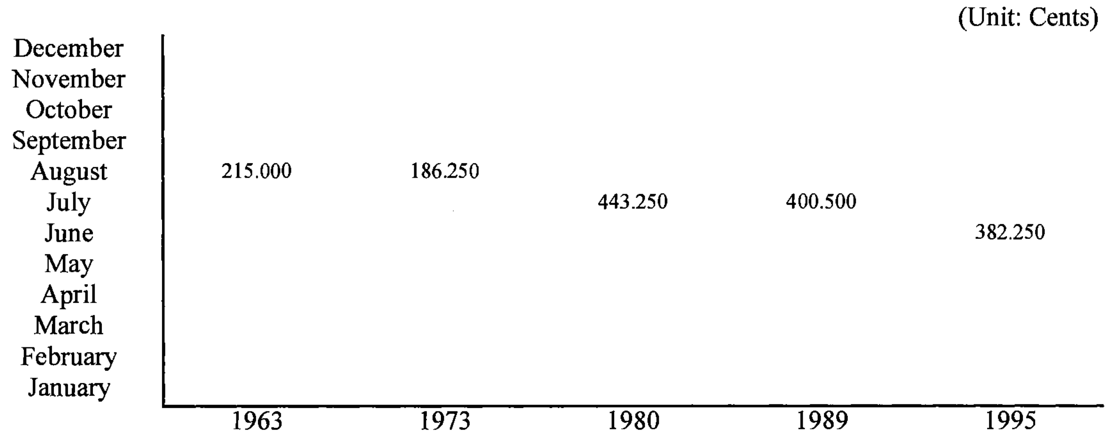


Figure 8. Rollover Hedging Signals and Initial Futures Prices at the 10% Entry Level for Wheat, 1948-1999

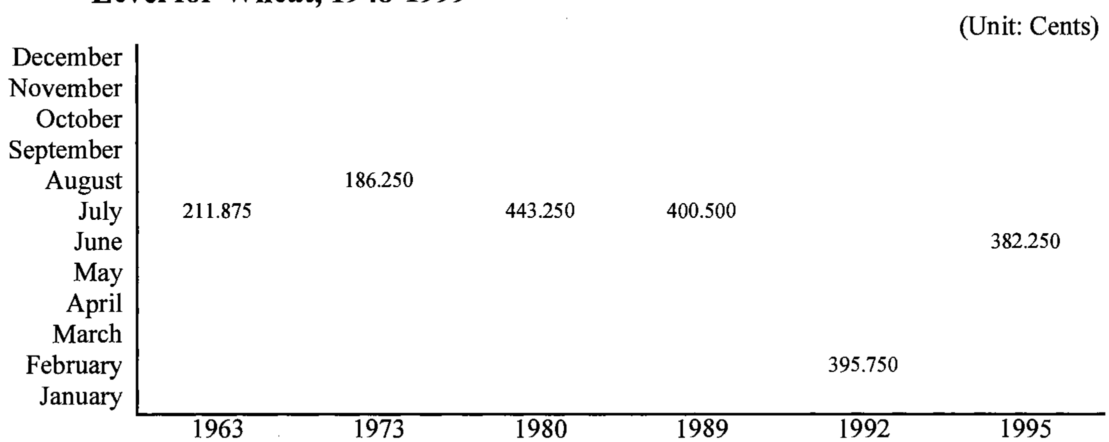
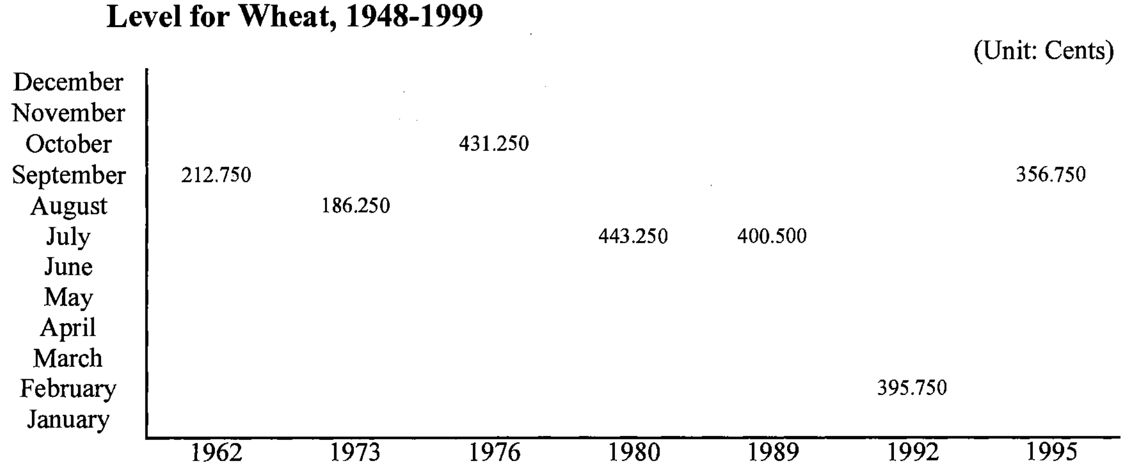


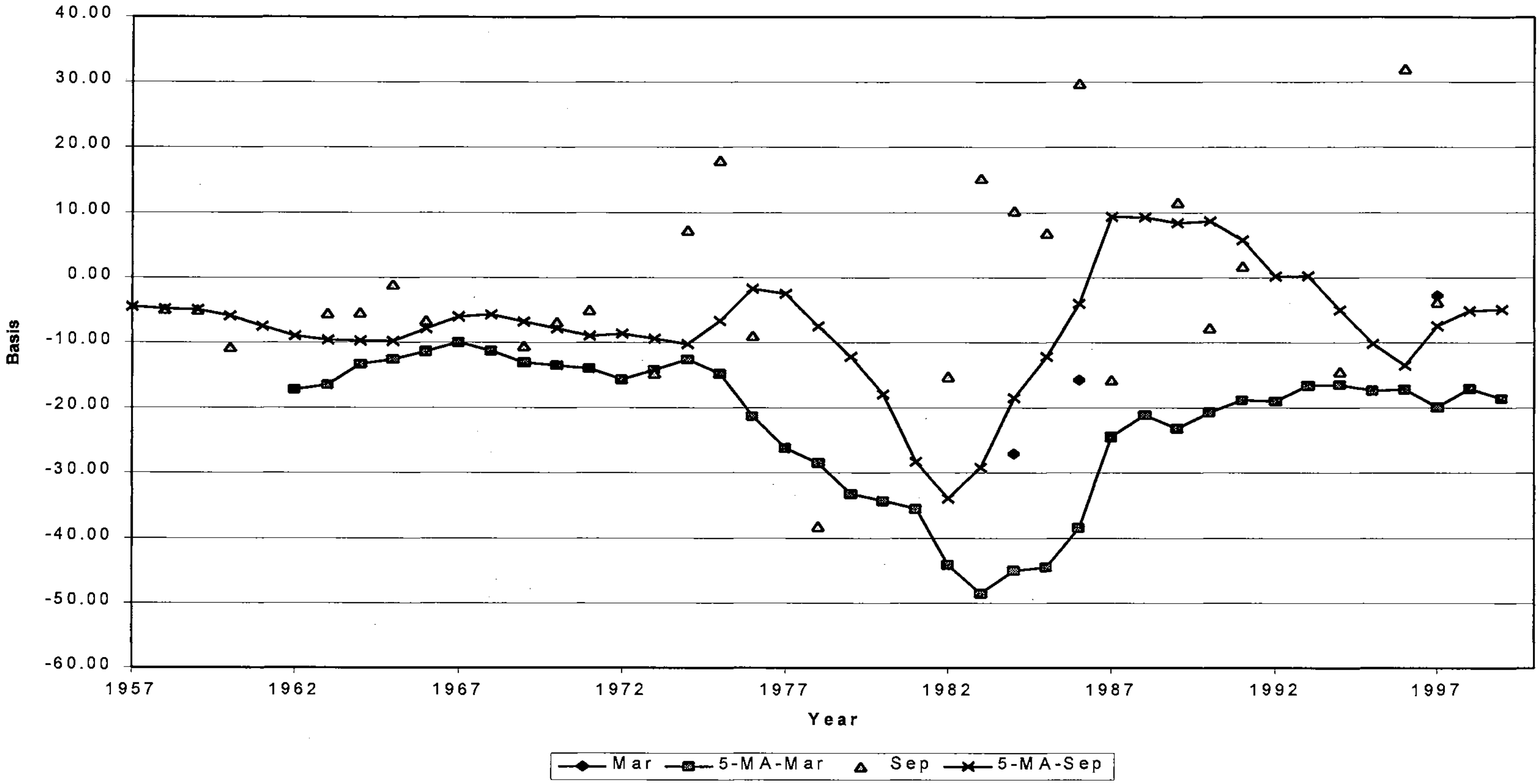
Figure 9. Rollover Hedging Signals and Initial Futures Prices at the 15% Entry Level for Wheat, 1948-1999



Appendix B

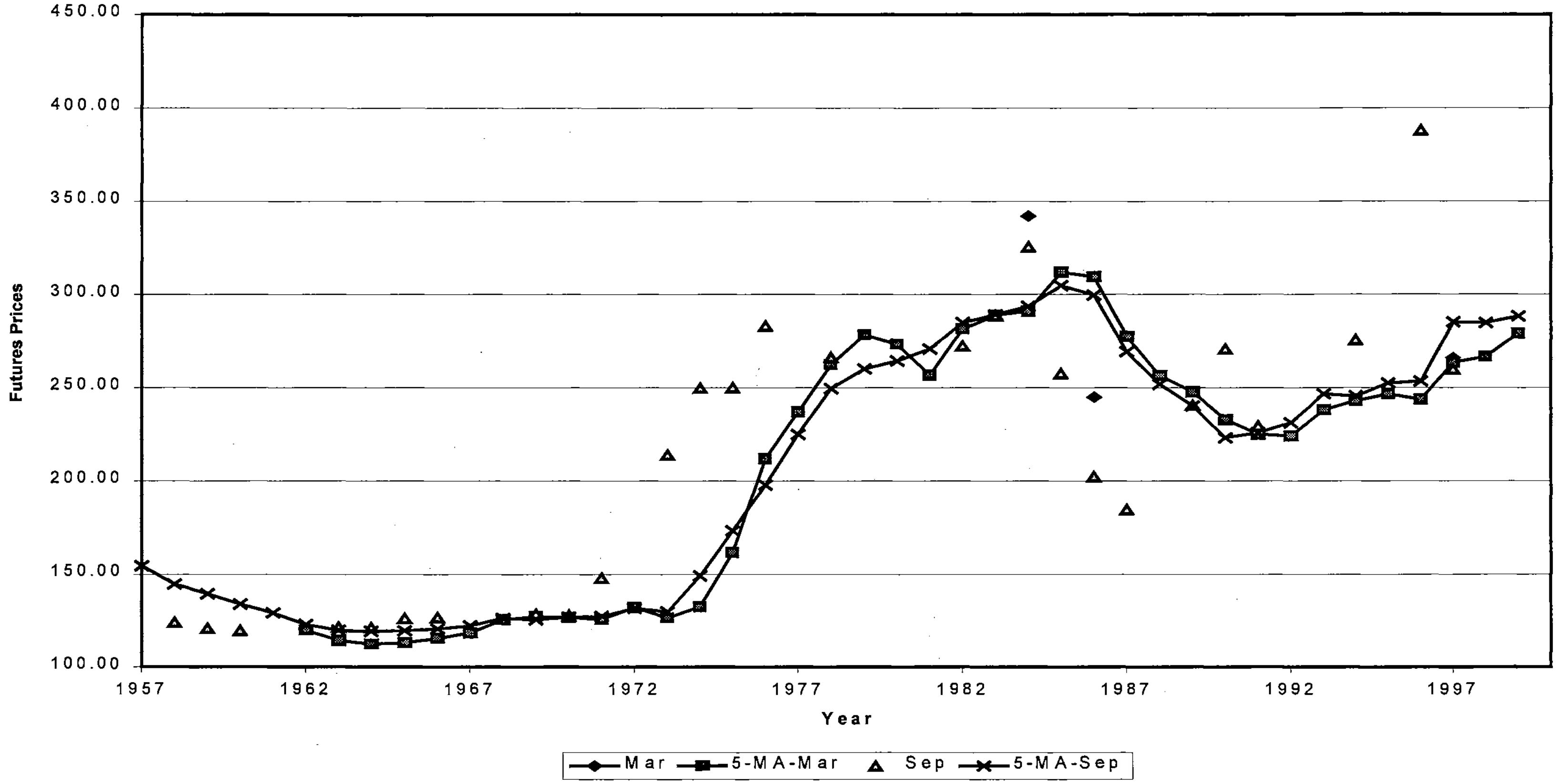
BASIS, FUTURES PRICES, AND STOCKS WHEN MARKETS ARE INVERTED

Figure 1. Basis for Corn When Markets are Inverted, 1957-1999



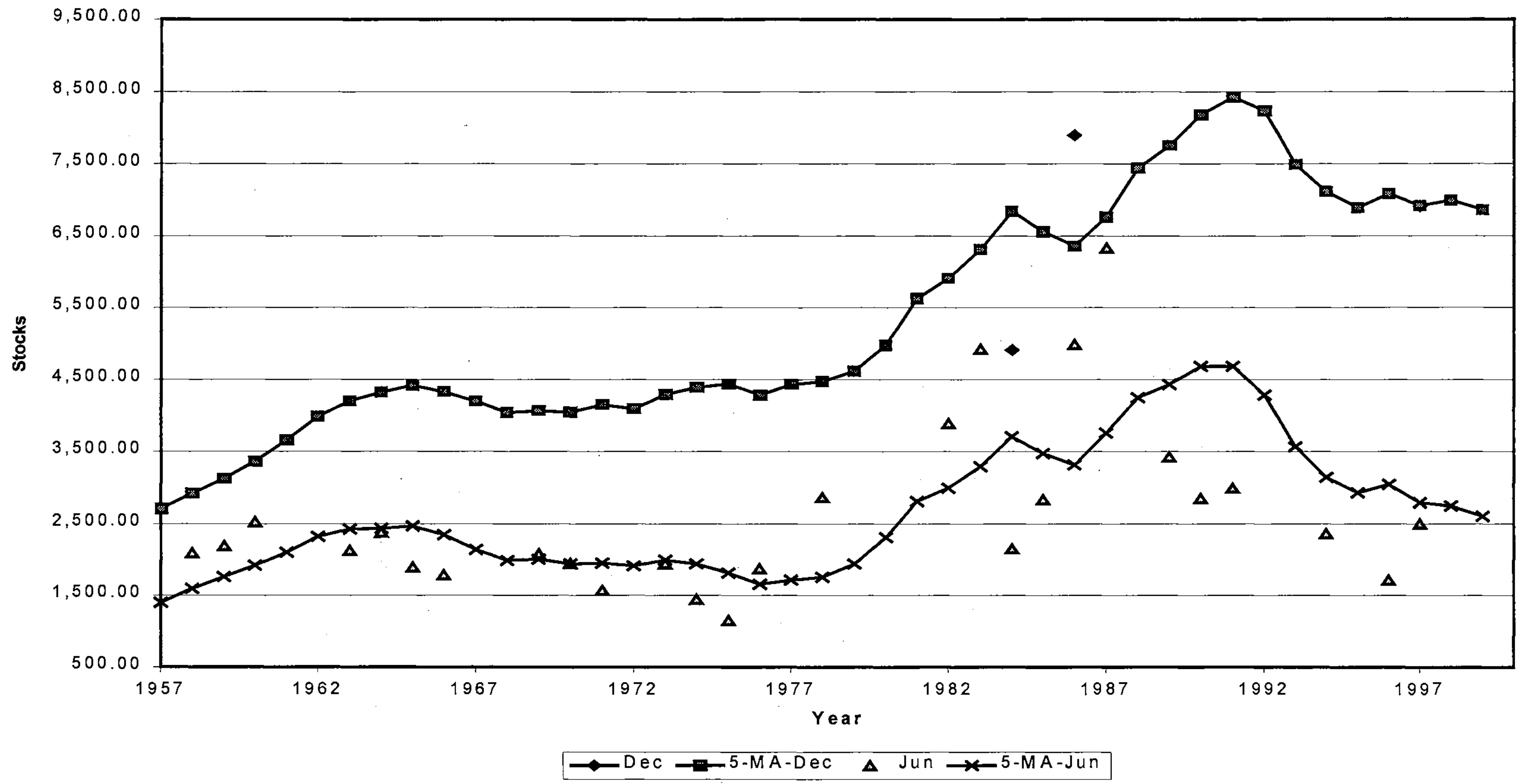
Note: The March basis was observed on December 1 when the December-March spread showed a market inversion, and compared with the 5-year moving average of the March basis. The September basis was observed on June 1 when the July-September spread showed a market inversion, and compared with the 5-year moving average of the September basis.

Figure 2. Futures Prices for Corn When Markets are Inverted, 1957-1999



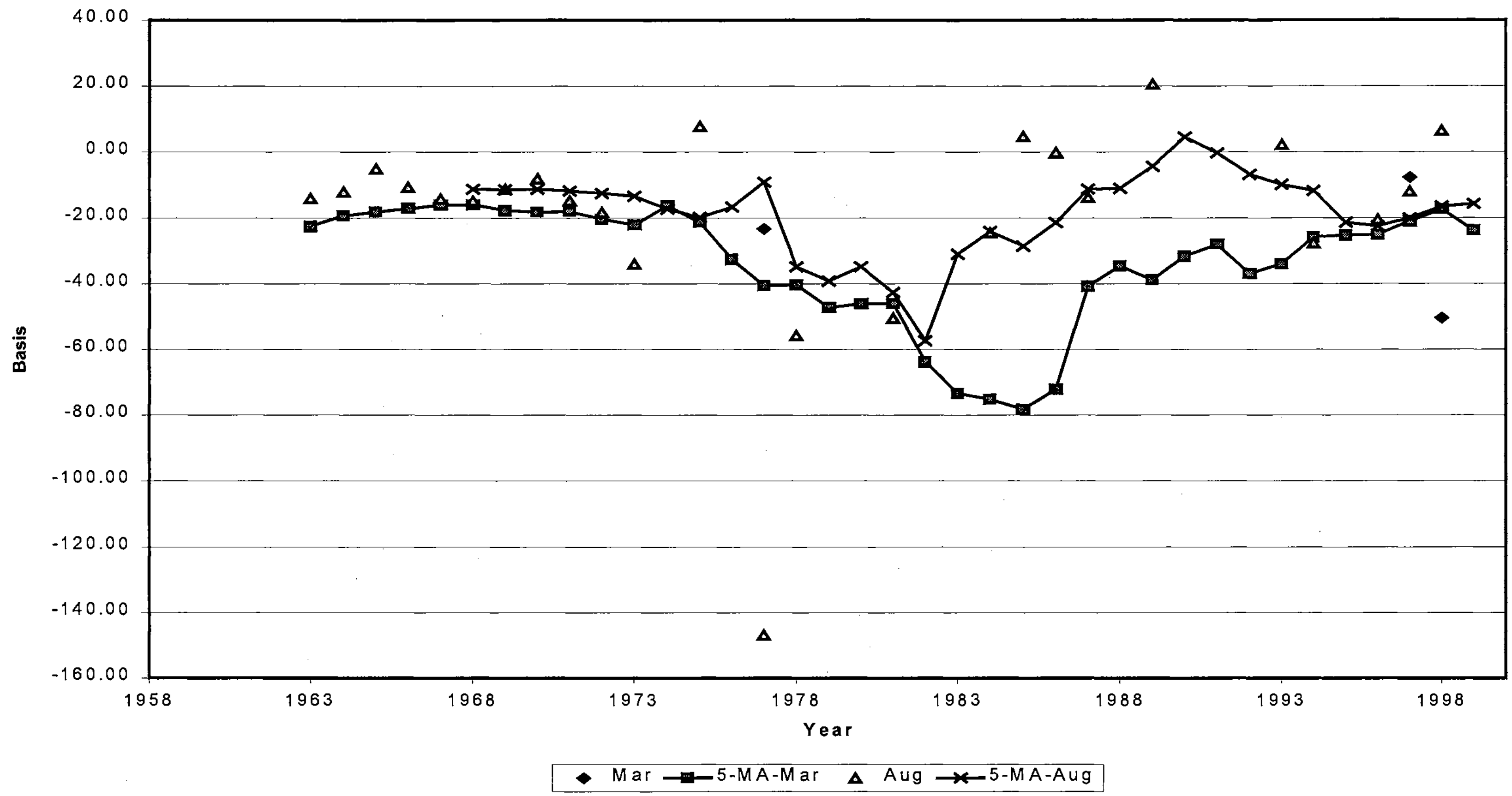
Note: The March futures price was observed on December 1 when the December-March spread showed a market inversion, and compared with the 5-year moving average of the March futures price. The September futures price was observed on June 1 when the July-September spread showed a market inversion, and compared with the 5-year moving average of the September futures price.

Figure 3. Level of Stocks for Corn When Markets are Inverted (in Million Bushels), 1957-1999



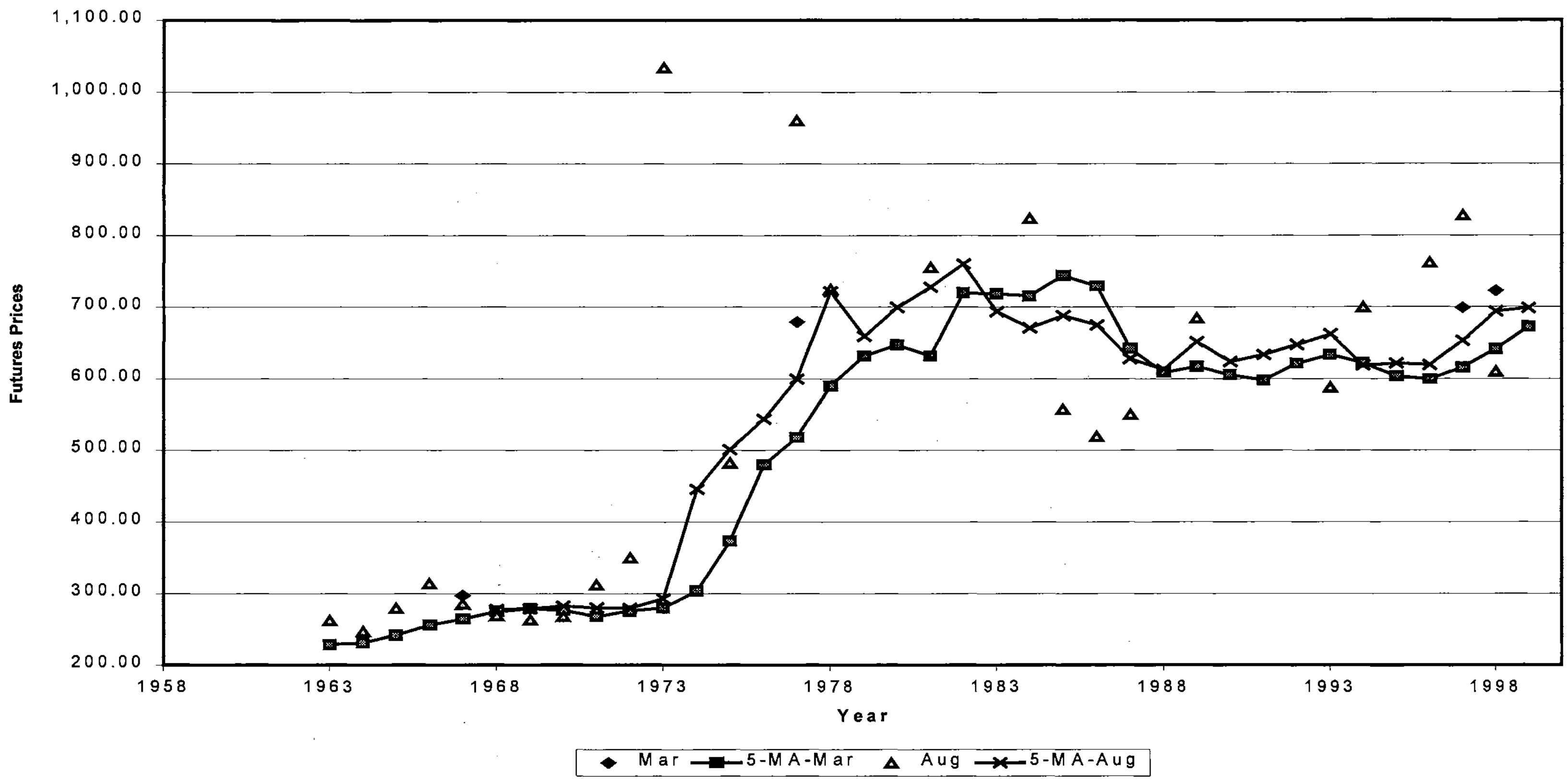
Note: December stocks were observed on December 1 when the December-March spread showed a market inversion, and compared with the 5-year moving average of the December stocks. June stocks were observed on June 1 when the July-September spread showed a market inversion, and compared with the 5-year moving average of the June stocks.

Figure 4. Basis for Soybeans When Markets are Inverted, 1958-1999



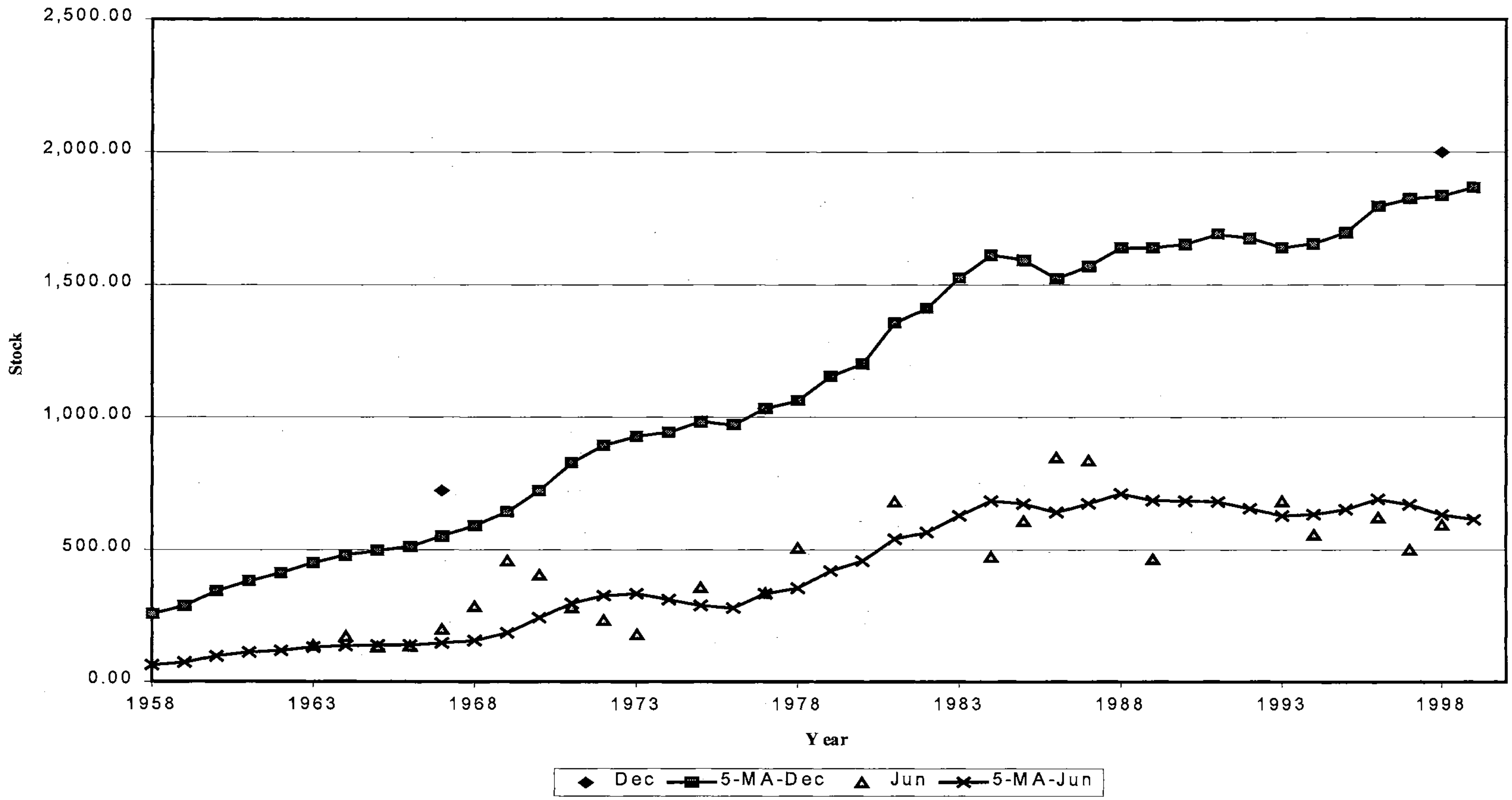
Note: The March basis was observed on December 1 when the January-March spread showed a market inversion, and compared with the 5-year moving average of the March basis. The August basis was observed on June 1 when the July-August spread showed a market inversion, and compared with the 5-year moving average of the August basis.

Figure 5. Futures Prices for Soybeans When Markets are Inverted, 1958-1999



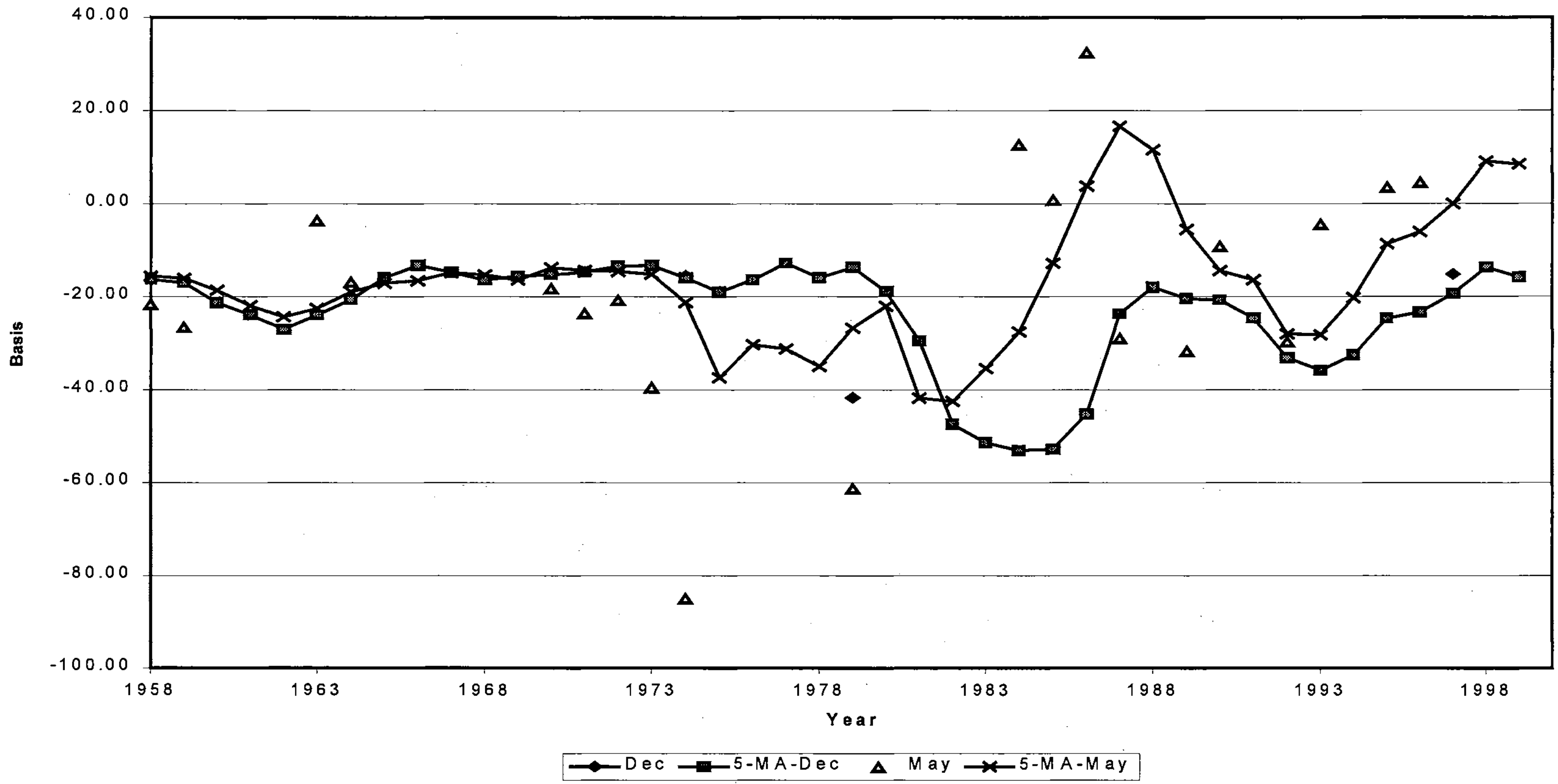
Note: The March futures price was observed on December 1 when the January-March spread showed a market inversion, and compared with the 5-year moving average of the March futures price. The August futures price was observed on June 1 when the July-August spread showed a market inversion, and compared with the 5-year moving average of the August futures price.

Figure 6. Level of Stocks for Soybeans When Markets are Inverted (in Million Bushels), 1958-1999



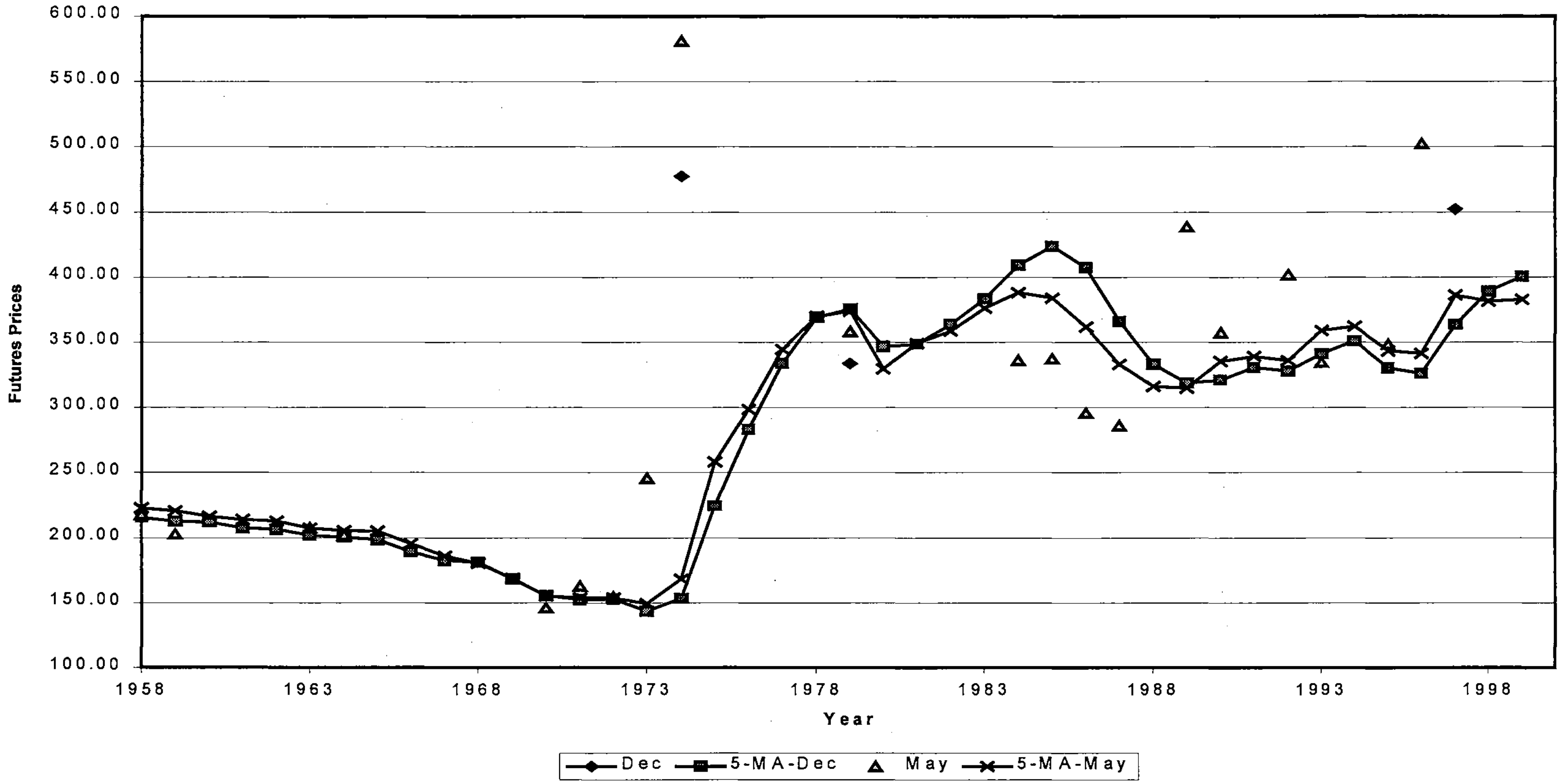
Note: December stocks were observed on December 1 when the January-March spread showed a market inversion, and compared with the 5-year moving average of the December stocks. June stocks were observed on June 1 when the July-September spread showed a market inversion, and compared with the 5-year moving average of the June stocks.

Figure 7. Basis for Wheat When Markets are Inverted, 1958-1999



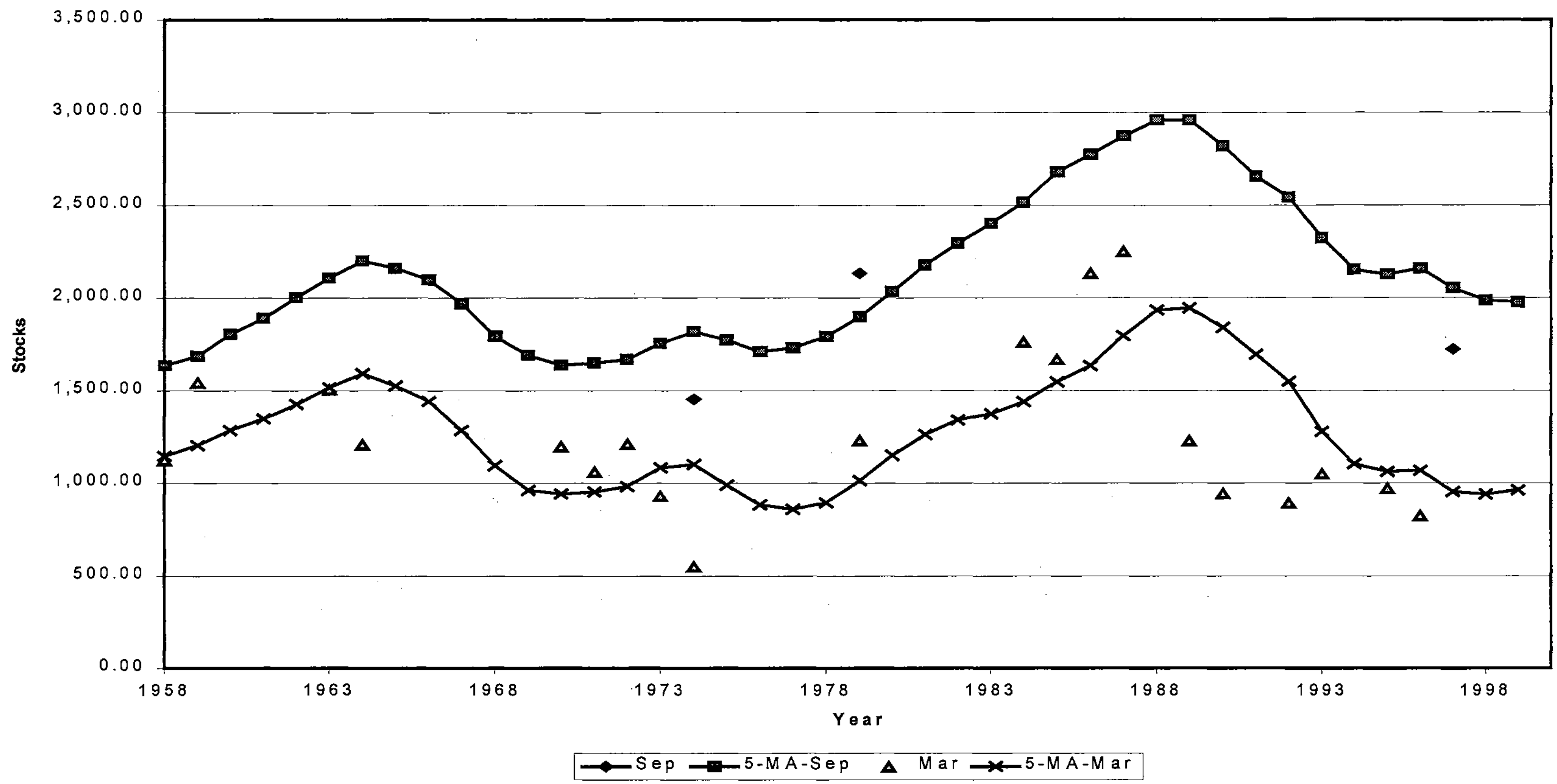
Note: The December basis was observed on September 1 when the September-December spread showed a market inversion, and compared with the 5-year moving average of the December basis. The May basis was observed on March 1 when the March-May spread showed a market inversion, and compared with the 5-year moving average of the May basis.

Figure 8. Futures Prices for Wheat When Markets are Inverted, 1958-1999



Note: The December futures price was observed on September 1 when the September-December spread showed a market inversion, and compared with the 5-year moving average of the December futures price. The May futures price was observed on March 1 when the March-May spread showed a market inversion, and compared with the 5-year moving average of the May futures price.

Figure 9. Level of Stocks for Wheat When Markets are Inverted (in Million Bushels), 1958-1999



Note: September stocks were observed on September 1 when the September-December spread showed a market inversion, and compared with the 5-year moving average of the September stocks. March stocks were observed on March 1 when the March-May spread showed a market inversion, and compared with the 5-year moving average of the May stocks.

VITA

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