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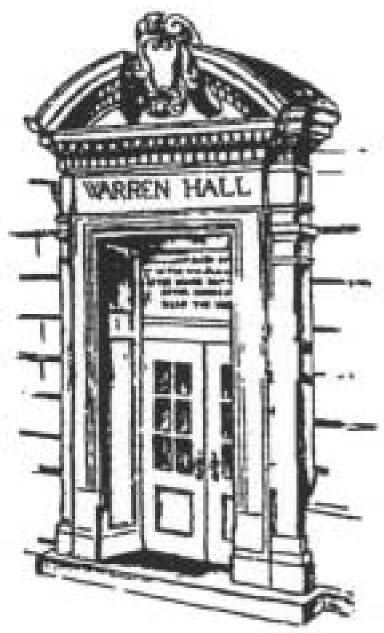

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Income Enhancing and Risk Management Properties of Marketing Practices

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Abstract: A rational expectations storage model is used to simulate monthly corn prices, which are used to evaluate marketing strategies to manage price risk. The data are generated and analyzed in two formats: for long-run outcomes over 10,000 "years" of monthly prices and for 10,000 cases of 40-year "lifetimes." Three categories of strategies are analyzed: frequency of post-harvest cash sales, unconditional hedges, and conditional hedges. The comparisons are based on the simulated probability distributions of net returns. One conclusion is that diversifying cash sales, without hedging, is not an efficient means of risk management. Unhedged storage does not reduce risk and, on average, reduces returns. The analysis of the 40-year lifetimes demonstrates, however, that rational decision-makers can face "lucky" and "unlucky" time periods. Thus, although the long-run analysis suggests that routine hedging reduces the variance (and the mean) of returns compared to the base case of selling in the spot market at harvest, the variance of returns (and their means) from both strategies will vary from lifetime to lifetime. Efficient strategies for producers with increasing utility functions vary from lifetime to lifetime, suggesting that efficient strategies likely vary from year-to-year. Nonetheless, strategies that take advantage of locking in returns to storage when relative prices are favorable are efficient in the second-degree sense and appear robust across different lifetimes. We also illustrate that conclusions are influenced by the measure of risk used. Perhaps the major conclusion is, however, that risk-management analysis is complex and potentially filled with pitfalls.

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Income Enhancing and Risk Management Properties of Marketing Practices

Farming is a risky business. Among other things, commodity prices fluctuate in an unpredictable way, and large adverse changes can result in business failures. An objective of government policies was to shield producers from price risk (Chambers), and led to various price support and stabilization schemes. In the last decade, however, U.S. agricultural policies have become more market-oriented. The levels of price supports and of trade barriers have been lowered.

Managers respond to price risk in different ways. Some adjust output and input levels; others diversify their enterprises, purchase insurance, choose among various marketing strategies, or use a combination of these alternatives. The marketing alternatives can be categorized into spot market strategies (such as diversifying the frequency of sales), the use of forward (marketing) and deferred pricing contracts, and hedging via standardized options and futures contracts. It is possible to sell not only the current year's crop, but also next year's crop, using futures contracts. Alternatively, futures positions and some forward contracts can be rolled over from maturing to more distant contracts. Since every decision yields different outcomes, a firm's manager faces a portfolio problem: what is an *optimal* portfolio that maximizes, for example, expected returns subject to an acceptable degree of risk?

Various "optimal" marketing strategies have been proposed. The traditional literature in grain marketing, which analyzes cash and futures positions under price risk only, suggests hedging almost 100 percent of the cash position (e.g., Johnson). More sophisticated models derive optimal portfolios considering additional marketing alternatives and sources of risk (see Tomek and Peterson for a review). Complex marketing strategies combining cash, forward, and futures and options transactions are available by subscription through marketing advisory services, and farm and extension journals have carried articles with captivating titles such as "The $100,000 Difference (*Top Producer*, November 1998)" and "Take on the Market (*Farm Journal*, Mid-January 1989)."

The conceptual literature unanimously agrees that marketing practices can shift or reduce risk exposure at some cost. Nonetheless, we do not yet know, for example, how effective alternative risk management strategies are, and a debate continues about whether or not marketing practices can enhance farmers' incomes (e.g., Wisner, Baldwin, and Blue versus Zulauf and Irwin). An on-going project at University of Illinois is evaluating recommendations of advisory services for marketing wheat, soybeans, and corn. Their results, based on 1995 to 1998 data, suggest that, on average, market advisory services can not outperform "the market," and that their future performance can not be predicted from past performance (Irwin et al.).

The literature that assesses the income-enhancing and risk-shifting performance of marketing strategies is not small. This research literature has examined post-harvest marketing of grains, comparing simple "optimal" strategies with an even simpler benchmark strategy, such as marketing all at harvest, using historical prices (e.g., Rister, Skees, and Black). Recently, Blakeslee developed a method of finding optimal (expected utility-maximizing) sequences of post-harvest grain marketing decisions (proportions of crop sold at a given time), assuming prices follow a first-order autoregressive process. The results, however, cannot be generalized easily, since they are specific to the sample period and location. Simulated prices are commonly based on time-series or structural models, which do not replicate documented features of price behavior (Tomek and Myers; Brorsen and Irwin). When both cash and futures prices are used, the relationship between the two is assumed to be fixed and exogenous (e.g., Harrison et al.).

These observations illustrate obstacles to analyzing marketing alternatives. In particular, the number of observations that are relevant to current economic conditions can be extremely limited. Markets undergo frequent structural change, and are difficult to model. Moreover, it is difficult to estimate costs of various alternatives for valid comparisons.

This paper analyzes income-enhancing and risk-reducing properties of marketing practices using theory-consistent cash and futures prices that are simulated from a rational expectations competitive storage model for corn (Peterson and Tomek). The model is able to reproduce monthly price distributions that are comparable to those estimated from a recent, short sample. Moreover, rational price expectations comparable to observed futures prices are endogenous. Since the model generates intra- and inter-year price series similar to those faced by corn producers, it can be used to analyze long-run performance of marketing practices under a constant structure. In other words, this paper uses simulated, but realistic prices for corn to analyze representative marketing strategies. The analysis overcomes the short-sample problem by generating thousands of observations.

The remainder of the paper is organized as follows. First, the rational expectations corn storage model is reviewed and the implied price behavior is summarized. Next, the impacts of three basic marketing practices on the mean and spread of returns are analyzed (relative to a base scenario of selling the entire crop at harvest): increasing the frequency of cash sales, unconditional scale-up strategies, and conditional hedging. Then, the marketing strategies are ranked by stochastic efficiency criteria. The results are presented for two types of simulation: one pertaining to long-run outcomes and another to outcomes that may be encountered during a lifetime. A final section explores the implications of alternative measures of price risk and market information.

Rational Expectations Corn Storage Model

The storage model incorporates the minimum key features of the U.S. corn market in the 1990s (Peterson and Tomek); nine crop years from 1989/90 through 1997/98 are used as a calibration period. The crop is planted in April and harvested from September through November by producers who are assumed to be expected profit maximizers. The planting decision is conditional on a realized supply shock. Between planting and harvest, monthly crop estimates provide information on the expected new crop size, and starting in August, news arrives regarding how much of the annual crop will be harvested next month. A larger-than-average proportion of the annual crop may be harvested in September of an "early" year, or in November of a "late" year. Agents adjust their expectations accordingly. Available supply at the beginning of each month is either consumed or stored. Monthly demand is subject to shocks, and risk-neutral arbitrageurs, who behave like risk-averse individuals in Just's sense, make monthly storage decisions. All decisions depend upon the state of the world, defined by the month of the year, available supply, the realization of demand and supply shocks, expected crop size, and expected timing of harvest. Cash prices are solved as functions of these states.

In a competitive storage model, the relationship between prices in adjacent periods is defined by the non-arbitrage condition, implying that expected prices appreciate by the carrying cost:

$$\frac{\mathrm{E}\left[P_{m+1} \mid \boldsymbol{\theta}_m\right]}{(1+r)} \leq P_m + K'_{\boldsymbol{\theta}_m}\left[s_m\right], \quad s_m \geq 0,$$

where P is the price, E[·] is the expectation operator, $\boldsymbol{\theta}_m$ represents information available at period m, r is the period-specific interest rate, s is storage, and $K'[\cdot]$ is the marginal carrying cost. If the carrying cost consists only of a constant physical storage cost, which is the case in standard models (e.g., Williams and Wright; Deaton and Laroque), prices, on average, increase indefinitely relative to the previous month. The only possible cause of price backwardation is stock-outs. In reality, an aggregate stock-out has never occurred for corn, but price backwardation occurs between most old and new crop years. To replicate typical market behavior, "convenience yield" is included as a component of the carrying cost, which encourages storage (see Frechette and Fackler for alternative explanations of price backwardation). Although its existence is controversial, this term can be viewed as a risk premium required by risk-averse storers; the specification is thus equivalent to relaxing the assumption of risk-neutrality. Alternatively, it is analogous to the benefit of an option contract, which increases as inventories decline, since the holders of inventory can meet unexpected demands.

Conditional or state-dependent price distributions are also derived from the model by simulating many time paths from a given initial state to a fixed contract maturity month. The mean of a conditional price distribution is a price expectation based on available information, and coincides with a futures price in an efficient market. Hence, the model is used to generate probability distributions of December and May futures prices, conditional on the state in each month starting from a year prior to maturity. The model's futures prices are then solved as functions of states, analogous to the cash prices.

Equilibrium cash price functions imply monthly price distributions that are positively skewed and exhibit a seasonality in means and standard deviations consistent with those estimated from the sample observations. The season-high prices occur in May and the season-low in November. Price variability is the smallest in November and highest during the growing season (May through August). In general, the model also replicates the seasonal pattern in skewness, which is also highest (i.e., the distribution is least symmetric) during the growing season and lowest at harvest.

Simulated December and May futures price distributions exhibit a time-to-maturity effect similar to those estimated from the historical sample, where the monthly variance increases as maturity approaches. Within the short sample, the means of monthly futures prices for corn exhibit a systematic pattern, seemingly inconsistent with the efficient market hypotheses. The simulated futures prices do not, by design, exhibit such a systematic pattern.

The relationship between the simulated price level of old crop (May) futures and the spread between new (December) and old crop futures prices in April is plotted in Figure 1. This relationship is similar to that depicted by historical data (see Lence and Hayenga, Figure 3). At low levels of May futures prices, the spread is a small negative number. As the price level increases, the spread decreases at an increasing rate until the rate of change becomes unity. Consequently, high prices in May are associated with a large in absolute value spread, implying that a high price cannot be obtained for the new crop by rolling over a hedge into the December contract.

Regarding hedging decisions as a simple portfolio problem, the hedge ratio that minimizes the variance of returns is computed from the simulated prices. For post-harvest and pre-harvest hedges, the ratios were 0.994 and 0.987, respectively.[1] Several estimated hedge

[1] A post-harvest hedge assumes that a farmer harvests her crop in November, sells May futures, and offsets her position at maturity. The variance-minimizing hedge is given by $\rho\sigma_S/\sigma_F$, where σ_S and σ_F are the standard deviations of changes in the spot and futures prices during the life of the hedge (ΔS and ΔF), respectively, and ρ is the correlation coefficient between ΔS and ΔF (Hull). A pre-harvest hedge is assumed to be placed in May using a December futures contract, and is lifted at maturity. The variance-minimizing hedge is calculated using the correlation coefficient between the December spot price and ΔF between May and December, and their respective standard deviations.

ratios for corn are reported in the literature. For example, Myers and Thompson report a range of 0.85 to 1.04 for the 1977-85 period, using cash prices from Michigan. Using daily cash and futures contract prices for contracts maturing in 1986, Baillie and Myers estimated GARCH-based hedge ratios ranging from 0.5 to 1.5; a constant hedge ratio estimated by ordinary least squares was 0.61. Treating weekly central Illinois elevator bid price in 1976-1992 as cash prices, time-varying hedge ratios estimated by McNew and Fackler ranged between 0.78 and 1.14, with an average of 0.96. Hence, our results are similar to those in the empirical literature, providing further evidence that the simulated price behavior is consistent with that observed.[2]

The simulated distributions place some probability mass on events outside the observed range during the 1989/90 to 1997/98 time-frame, which is appropriate. The model is intended not only to represent recent history, but also to allow for events outside of, yet consistent with, historical experience. The model solutions allow for various seasonal patterns, including unlikely ones, and the results are robust with respect to changes in parameter values. Overall, the price behavior implied by the model is similar to that faced by corn producers in the 1990s, and provides a reasonable base to analyze marketing practices. This framework can not, however, address basis risk, because the basis always converges to zero as contract maturity approaches under rational expectations.

Methodology

Because countless marketing strategies are possible, it is impossible to analyze them all, but strategies can be meaningfully categorized into groups of practices. This paper compares

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[2] The estimated ratio must be regarded as an upper limit of the true, but unknown, variance-minimizing hedge, because yield and basis risk are ignored. That is, given the specification of the simulation model, the optimal hedge ratio should be approximately one, and the estimated ratios simply help confirm the internal consistency of the model.

representative examples from three groups to a base case, where the crop is sold for cash at harvest. Given the data set, the marketing tools are limited to cash sales and sales via December and May futures contracts. The marketing window for the crop harvested in the fall extends from the preceding February through the following July.[3]

The specific strategies analyzed are summarized in Table 1. The first category of strategies is diversified cash sales. The assumption is that diversification can reduce risk, since cash prices are not perfectly correlated from month to month. On average, prices are higher in the spring than at harvest, but price variability also increases after harvest. The higher average price may not compensate for the potential increase in risk. To investigate this tradeoff, three simple post-harvest strategies are considered: selling thirds of the crop in November, January, and April (Cash1), selling thirds in January, April, and July (Cash2), and spreading the sales evenly across nine months from November through July (Cash3).

The second and third groups use futures contracts. Hedging is designed to shift risk, but it does not necessarily improve overall financial returns (Hull). Many producers do not hedge in futures, even though research has identified benefits from certain hedging practices (Harwood et al.). On the other hand, some farmers subscribe to advisory services that recommend various marketing strategies—many of which include hedging—with unknown merit (see AgMAS project reports, e.g., Irwin et al.). Most likely, some hedging practices shift risk more effectively than others; perhaps, a few worsen the outcome relative to simple cash sales. Certain hedges that successfully shift intra-year price variability may not reduce inter-year variability in returns. For

[3] Another category—not analyzed—involves speculative strategies, typically using futures markets. These implicitly assume that the farmers (or their advisors) have superior forecasting ability. Because they are conditional on a private forecast, they are difficult to evaluate. Moreover, it is unlikely that farmers have superior forecasting ability.

example, does a routine hedging strategy perform well if consistently followed year after year? Or, is there an advantage to observing changes in economic fundamentals and conditioning hedging decisions on these observations?

In this context, group two strategies use routine (unconditional) hedging practices, to be followed every year. They range from selling the entire crop in a single transaction to “scale-up” strategies that sell small increments of the crop at regular intervals. In principle, a futures market permits increased diversification, because contracts can be sold prior to harvest. Selective hedges, used in group three strategies, may be able to “lock in” a profitable return when prices are favorable relative to costs, which is distinct from trying to profit from speculation in futures (Heifner; Zulauf and Irwin; Kastens and Dhuyvetter).

Five unconditional strategies are considered. The first (UH1) sells the entire expected crop in May (preceding harvest) using December futures and lifts the hedge (i.e., buys back the futures position and sells the crop for cash) at contract maturity, where yield risk is ignored. The second strategy (UH2) sells the entire harvested crop in November using May futures and lifts the hedge in May. The next strategy (UH3) combines the first two: the hedge is placed in May using December futures, and then the entire position is rolled over to May futures in December, which is then offset in May when the crop is sold in the cash market.

The fourth strategy (UH4) is a scale-up hedge that uses December futures only, selling an equal proportion of the expected crop in four months prior to harvest—February, April, June, and August—and lifting the hedge in December (UH4).[4] Lastly, a scale-up strategy that closely resembles an actual marketing advisory program is considered (UH5). A typical, scale-up

[4] Strictly speaking, this strategy assumes that the farmer knows the quantity produced by the prior February.

approach sold (on average from 1995 to 1997) 12 and 33 percent of the crop by May 1 and October 1 of crop year, respectively, and used seven transactions during a duration of 465 marketing days ending the following spring and summer (Irwin, Good, and Jackson). Although these advisory programs do not necessarily use futures contracts for their forward transactions, the forward marketing analyzed here is carried out with December futures. Hence, one-tenth of the expected crop is sold in February and April, and another one-fifth in June, using December futures. The positions are offset in December, and the remaining crop is sold equally in the cash market in February and April.

The first of the third category of marketing practices that involves conditional hedging decisions (CH1) is a post-harvest strategy, where a decision is made in November conditional on the expected basis convergence. Specifically, the farmer stores the entire crop and sells May futures, if the May futures price in November is higher than the spot price plus costs (including carrying and transaction costs); otherwise, the crop is sold immediately for cash. This strategy should assure a positive return to storage when relative prices are favorable at harvest.

The second strategy (CH2) routinely (unconditionally) hedges the entire crop in May using December futures, but the continuation of a hedge is conditional on the basis between May futures and December cash prices in December. If it is favorable, the position is rolled over to May futures; otherwise, the December futures position is offset and the entire crop is sold in the cash market. Hence, this strategy is essentially the third unconditional hedge (UH3) with a conditional decision at mid-point of the marketing season.

The third conditional strategy (CH3) is similar to one proposed by Wisner, Blue, and Baldwin. Namely, the decision about the timing of the sale depends on whether the crop harvested the previous fall is "ex post short," which is defined as the case when production in the current crop year is less than utilization in the prior crop year. Defining the current crop year as year t-1, the year t crop is sold in February using a December futures contract, when the crop harvested in t-1 is small relative to year t-2 utilization. Otherwise, the crop is sold in May, again using December futures.[5]

All twelve strategies are executed simultaneously for 10,000 "years" in the simulated corn market to derive and analyze long-run distributions of marketing returns.[6] Spot and futures prices are determined by the equilibrium price functions, as described above. Yet, a typical producer will be in business for no more than 40 to 50 years, and such a finite period may be lucky in the sense that relatively speaking, prices are high with low variability. It is also possible for producers to be unlucky during their lifetime. Hence, the same strategies are subsequently simulated for 40-year periods, 10,000 times to gain further insight regarding price behavior faced by producers.[7]

For valid comparisons, the prices received are standardized to represent dollars received per bushel for corn harvested in November of each year t, net of opportunity, storage, and brokerage costs. The monthly interest rate (r) and physical monthly storage cost (k) are assumed

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[5] Wisner, Blue, and Baldwin report that during 1975-96, the prices of December futures were, on average, higher earlier in the life of the contract—the high occurred in February following a short crop, and during May and July following a normal crop.

[6] That is, the exercise simulates the returns of twelve farmers who live for the same 10,000 years, where each farmer follows one of the strategies his whole life.

[7] Now, the exercise simulates the returns of twelve farmers who have 10,000 40-year lives and live for the same 40 years each time. Each farmer follows one of the strategies his whole life. To eliminate the impact of the initial condition, each "lifetime" is simulated for more than 40 "years," and first several "years" are discarded.

to be one-twelfth of 10 percent and three cents per bushel, respectively, consistent with the model specification. In addition, the brokerage cost (*b*) is assumed to be one cent per bushel for a round-turn futures transaction.[8] Storage costs are accumulated while the crop remains in storage, and are subtracted from cash receipts when the crop is taken out of storage. The brokerage cost is assumed to be incurred at the initial futures transaction. All prices and costs are discounted or compounded by the interest rate to November during harvest.[9]

Transactions are defined in terms of the proportions of the crop marketed, so that the final result is an average of prices received from various transactions weighted by the proportions marketed in each transaction. Hence, this analysis does not account for yield risk; the effectiveness of the marketing practices in question is solely that of managing price risk. Moreover, the indivisibility of futures contracts is not considered. Also, there are some transaction costs associated with frequent marketing that are difficult to evaluate.

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[8] Jackson, Irwin, and Good assume 50 dollars per contract for a round-turn for futures transactions, and the contract size for corn futures at the Chicago Board of Trade is 5,000 bushels.

[9] For example, the price received from the first unconditional hedging strategy (UH1) is calculated as follows. In May, the brokerage fee for a single round-turn futures transaction is incurred for selling the entire crop with a December futures contract, which is compounded by the monthly interest rate for six months between May and November (= $-b(1+r)^6$). In December, the difference between the December futures price in May (DFP_5) and December cash price (P_{12}) is earned (or lost) from lifting the hedge without basis risk, which is discounted by one month back to November (= $(DFP_5 - P_{12})/(1+r)$). In addition, the crop is sold for December cash price less one month of storage cost, and the revenue is discounted (= $(P_{12} - k)/(1+r)$). Hence, the receipt from UH1 in November terms is: $-b(1+r)^6 + (DFP_5 - k)/(1+r)$.

Long-Run Analysis

Simulation Results

As background, the annual receipts from all marketing strategies are illustrated for a 40-year period in Figure 2. Separate panels are used for the three categories, and returns from the base strategy are plotted in all panels in circles. Some strategies yield higher returns than others in certain years, but each strategy is influenced by the same economic conditions. It is not surprising, therefore, that the receipts are highly correlated. When the base strategy yields high returns, it is matched by the cash and conditional hedging strategies, but exceeds the returns from unconditional hedges. In low-return years, the base strategy sometimes generates higher returns than cash and unconditional strategies, but rarely outperforms conditional hedging.

The long-run distributions of marketing returns from the 10,000-year simulation are illustrated as histograms in Figure 3. In each panel, the distribution of the base scenario is included for ease of comparison. The statistics of the distributions are summarized in Table 2. In addition, the probabilities (proportions of occurrences) of receipts exceeding the base mean ($2.57 per bushel) and the loan rate (support price of $1.89 per bushel) are reported. For the base strategy, the probability of returns above its own mean is less than 0.5, implying the distributions are positively skewed.

The Cash1 strategy is essentially the same as the base case with an identical mean and standard deviation, although both the mean and standard deviation of Cash1 are slightly higher than the base. The distributions from the Cash2 and Cash3 strategies lie generally to the left of the base, and both their means and standard deviations are lower than the base. Since the marketing period of Cash3 overlaps with that of Cash 1 and Cash2, the distribution from Cash3 is a linear combination of Cash1 and Cash2.

Thus, different ways of spreading sales across the marketing season impact the return distribution in different ways. If marketing is spread across months soon after harvest, the return distribution is nearly the same as selling all at harvest; if selling more frequently incurs costs, selling all at harvest is likely to be more efficient. If the sales are postponed until January and thereafter, the producer must expect, on average, a decrease in returns of about five cents per bushel. With 1,000 acres yielding 120 bushels per acre, this change translates to a reduction in annual revenue of $6,000.[10] Increasing the frequency of sales has little effect on the riskiness of returns. Despite the fact that the standard deviations of Cash2 and Cash3 are the same, the median and the probabilities of returns above the base mean and the loan rate are smaller for Cash2, suggesting an opportunity cost of delaying marketings until spring.

The five unconditional hedging strategies reduce the spread of the price received, implying that without basis or yield risk, routine hedging reduces price risk. This is driven by the seasonality in the variances of cash and futures prices during the recent decade, which is replicated by the model. For example, the December contract price has smaller variability in spring than at maturity, and May futures contract price is less volatile than cash price in November. All of these strategies, therefore, have smaller probabilities of falling below the loan rate than the base or cash strategies. Strategies UH3 and UH4—selling the crop before harvest—resulted in the lowest standard deviation, more than 40 percent lower than the base case. Lower standard deviations result from reducing the probability mass on both low and high prices. In the case of a producer with 1,000 acres yielding 120 bushels per acre, the maximum annual revenue attained following UH3 is $532,800, compared to $824,400 for the base strategy.

[10] The analysis does not consider possible tax benefits from deferred marketing.

With the exception of the distribution for UH5, which seems to lie slightly below the others, the modes are similar to the base case (Figure 3). Since unconditional hedges reduce the probability mass on higher prices, the means of the unconditional hedging strategies are all lower than the base. Prices generated by strategy UH1 have a slightly higher probability of being above the base mean than do the prices from the base strategy itself. That is, selling the crop in May results in a slightly lower mean return than selling in November, but the median return for May sales is above the base median.

Combining frequent pre-harvest futures sales with frequent post-harvest cash sales (UH5) was the worst performer among all unconditional hedges. Its average return was the lowest in the group and seven cents per bushel below the base; in terms of annual revenue from 1,000 acres yielding 120 bushels per acre, this difference translates to an income change of $8,400. The magnitude is comparable to the AgMAS comparison for 1995, where the recorded average yields for the region was 119 bushels per acre (Good et al.). Moreover, the standard deviation was the highest of the unconditional hedge strategies, and the probability of returns above the base mean was the smallest among all strategies. These results cast doubt on the effectiveness of scale-up strategies.

The conditional hedging strategies were triggered about one-half of the time (Table 2). That is, the basis (net of hedging costs) favored hedging and storage in both November and in December approximately 50 percent of the 10,000 “years.” Also, the condition described by Wisner, Blue, and Baldwin was met about 50 percent of the time in the simulations; they report a 31-percent occurrence in the years during 1975-1996.

The upper tail of the distribution from the first conditional hedge strategy (CH1) is indistinguishable from the base case, but there is less probability mass on the lower tail (Figure

3). The distributions from the remaining strategies (CH2 and CH3) have a smaller probability mass on both higher and lower prices. For all conditional hedging strategies, the odds of obtaining returns higher than the base mean are greater than for the base strategy, and the odds of falling below the loan rate are less than one percent (Table 2).

The first and second conditional hedging strategies (CH1, CH2) increased the mean (by $3,600 and $4,800, respectively, in annual revenue for 1,000 acres yielding 120 bushels per acre) and lowered variability relative to the base (Table 2). Compared with their fixed (unconditional) counterparts (UH2, UH3, respectively), these strategies increase both the mean and standard deviation. The increase in the mean is about five cents per bushel (2.4 percent), while the increase in standard deviation is about 25 percent for CH1 and 15 percent for CH2. Because CH2 is partially an unconditional pre-harvest hedge, the change in variability is not as large as that for CH1.

Conceptually, these two strategies allow the farmer to earn a positive return to storage when relative prices are favorable, and to avoid losses otherwise. Indeed, conditioning the decision on expected basis convergence (CH1) attains the high returns from the base strategy in favorable (high return) years and (through hedging) avoids the low returns from the base strategy when the prices are low (Figure 4a). Figure 4b compares CH2 to its unconditional counterpart UH3, UH1 (which is the unconditional part of CH2), and the base. Because of the decision to roll over is conditional on the expected basis convergence in December, CH2 is equivalent to the better outcome of UH1 and UH3, which can be better or worse than returns from the base strategy.

Our results do not support the claim by Wisner, Blue, and Baldwin that a conditional hedging strategy based on crop size relative to past demand (CH3) “can generate statistically higher average net returns than the naïve harvest marketing strategy with little increase in variability of the returns (p.293)." Rather, it effectively reduced the standard deviation by as much as some of the unconditional hedging strategies (UH3, UH4) with a small decrease in mean returns. Our result is not surprising, because one of the empirical "facts" needed for their result is not replicated by our model. Namely, they report that following harvest of a short crop—where production in the current crop year is less than utilization in the previous year—futures prices for December delivery are almost always higher in February than subsequently at harvest. Specifically, in their sample, December corn futures in late February averaged $0.36 per bushel above the December futures price in early November. In our model, the December futures price in February exceeds the December futures price at harvest in 55.7 percent of the ex post short crop years, but the average difference is only $0.009 per bushel.

Characterizing the marketing returns in mean-variance (E-V) space provides a further perspective (Figure 5). According to the E-V criterion, the alternatives are ranked solely in terms of the first and second moments of the distribution, which corresponds exactly to a ranking based on expected utility if the utility function is quadratic (Anderson, Dillon, and Hardaker).[11] All conditional hedging strategies are on the E-V frontier, as well as the unconditional hedging strategy UH3, which minimizes variance. The scale-up strategy analogous to advisory services recommendations is inefficient according to the E-V criterion.

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[11] The E-V ranking also coincides with expected utility if returns are normally distributed and the utility function is of the form $u(X) = a - e^{-bX}$. Since marketing returns are not normal (Figure 3), this interpretation is not valid here.

Other Comparisons

The solution to a rational expectations storage model is equivalent to the social planner's decision rule (Williams and Wright). Therefore, in a rational expectations equilibrium, the proportion of monthly availability that is not consumed represents the socially optimal amount of storage. A marketing strategy for an individual farmer that follows this optimal storage rule would provide an additional benchmark. To compute the returns from this benchmark, the crop is assumed to be marketed after harvest (beginning in November) according to the proportion of aggregate monthly availability that is consumed. The crop in year *t* continues to be marketed until the sum of the monthly proportions sold exceeds one, or through the following October. The proportion sold in the final marketing month is adjusted so that the proportions sum to unity, and analogous adjustments are made for opportunity and storage costs.

The long-run returns from the optimal storage rule are similar to the base strategy, with a mean of $2.55 per bushel and a standard deviation of $0.48. The range between maximum and minimum returns slightly exceeds that of the base. Since the equilibrium is adjusted every month as new information is revealed, our results confirm that even with rational expectations, one cannot outperform what becomes known in hindsight. This apparent "forecast error" does not indicate irrationality or a market failure (Williams and Wright).

A routine rollover hedging strategy was also analyzed, where a position in old crop futures is sold and a position in new crop futures is simultaneously established. Specifically, May futures is sold at harvest and offset in April, when an equivalent amount of December futures is sold; the December futures position is offset at maturity. When this strategy is simulated analogously to other marketing strategies, discounted to harvest month and adjusted for transaction costs, the mean return is $2.20 per bushel with a standard deviation of $0.33. The probability of returns above the mean return from the base strategy is 12.1%, and the probability of receiving a return below the loan rate is 82.8%. The simulation results confirm Lence and Hayenga's claim that it is difficult to maintain a high average price by rolling positions from old-crop to new-crop futures. Having sold May futures, a rollover near maturity can result in buying May futures at a high price and selling new crop futures at a low price. Even though rollover strategies change the nominal mean return very little, they make a farmer worse off when the time value of money is taken into account.

Some farmers hold the entire crop in on-farm storage until spring without hedging. Based on the simulations that account for time, routine sales in May reduce the mean return by $0.02 per bushel and increase the return variability by 20 percent, relative to sales at harvest. (This is consistent with the conclusions regarding comparisons of various cash sales strategies.) One may speculate that the maximum return from May sales would be higher than that from harvest sales, since the May price distribution is centered to the right of the December distribution, but the simulation results provide evidence to the contrary when opportunity and storage costs are taken into account.[12]

A similar marketing practice is conditional storage, whereby farmers delay crop sales until spring only if the November basis suggests that storage is favorable. If the stored crop is hedged, this practice is identical to the conditional hedge strategy CH1. If no hedge is placed, storage incurs a loss 45.4 percent of the time (that is, the return from selling at harvest in these cases exceeds the discounted return from May) even though the November basis provides an

[12] The lower simulated returns from May sales may also be due to the difference in skewness between the simulated December and May distributions. The model does not fully replicate the difference in the magnitudes of skewness implied by the recent sample observations.

incentive to store. The loss on average is \$0.24 per bushel, which translates to \$28,800 for a 1,000-acre farm with a 120-bushel-per-acre yield. For the 54.6 percent of the cases where the basis is favorable and one is better off storing without hedging, the gain on average is \$0.34 per bushel. The mean of this no-hedge counterpart of CH1 exceeds that of CH1 by less than one cent per bushel, while the standard deviation is 16.6 percent greater.

Stochastic Efficiency

In sum, the two hedging strategies that condition the decision on expected basis convergence yielded the highest mean return, with variances smaller than the base case. Factoring in all costs associated with storage, waiting until the Spring following harvest to sell the crop in the cash market decreased the mean return. Thus, a risk-neutral producer would unambiguously avoid this strategy. Yet, because the same strategy also has a smaller variance than the base strategy, if there is concern about financial stability, farmers may be willing to sacrifice some returns for a reduction in risk and would choose a strategy such as this. Coble et al. report that 33 percent of producers were willing to accept a lower price to lower risk. Since individual preferences are unknown, an optimal strategy cannot be identified for everyone. Nonetheless, the concept of stochastic efficiency allows candidates for optimal strategies to be identified.

Stochastic efficiency criteria compare distributions of risky prospects to separate attractive from unattractive alternatives where decision-maker's utility functions are unspecified. The first-degree stochastic dominance (FSD) rule assumes only that the utility function is monotonically increasing (Anderson, Dillon, and Hardaker). FSD is performed numerically using a MATLAB routine for all pair-wise combinations of marketing strategies, based on the long-run distributions depicted in Figure 3.[13] The results of these comparisons are reported in Table 3, where the entry in each cell is 1 (–1) if the strategy in that row dominates (is dominated by) the strategy in that column by FSD, and 0 otherwise.

The first-degree stochastic efficient strategies (marked with an asterisk) are the base, all three cash sale strategies (Cash1-Cash3), the second unconditional hedge (UH2), and all conditional hedging strategies (CH1-CH3). Reading across the rows, these strategies have no entries of –1. No rational individual, who prefers more to less, would choose any of the remaining strategies, which are dominated by at least one of those in the efficient set.

There is an unambiguous return to observing economic fundamentals and conditioning hedging decisions on them. For example, the strategy CH2 always sells December futures in the May prior to harvest, and either sells the commodity or rolls over the futures position in December, conditional on market conditions at harvest. This strategy dominates the analogous unconditional strategies that always sell the commodity with a one-time pre-harvest hedge or multiple pre-harvest hedges (UH1, UH4), or roll the positions to May futures (UH3) in December regardless of market conditions. The conditioning information is so readily accessible that the cost of obtaining it is negligible. The strategies UH2 and CH1, which are the unconditional and conditional selling of May futures after harvest, were also both first-degree stochastic efficient.

The traditional scale-up marketing strategy (UH5) was eliminated from the efficient set; it was dominated by the CH1 strategy. The scale-up strategies, because it spreads post-harvest

[13] The stochastic dominance routines were provided by Jeffrey Peterson.

cash sales, are in this sense inefficient. The Wisner, Blue, and Baldwin strategy (CH3), however, remained in the efficient set.

While the FSD rule eliminated several marketing strategies, a more informative rule would further refine the efficient set of strategies. Second-degree stochastic dominance (SSD) is such a refinement. It assumes increasing and strictly concave utility functions and eliminates strategies that no risk-averse individuals would choose (Anderson, Dillon, and Hardaker). Table 4 reports the results of numerical SSD performed analogously to FSD. A double asterisk indicates a second-degree stochastic efficient strategy; single asterisks are carried over from Table 3. All cash sales, including the base strategy, the unconditional hedging strategy (UH2), and the third conditional hedging strategy (CH3) are eliminated by SSD. Only the second-degree stochastic efficient strategies dominate the base case and the first cash sales (Cash1), while the other cash sale strategies (Cash2, Cash3) are dominated by some of the unconditional hedging strategies as well. A risk-averse individual would always select one of the two conditional hedging strategies (CH1, CH2) over the other alternatives; both of these strategies yield higher means and lower variances relative to the base (Table 2).

Figure 6 plots the cumulative distribution functions of the two second-degree efficient strategies, CH1 and CH2. They cross at the price level of $2.63, implying that CH1 leads to a higher probability of returns below $2.63, even though mean returns are higher. Thus, a highly risk-averse individual would select the combination of a regularly placed hedge and a conditional roll-over provision (CH2), while less risk-averse individuals would optimally select to place a post-harvest hedge conditional on expected basis convergence (CH1).

Lifetime Analysis

Simulation Results

Statistics for simulations of lifetime monthly price distributions, based on 10,000 simulations of 40-year periods, are reported in Table 5. For example, the November mean is $2.56 per bushel, and the standard deviation of the means over 10,000 40-year periods is $0.13. The results indicate considerable variability across different 40-year periods. Ranges between the maximum and minimum monthly means vary from $0.85 per bushel in October to $1.29 in August; the underlying seasonal variability is transmitted to variability across simulations. Consistent with the central limit theorem, monthly price distributions of the lifetime-means appear to be symmetric and bell-shaped based on an inspection of histograms. Within most lifetimes, monthly prices are positively skewed, as indicated by the high frequency that lifetime mean prices exceed the median (Table 5).

The average of lifetime standard deviations over 10,000 lives ranges from $0.45 to $0.62 per bushel. In general, lifetime standard deviations vary substantially across different 40-year periods, and the distributions of lifetime standard deviations are highly skewed to the right. Differences in maximum and minimum standard deviations across lifetimes ranges from $0.89 to $1.74 per bushel. (For example, the largest standard deviation of August prices for a 40-year period was $1.74 more than the smallest standard deviation in another 40-year period.) The variability of standard deviations for the November price faced by a producer is 20 percent of its mean, while the variability of the average November price is 5 percent of its mean.

To further analyze possible differences in price behavior faced over alternate lifetimes, Spearman rank-correlation coefficients between means and standard deviations are computed for each month (Table 6). The rank-correlation coefficients range from 0.522 to 0.619, implying that high means tend to be associated with high variances, but the association is far from perfect. Hence, it is possible to farm during a 40-year period with relatively volatile prices without a corresponding compensation in price levels. Correlations are smallest during the immediate post-harvest months.

Using the mean-variance criterion with varying degrees of risk aversion, we can identify “lucky” and “unlucky” combinations of lifetime mean and variability of prices. For each of the 10,000 simulated lifetimes, $\mu - \lambda\sigma^2$ is calculated, where μ is the lifetime mean, σ^2 is the lifetime variance, and λ is one-half times the Arrow-Pratt absolute risk aversion coefficient. The literature suggests that for typical producers, this coefficient ranges from 0 to at most 0.2 (Saha, Shumway, and Talpaz). Hence, the coefficient λ was varied from 0.001 to 0.05; means and standard deviations of the lifetimes that give the maximum and minimum of this measure of utility are reported for selected values of λ in Table 6. For most months, the combinations were robust for all levels of risk aversion considered; for June and September, the maximum combination changed slightly for higher risk aversion. The mean-variance criteria identifies “lucky” lifetimes as those that yield high prices on average that compensate for above-average variability and “unlucky” lifetimes as those with low mean prices with below-average variability.

Simulations of lifetime-average marketing returns (Table 7) are mostly consistent with the long-run means (Table 2), but they vary from lifetime to lifetime. Namely, various cash and unconditional hedging strategies do not yield as high returns as the base strategy on average, while mean returns from the first two conditional hedging strategies (CH1 and CH2) exceed it. The standard deviations of lifetime means—the variability of mean returns over different lifetimes—reflect the long-run variability of average returns over alternative marketing practices; hedging strategies have lower variability than the base strategy, while the cash strategies have slightly larger standard deviations than the base case. The largest and smallest means from the 10,000 simulations are also shown in Table 7. The most diversified cash strategy (Cash 3), for example, had a *maximum* lifetime mean of $3.11 and a *minimum* of $2.13 per bushel. This range is about four cents larger than for the base case, a difference of $4,800 in annual revenue from 1,000 acres yielding 120 bushel per acre.

The proportions of occurrences when the conditional hedging strategies are implemented are reported in percentages. Depending on the lifetime, a wide spread exists in the likelihood of expected basis convergence in favor of storing. On average, conditional hedging conditions are met about 50 percent of the time, consistent with the long-run results, but the standard deviations are about 12 percentage points for CH1 and CH2. In one of the 40-year periods, the condition for CH1 was met in only six years (15 percent of the years). The odds of occurrence of the Wisner, Blue, and Baldwin's condition (CH3) vary less across lifetimes.

While mean returns appear to be distributed symmetrically across simulations for the various strategies, distributions of lifetime standard deviations are skewed to the right. Lifetime standard deviations are, on average, 26 to 45 cents per bushel, but it is possible to live through a lifetime where some marketing practices have a standard deviation of over a dollar per bushel. Although the magnitude of the variability of returns for a given strategy can vary widely from one 40-year period to the next, most hedging strategies considered reduce the variability of returns, relative to the base case, *within* and *across* lifetimes.

"Probability above the base mean" is calculated per lifetime as the proportion of years when returns exceeded the lifetime-average return from the base strategy (see bottom half of Table 7). On average, marketing returns are skewed to the right, consistent with the long-run results. Certain cash and hedging strategies (such as Cash2 or UH5) result in a relatively small likelihood of exceeding the base strategy mean during a lifetime. But, because of the variability of the performance of the strategies in different finite periods (under varying economic conditions), it is possible to do better than the base strategy in some 40-year periods even though the strategy is not better on average over all 40-year periods. Using all three conditional hedges and UH1 increases the odds of exceeding the respective lifetime base means. These odds are, however, more variable than for the other strategies, and thus it is possible to experience a lifetime where the conditional strategies result in smaller returns than the average return from the base strategy. The probabilities of returns falling below the loan rate of $1.89 are small and with relatively small variablity.

Stochastic Efficiency

It is impractical to perform stochastic efficiency analysis for all 10,000 simulations and consequently the analysis is performed on marketing returns for selected lifetimes. One lifetime of interest is where price distributions in post-harvest January through April maximized the mean-variance criteria reported in Table 6. During such a lifetime, all cash and unconditional hedging strategies and some unconditional hedging strategies were first-degree stochastic efficient, but only the unconditional hedging strategies were second-degree stochastic efficient.[14] The base strategy was inefficient in a first-degree sense. During the lifetime where these prices minimized the mean-variance criteria, the base strategy was again eliminated by the first-degree stochastic dominance, and only the first two conditional strategies (CH1 and CH2), along with an unconditional hedging strategy (UH4) were second-degree stochastic efficient.

[14] Results are available upon request from the authors.

During a lifetime where prices during the growing season (May-Aug) are favorable in the mean-variance sense, Cash1, UH4, and all three conditional strategies are first-degree efficient, and the Cash1 strategy is eliminated by the second-degree criterion. When these prices are not favorable, more strategies, including all three cash strategies, are first-degree efficient, but the same set of strategies remain second-degree efficient.

During a lifetime where the average harvest price is at the simulation median, all strategies, including the base strategy and excluding two unconditional hedging strategies (UH2 and UH3), are first-degree stochastic efficient. In the second-degree sense, only UH4, CH1, and CH2 are efficient. During a lifetime where the lifetime-variability of harvest price is at the simulation median, the base strategy is eliminated by the first-degree stochastic dominance, and only the second conditional strategy (CH2) remains second-degree efficient.

These comparisons suggest that first-degree efficient strategies can vary from lifetime to lifetime, but second-degree efficient strategies, in particular, the second conditional hedging strategy (CH2), are relatively robust across different price paths, consistent with the long-run analysis. Moreover, we infer that efficient strategies vary from one year to the next. The difficulty is, of course, that these efficient strategies can only be identified in hindsight.

Further Implications for Risk Management

This section considers, first, alternatives to quantifying price risk by the variance. Then, the quality of observable conditioning information is discussed.

Alternative Measures of Price Risk

Since the standard deviation is a common measure of risk, it is calculated from observations for each marketing strategy and used to rank the strategies from the most to the least risky. The first column of Table 8 reports the estimated standard deviations (identical to those for the long-run distributions in Table 2) and the implied ranking of the strategies is shown in column two. Cash strategies, including the base, have the largest price risk, while the unconditional hedging strategy with a roll over provision (UH3) is the least risky.

Variance measures use both upward and downward deviations from the mean, although farmers' financial positions are jeopardized only by the downward movement in prices. Moreover, a serious concern is the probability of bankruptcy (e.g., Collins), or receiving returns below a threshold level. Several measures could be conceived to more appropriately reflect this type of downside risk. One such measure uses the negative deviations from the *base mean* to calculate a "downside variance," or lower semi-variance. This measure of risk appears on the third column of Table 8, and marketing strategies are ranked accordingly in the fourth column.

The difference in rankings from the second column is noteworthy. The least risky alternative is now the second conditional hedging strategy (CH2). Cash sales strategies still have the largest risk, but the ranking within them has changed. Cash1, which was the most risky by the standard deviation criterion, is now the least risky of the cash sales strategies. Cash2 is now more risky than Cash3, and both of them are riskier than the base case.

Because the magnitude of differences among the risk measures is small, however, the economic significance is doubtful. For example, a small difference like one-tenth of a cent per bushel translates to a difference in gross revenue of $120 for a farmer with 1,000 acres and a yield of 120 bushels per acre. Nonetheless, the largest price risk is almost 13 cents per bushel higher than the smallest, which translates into a difference of $15,600 for the same farmer.

The analysis above focused on how specific categories of marketing practices compare with the base strategy of selling all at harvest. A marketing practice is an effective risk management tool if it can prevent the realization of returns lower than the base strategy when the prices are low. Of particular interest is the frequency that returns are lower than the base return in "bad" years. A measure of price risk can then be conceived based on the negative deviations from the base outcome in low-return years. Formally, this measure is a semi-variance of marketing returns from the base return, for observations where the marketing return is below the base return *and* the base return is below its mean.

For example, consider the deviation for the following observation: return from the first cash strategy (Cash1) of $2.07 per bushel and a base return of $2.09. Because the Cash1 return is below the base, and the base is below its mean of $2.56, the deviation recorded to calculate the risk measure is –$0.02. Analogous to above, the final risk measure is the square root of the average squares of all such deviations over the total number of simulations. These statistics are reported in the fifth column of Table 8, and the sixth column reports the percentage of observations that are below the base when the base is below its mean. The implied ranking of marketing strategies is in the last column. A semi-variance of marketing returns from means of respective strategies was also computed, but the ranking was similar to the one based on the standard deviation.

The rearrangement of rankings is again striking. The two hedging strategies (UH3, CH3), which have consistently ranked as least risky, yield the largest negative deviations from the base return in low-return years. On the other hand, the conditional post-harvest hedge (CH1) never performs worse than the base strategy in "bad" years.[15] In bad years, the returns from UH3 fall below the base return only one year in five, but the low ranking of this strategy implies that these relatively infrequent deviations must be large. Despite its smallest standard deviation,

[15] By construction, the CH1 return will equal or exceed the base return.

UH3 may not be attractive to farmers, if infrequent losses are sufficient to lead to bankruptcy. On the other hand, the negative deviations for Cash1 are small on average but occur frequently.

Measures of price risk influence how marketing strategies compare with each other. In addition to the conventional focus on variance, dissecting the variability in alternative, relevant ways reveals more information. The performance of risk measures is difficult to assess; one measure of price risk is not superior to another. Rather, looking at several measures provides more useful and less misleading perceptions of risk than from a single measure.

Market Outcomes as Information

The realized state variables, such as availabilities and crop estimates, are information that can be used by decision-makers. Because the model relates prices to each combination of states, a natural extension is to use them as decision-making tools, whereby the optimal management strategy would be identified for each state of the world. To explore this possibility, Figure 7 plots the monthly behavior of availability, crop estimates, and cash and futures prices during the first twelve "years" of simulations that correspond to those reported in Figure 2.[16] By construction of the model, similar levels of availability and crop estimates imply similar cash and futures prices, and thus bases. For example, in May of "year 3" and "year 4," availability is 3.79 and 3.83 billion bushels, and planted crop sizes are 8.612 and 8.607 billion bushels, respectively. Because these states are similar, the intertemporal price structure is also similar: the current price is \$2.90 and \$2.88, respectively, while the December and May futures are priced at \$2.97 and \$2.75, and \$2.96 and \$2.73 for the two years, respectively.

[16] Simulated futures prices in September and October are omitted in the figure, since they are probably misleading (see Peterson and Tomek).

An optimal course of action can be recommended ex post. For example, in “year 2,” an average crop is expected in May, but the final crop is smaller than average because of unfavorable growing conditions. In this situation, the return-maximizing strategy would have been to wait until harvest and sell the crop using May futures (at $3.10), because prices remain low through the early growing season ($2.42–$2.48 during April through July). On the other hand, an average crop is expected in May of “year 8,” but the final crop was above average. Accordingly, the crop would have been priced higher in the May prior to harvest using December and (following) May futures prices (at $3.00 and $3.10, respectively), because the realized cash prices immediately after harvest were lower. It turns out, however, that the “year 9” crop is catastrophically low. Thus, one would be even better off to wait to sell the “year 8” crop until the new crop is planted to take advantage of high spot prices.

As these examples make clear, the difficulty is that future events are uncertain. A rational expectation model assumes efficient markets, where all available information is immediately incorporated into current price levels and basis. It follows that the model itself cannot identify strategies that outperform the market. Nevertheless, the market does identify the relative prices that can profitably be locked in. Post-harvest prices can indicate profitable storage opportunities. Given that the model has found positive returns to storage and hedging, their relatively uncommon use by farmers is a puzzle that remains unresolved.

The model assumes that conditioning information is correct at any point in time (monthly interval). In reality, many of these reports are provisional and are subsequently revised; available stocks are reported only quarterly. In addition, reporting errors regarding crop size and availability are possible. The market will adjust expectations according to the available information, even if it is incorrect.

Concluding Remarks

An impediment to statistically reliable analyses of income-enhancing and risk-reducing properties of marketing strategies is the lack of observations over a long period. Existing studies rely upon short sample periods, or simple time-series or structural models that do not capture commodity price behavior adequately. In this paper, we circumvent these problems by generating price observations from a structural model that incorporates rational expectations. The resulting cash and futures prices are consistent with recent historical data and conceptual expectations.

The rational expectations framework implies efficient markets—prices reflect all available information at a given point in time. Consequently, the model is incapable of examining hypotheses related to market inefficiency, nor can it address basis risk. Also, yield risk is not considered in this analysis. Hence, our analysis focused solely on managing price risk.

Our model permits analyses of a wide range of market outcomes for prices. Long-run probability distributions of returns are generated under three types of marketing strategies: frequent post-harvest cash sales and unconditional and conditional hedging. Relative to the base where the entire crop is sold in November, increasing the frequency of cash sales can increase or decrease the mean and standard deviation of returns, depending on the marketing period, while both unconditional and conditional hedges lowered the standard deviation. On average, waiting until spring to sell the crop decreased returns. Some conditional hedges improved the mean.

The analysis appraises the validity of the marketing practices that have been suggested in the literature and/or used by existing marketing advisory services. One conclusion is that spreading cash sales, without hedging, is not an efficient means of risk management, despite its widespread use. Hence, the analysis does not support the use of conventional scale-up strategies. Unless there are other compelling incentives (such as delaying income to another year for tax purposes), waiting until spring to begin selling the crop does not maximize returns *unless* the inventory has been hedged. Unhedged storage generates lower returns, does not reduce risk, and imposes a financial opportunity cost that can itself be large if interest rates are high. An extension of the model could investigate the effect of variable interest rates, although it is conjectured that the effect on the choice of marketing strategies is negligible.

First-degree stochastic efficient strategies were identified in each of the three categories. The SSD rule refined the efficient set of strategies to two: a conditional post-harvest hedge and a combination of a pre-harvest routine hedge and a post-harvest conditional hedge. Alternative measures of risk, however, generate a different set of rankings. These alternative rankings reveal differences among strategies that cannot be identified with a single risk measure.

Among the strategies analyzed, the differences in the means and variances of returns are rather small. Moreover, if markets are rational and efficient, prices adjust to changes in the state variables and so do not provide arbitrage opportunities for any considerable length of time. In such a world, marketing advisory services can not consistently help farmers enhance returns, unless the service indeed has acquired private, superior knowledge sooner than the market. Some advisors may have superior forecasting ability, but most probably do not. Thus, the belief that marketing advisers can help farmers "beat the market" on a consistent basis is not supported by our research.

In addition to long-run (10,000-year) simulations, the same marketing strategies were analyzed for different 40-year periods. Even with assumptions of an efficient market and rational decision-makers, uncertainty about the factors determining prices implies many possible outcomes. Because random events cannot be predicted, a rational farmer is sometimes "lucky" and sometimes "unlucky." The results confirm the laws of probability, where the best strategy identified from a 10,000-year simulation could nevertheless perform poorly over a farmer's 40-year career.

For example, routine hedging reduces both the mean and variance compared to the base strategy, but the returns of both strategies (and their deviations around the respective means) vary from lifetime to lifetime. Efficient strategies for producers with increasing utility functions are mostly inconsistent from lifetime to lifetime, suggesting that efficient strategies likely vary from year to year. Moreover, while the analysis provides general "rules-of-thumb" about long-term performance, the "optimal" strategy varies from farmer to farmer, depending on their risk preferences, financial and tax situation, and other factors.

Nonetheless, efficient strategies in the second-degree stochastic sense appear robust across different lifetimes. These strategies take advantage of the benefit of locking in the returns to storage when market conditions so indicate. As such, it highlights an existing puzzle—if there are apparent gains, why do so few producers take advantage of them? Could the majority of producers actually be risk neutral, as indicated by several surveys? As implied above, farmers who do not hedge the grain held in storage face significant probabilities of losses. Evidently, farmers attach additional costs to hedging, perhaps due to information constraints, basis risk, or non-pecuniary costs, which have not yet been identified.

Table 1 Summary of Marketing Strategies[a]

		Year *t* --->							|---- Year *t* harvest ----|				Year *t*+1 --->						
	Strategy	Feb.	*Mar.*	**Apr.**	May	*June*	**July**	Aug.	*Sep.*	**Oct.**	Nov.	*Dec.*	**Jan.**	Feb.	*Mar.*	**Apr.**	May	*June*	**July**
	Base										Sell cash 100%								
Cash	Cash1										Sell cash 33.3%		**Sell cash 33.3%**			**Sell cash 33.3%**			
Cash	Cash2												**Sell cash 33.3%**			**Sell cash 33.3%**			**Sell cash 33.3%**
Cash	Cash3										Sell cash 11.1%		--->						
Unconditional Hedge	UH1				Sell Df 100%							*Buy back Df 100%* *Sell cash 100%*							
Unconditional Hedge	UH2										Sell Mf100%						Buy back Mf 100% Sell cash 100%		
Unconditional Hedge	UH3				Sell Df 100%							*Buy back Df 100%* *Sell Mf 100%*					Buy back Mf 100% Sell cash 100%		
Unconditional Hedge	UH4	Sell Df 25%		**Sell Df 25%**		*Sell Df 25%*		Sell Df 25%				*Buy back Df 100%* *Sell cash 100%*							
Unconditional Hedge	UH5	Sell Df 10%		**Sell Df 10%**		*Sell Df 10%*						*Buy back Df 40%* *Sell cash 40%*		Sell cash 20%		**Sell cash 20%**			**Sell cash 20%**
Conditional Hedge	CH1										If A, sell Mf 100%, else sell cash 100%[b]						If A, buy back Mf 100% & sell cash 100%[b]		
Conditional Hedge	CH2				Sell Df 100%							*Buy back Df 100%* *If B, sell Mf 100%, else sell cash 100%*[c]					If B, buy back Mf 100% & sell cash 100%[c]		
Conditional Hedge	CH3	If C, sell Df 100%[d]			Else sell Df 100%							*Buy back Df 100%* *Sell cash 100%*							

[a] "Df" and "Mf" denote December and May futures, respectively.

[b] "A" is $(MFP_{11} - 5k)/(1+r)^6 - b > P_{11}$ (notation defined in text).

[c] "B" is $(MFP_{12} - 4k)/(1+r)^6 - b/(1+r) > P_{12}/(1+r)$.

[d] "C" is $H_{t-1}^{11} < \sum_{m=1}^{8} q_{t-2}^{m} + \sum_{m=9}^{12} q_{t-1}^{m}$

Table 2 Descriptive Statistics of Long-Run Distributions of Simulated Marketing Returns, by Strategy[a]

	----------------------------	----------------------------	$/bushel	----------------------------	----------------------------	Probability	Probability
Strategy	Mean	Median	Standard Deviation	Maximum	Minimum	Probability Above Base Mean[b]	Probability Above Loan Rate[b]
Base	2.56	2.49	0.48	6.87	1.49	0.438	0.959
Cash 1	2.56	2.50	0.48	7.15	1.48	0.437	0.959
Cash 2	2.51	2.44	0.46	6.89	1.47	0.385	0.947
Cash 3	2.53	2.47	0.46	6.50	1.45	0.411	0.957
Uncond. Hedge 1 (UH1)	2.55	2.51	0.35	4.63	1.62	0.450	0.989
Uncond. Hedge 2 (UH2)	2.54	2.49	0.35	5.76	1.70	0.398	0.991
Uncond. Hedge 3 (UH3)	2.53	2.49	0.28	4.44	1.81	0.405	0.999
Uncond. Hedge 4 (UH4)	2.52	2.49	0.29	4.13	1.75	0.402	0.996
Uncond. Hedge 5 (UH5)	2.49	2.45	0.36	5.46	1.63	0.368	0.980
Conditional Hedge 1 (CH1) (51.64% triggered)[c]	2.60	2.51	0.44	6.87	1.70	0.443	0.991
Conditional Hedge 2 (CH2) (49.27% triggered)[c]	2.59	2.54	0.32	4.63	1.81	0.477	0.999
Conditional Hedge 3 (CH3) (50.68% triggered)[c]	2.55	2.55	0.29	4.44	1.62	0.479	0.991

[a] Returns are measured in $/bushel, discounted to November of the harvest year.

[b] Proportion of occurrences where returns exceeded the specified level. The loan rate is $1.89/bushel.

[c] Percent triggered is the proportion of occurrences where the condition of the strategy was satisfied.

Table 3 Comparison of Marketing Strategies by First-Degree Stochastic Dominance [a]

	Strategy B											
Strategy A	Base	Cash1	Cash2	Cash3	UH1	UH2	UH3	UH4	UH5	CH1	CH2	CH3
Base*	0	0	0	0	0	0	0	0	0	0	0	0
Cash1*	0	0	0	0	0	0	0	0	0	0	0	0
Cash2*	0	0	0	0	0	0	0	0	0	0	0	0
Cash3*	0	0	0	0	0	0	0	0	0	0	0	0
UH1	0	0	0	0	0	0	0	0	0	0	-1	0
UH2*	0	0	0	0	0	0	0	0	0	0	0	0
UH3	0	0	0	0	0	0	0	0	0	0	-1	0
UH4	0	0	0	0	0	0	0	0	0	0	-1	0
UH5	0	0	0	0	0	0	0	0	0	-1	0	0
CH1*	0	0	0	0	0	0	0	0	1	0	0	0
CH2*	0	0	0	0	1	0	1	1	0	0	0	0
CH3*	0	0	0	0	0	0	0	0	0	0	0	0

[a] The entry in each cell is 1 if Strategy A dominates Strategy B, -1 if B dominates A, and 0 otherwise.
* Denotes a first-degree stochastic efficient strategy.

Table 4 Comparison of Marketing Strategies by Second-Degree Stochastic Dominance [a]

	Strategy B											
Strategy A	Base	Cash1	Cash2	Cash3	UH1	UH2	UH3	UH4	UH5	CH1	CH2	CH3
Base*	0	0	0	0	0	0	0	0	0	-1	-1	0
Cash1*	0	0	0	0	0	0	0	0	0	-1	-1	0
Cash2*	0	0	0	0	-1	-1	-1	-1	0	-1	-1	-1
Cash3*	0	0	0	0	-1	-1	0	0	0	-1	-1	-1
UH1	0	0	1	1	0	0	0	0	1	0	-1	-1
UH2*	0	0	1	1	0	0	0	0	1	-1	-1	0
UH3	0	0	1	0	0	0	0	1	1	0	-1	0
UH4	0	0	1	0	0	0	-1	0	1	0	-1	0
UH5	0	0	0	0	-1	-1	-1	-1	0	-1	-1	-1
CH1**	1	1	1	1	0	1	0	0	1	0	0	0
CH2**	1	1	1	1	1	1	1	1	1	0	0	1
CH3*	0	0	1	1	1	0	0	0	1	0	-1	0

[a] The entry in each cell is 1 if Strategy A dominates Strategy B, -1 if B dominates A, and 0 otherwise.
* Denotes a first-degree stochastic efficient strategy.
** Denotes a second- (and first-) degree stochastic efficient strategy.

Table 5 Selected Statistics for Simulated Corn Prices Based on 10,000 40-Year Lifetimes

Lifetime Statistics:[a]	Mean					Standard Deviation					Mean Minus Median			
Simulation Statistics:[b]	Mean	Median	Std.Dev.	Max	Min	Mean	Median	Std.Dev.	Max	Min	Pr(>0)	Mean	Max	Min
January	2.660	2.656	0.132	3.207	2.242	0.460	0.447	0.096	1.105	0.218	0.872	0.062	0.326	-0.127
February	2.713	2.707	0.134	3.282	2.290	0.465	0.452	0.098	1.173	0.227	0.876	0.063	0.338	-0.149
March	2.766	2.761	0.136	3.336	2.340	0.471	0.458	0.100	1.192	0.231	0.877	0.063	0.364	-0.159
April	2.819	2.814	0.138	3.394	2.386	0.477	0.465	0.102	1.184	0.237	0.882	0.064	0.379	-0.130
May	2.852	2.845	0.157	3.611	2.407	0.572	0.555	0.119	1.373	0.269	0.942	0.109	0.503	-0.171
June	2.830	2.822	0.158	3.576	2.406	0.585	0.572	0.123	1.574	0.319	0.914	0.093	0.463	-0.183
July	2.782	2.774	0.158	3.575	2.360	0.576	0.561	0.124	1.331	0.308	0.919	0.092	0.580	-0.129
August	2.738	2.729	0.167	3.535	2.245	0.621	0.604	0.141	2.042	0.299	0.937	0.109	0.553	-0.121
September	2.578	2.570	0.148	3.176	2.152	0.607	0.592	0.117	1.267	0.345	0.896	0.087	0.399	-0.161
October	2.503	2.496	0.135	2.982	2.130	0.556	0.541	0.113	1.285	0.273	0.904	0.083	0.402	-0.113
November	2.557	2.549	0.129	3.092	2.151	0.450	0.439	0.094	1.130	0.217	0.868	0.060	0.333	-0.146
December	2.608	2.601	0.131	3.142	2.197	0.455	0.443	0.096	1.148	0.216	0.870	0.061	0.347	-0.132

[a] Defined over 40 years. For example, "Mean" = $\mu_l = \sum_{n=1}^{40} p_n \big/ 40$

[b] Defined over 10,000 simulations. For example, "Mean" = $\sum_{l=1}^{10000} \mu_l \big/ 10000$

Table 6 Most and Least Preferred Monthly Price Distributions During a 40-Year Lifetime, According to Mean-Variance Framework

	Rank	λ = .001-0.05				λ = .1				λ = .5			
	Correlation	$\max(\mu-\lambda\sigma^2)$		$\min(\mu-\lambda\sigma^2)$		$\max(\mu-\lambda\sigma^2)$		$\min(\mu-\lambda\sigma^2)$		$\max(\mu-\lambda\sigma^2)$		$\min(\mu-\lambda\sigma^2)$	
Prices	Mean-Stdev	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
January	0.527	3.207	0.630	2.242	0.316	3.207	0.630	2.242	0.316	3.207	0.630	2.242	0.316
February	0.527	3.282	0.643	2.290	0.317	3.282	0.643	2.290	0.317	3.282	0.643	2.290	0.317
March	0.527	3.336	0.656	2.340	0.327	3.336	0.656	2.340	0.327	3.336	0.656	2.340	0.327
April	0.531	3.394	0.651	2.386	0.334	3.394	0.651	2.386	0.334	3.394	0.651	2.386	0.334
May	0.567	3.611	0.811	2.407	0.341	3.611	0.811	2.407	0.341	3.611	0.811	2.407	0.341
June	0.568	3.576	1.193	2.406	0.414	3.570	0.759	2.406	0.414	3.570	0.759	2.406	0.414
July	0.585	3.575	1.247	2.360	0.364	3.575	1.247	2.360	0.364	3.575	1.247	2.360	0.364
August	0.619	3.535	1.001	2.245	0.499	3.535	1.001	2.245	0.499	3.535	1.001	2.245	0.499
September	0.571	3.176	0.921	2.152	0.428	3.176	0.921	2.152	0.428	3.176	0.921	2.152	0.428
October	0.564	2.982	0.908	2.130	0.443	2.982	0.908	2.130	0.443	2.982	0.908	2.130	0.443
November	0.522	3.092	1.130	2.151	0.312	3.092	1.130	2.151	0.312	3.078	0.637	2.151	0.312
December	0.525	3.142	1.148	2.197	0.313	3.142	1.148	2.197	0.313	3.130	0.629	2.197	0.313

Table 7 Distributions for Simulated Marketing Strategies Based on 10,000 40-Year Lifetimes

Strategy	Mean[a]					Standard Deviation[a]				
	Mean[b]	Median	Std.Dev.	Max	Min	Mean[b]	Median	Std.Dev.	Max	Min
Base	2.557	2.549	0.129	3.092	2.151	0.450	0.439	0.094	1.130	0.217
Cash 1	2.558	2.550	0.130	3.092	2.149	0.452	0.440	0.095	1.105	0.221
Cash 2	2.499	2.490	0.134	3.094	2.105	0.426	0.414	0.097	1.057	0.205
Cash 3	2.527	2.519	0.134	3.113	2.133	0.427	0.414	0.097	1.105	0.198
Uncond.Hedge 1 (UH1)	2.546	2.544	0.096	2.951	2.270	0.332	0.328	0.058	0.606	0.184
Uncond.Hedge 2 (UH2)	2.533	2.529	0.095	2.935	2.229	0.330	0.321	0.067	0.843	0.157
Uncond.Hedge 3 (UH3)	2.523	2.522	0.065	2.790	2.338	0.265	0.262	0.041	0.437	0.161
Uncond.Hedge 4 (UH4)	2.515	2.513	0.086	2.854	2.245	0.266	0.263	0.049	0.455	0.132
Uncond.Hedge 5 (UH5)	2.488	2.482	0.113	2.954	2.149	0.332	0.326	0.075	0.768	0.160
Cond. Hedge 1 (CH1)	2.594	2.586	0.119	3.098	2.236	0.415	0.402	0.097	1.126	0.183
(% triggered)	51.58	52.50	11.79	90.00	15.00					
Cond. Hedge 2 (CH2)	2.583	2.580	0.085	2.961	2.347	0.308	0.303	0.056	0.571	0.169
(% triggered)	49.53	50.00	12.03	85.00	12.50					
Cond. Hedge 3 (CH3)	2.545	2.544	0.081	2.870	2.294	0.279	0.277	0.044	0.473	0.147
(% triggered)	50.43	50.00	5.04	67.50	35.00					

	Probability Above Base Mean					Probability Above Loan Rate				
	Mean[b]	Median	Std.Dev.	Max	Min	Mean[b]	Median	Std.Dev.	Max	Min
Base	0.444	0.450	0.052	0.650	0.250	0.960	0.975	0.042	1.000	0.725
Cash 1	0.446	0.450	0.052	0.650	0.250	0.959	0.975	0.042	1.000	0.725
Cash 2	0.393	0.400	0.054	0.550	0.200	0.947	0.950	0.052	1.000	0.625
Cash 3	0.420	0.425	0.054	0.600	0.250	0.958	0.975	0.046	1.000	0.700
Uncond.Hedge 1 (UH1)	0.453	0.450	0.079	0.750	0.150	0.989	1.000	0.020	1.000	0.850
Uncond.Hedge 2 (UH2)	0.427	0.425	0.069	0.700	0.175	0.993	1.000	0.017	1.000	0.875
Uncond.Hedge 3 (UH3)	0.422	0.425	0.124	0.800	0.050	0.999	1.000	0.006	1.000	0.925
Uncond.Hedge 4 (UH4)	0.419	0.425	0.085	0.725	0.075	0.996	1.000	0.013	1.000	0.875
Uncond.Hedge 5 (UH5)	0.378	0.375	0.060	0.575	0.175	0.981	1.000	0.033	1.000	0.750
Cond. Hedge 1 (CH1)	0.460	0.450	0.058	0.700	0.250	0.993	1.000	0.017	1.000	0.875
Cond. Hedge 2 (CH2)	0.495	0.500	0.099	0.825	0.150	0.999	1.000	0.006	1.000	0.925
Cond. Hedge 3 (CH3)	0.485	0.500	0.096	0.825	0.100	0.991	1.000	0.017	1.000	0.875

[a] Defined over 40 years. [b] Defined over 10,000 simulations.

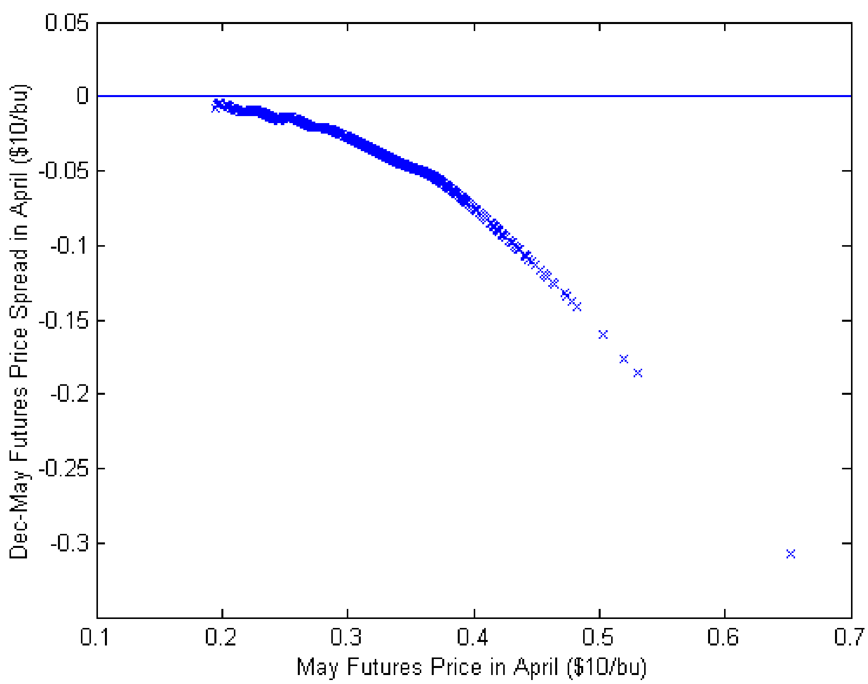
Table 8 Alternative Measures of Price Risk

	Standard Deviation		Measure A		Measure B		
Strategy	Value	Rank	Value	Rank	Value	%[a]	Rank
Base	0.479	11	0.290	9	na	na	na
Cash1	0.480	12	0.290	9	0.023	47.6	2
Cash2	0.461	9	0.315	12	0.120	60.2	5
Cash3	0.461	9	0.297	11	0.101	53.8	4
UH1	0.350	6	0.231	5	0.175	28.1	9
UH2	0.349	5	0.233	7	0.049	13.3	3
UH3	0.275	1	0.200	2	0.233	21.6	11
UH4	0.285	2	0.213	4	0.160	25.5	7
UH5	0.362	7	0.270	8	0.122	43.1	6
CH1	0.444	8	0.232	6	0.000	0.0	1
CH2	0.324	4	0.187	1	0.168	21.0	8
CH3	0.293	3	0.210	3	0.193	23.2	10

A = square root of, (\$(*t*)-basemean)^2 summed over \$(*t*) less than basemean, divided by total number of observations

B = square root of, (\$(*t*)-base(*t*))^2 summed over \$(*t*) less than base(*t*) and base(*t*) less than basemean, divided by total number of observations

[a] Percentage of occurrence of {\$(*t*) less than base(*t*) and base(t) less than basemean}



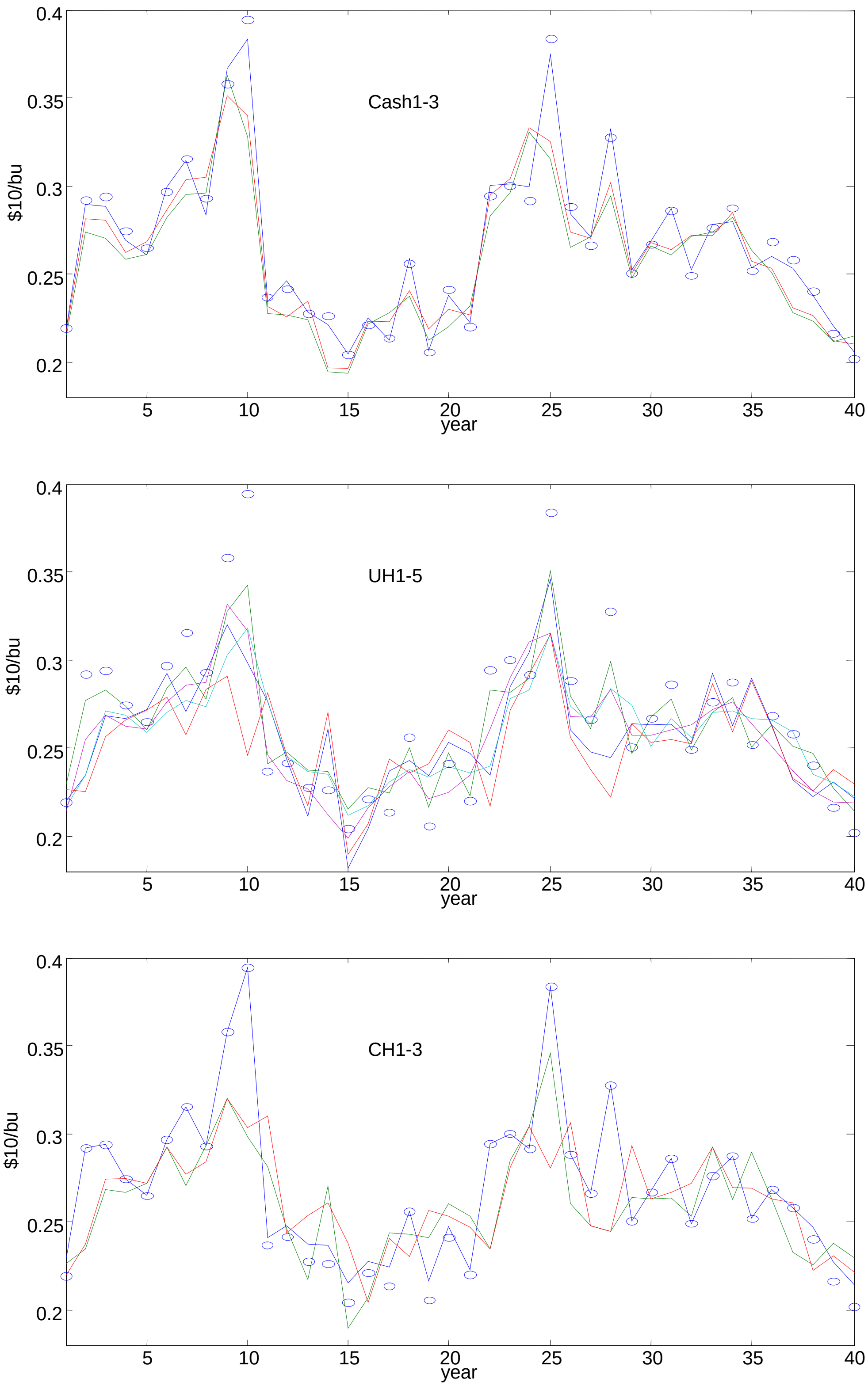


Figure 2 Annual Average Receipts from Various Marketing Strategies During a 40-Year Period

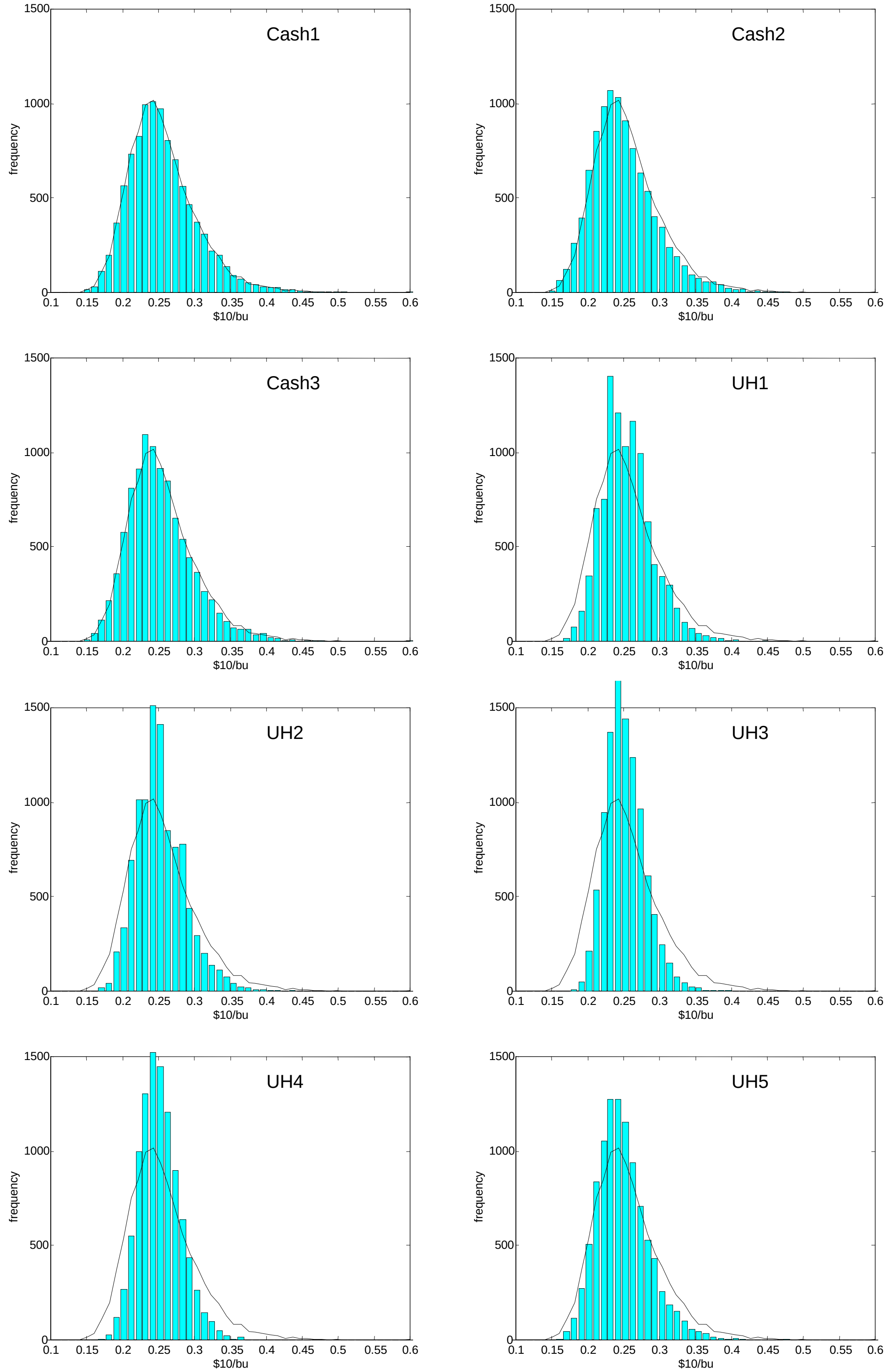
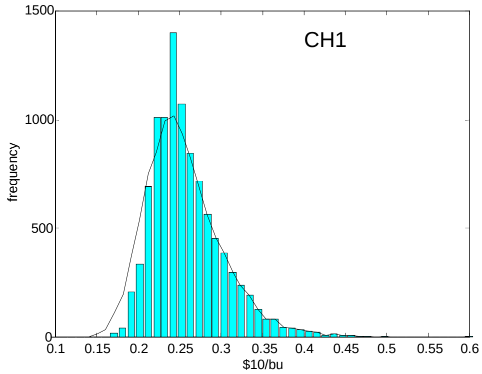
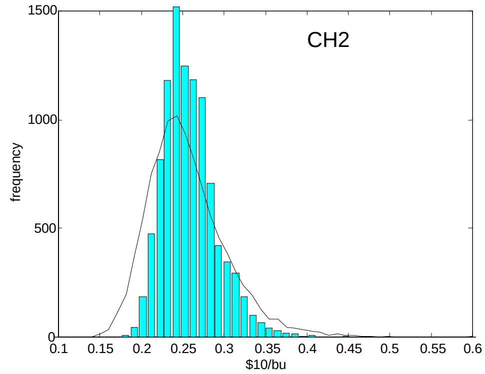
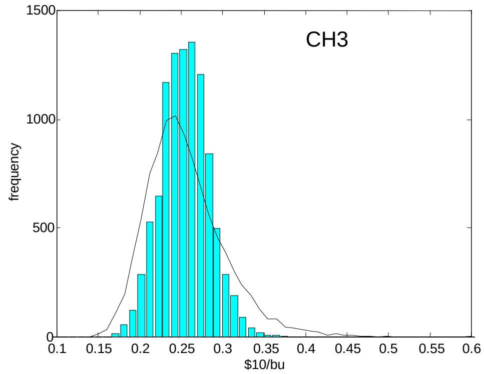


Figure 3 Distribution of Simulated Marketing Returns

Figure 3 (Continued)







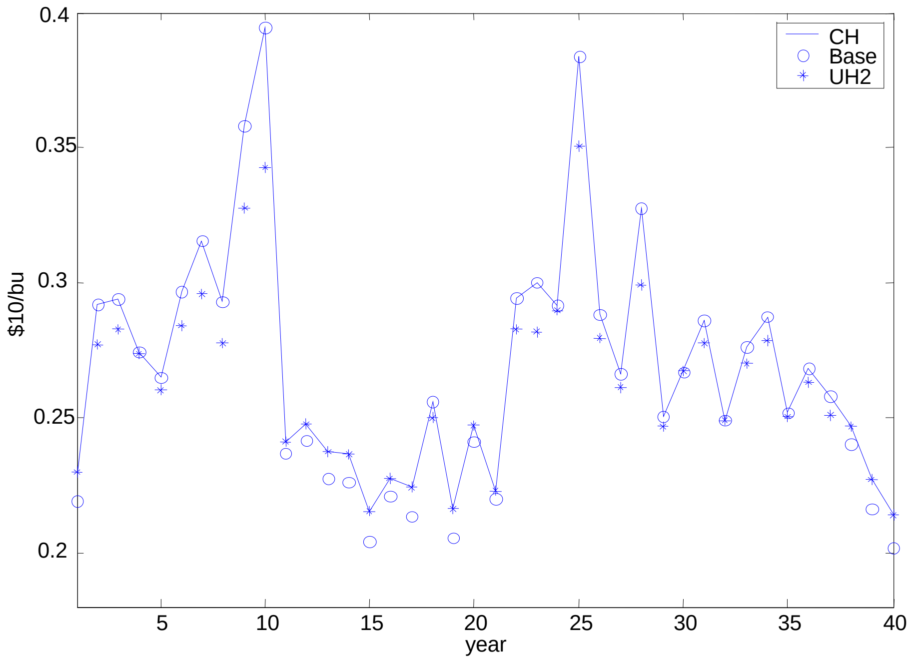


Figure 4a Conditional and Unconditional Hedging Strategies (CH1,UH1)

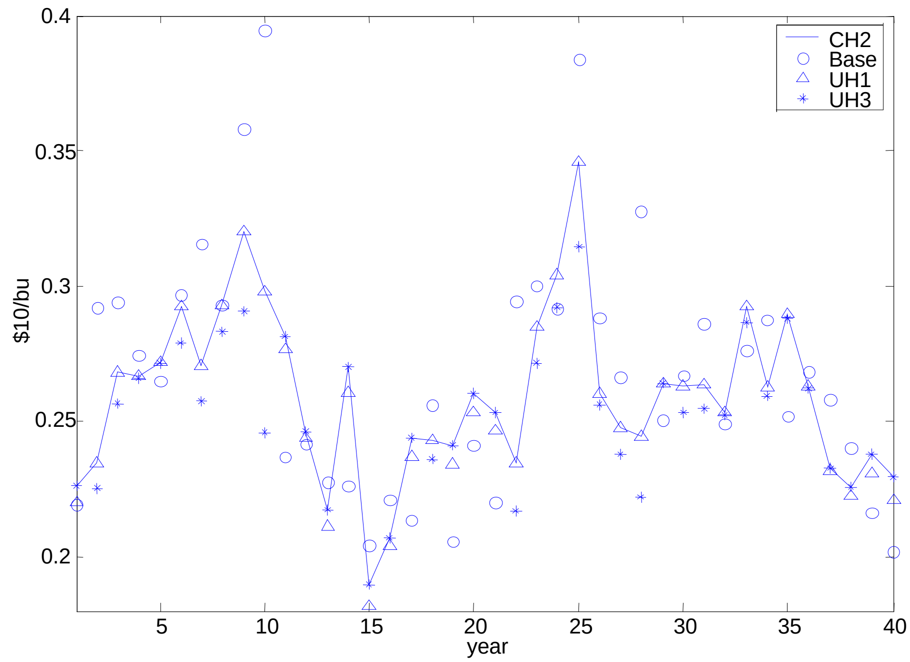


Figure 4b Conditional and Unconditional Hedging Strategies (CH2, UH1, UH3)

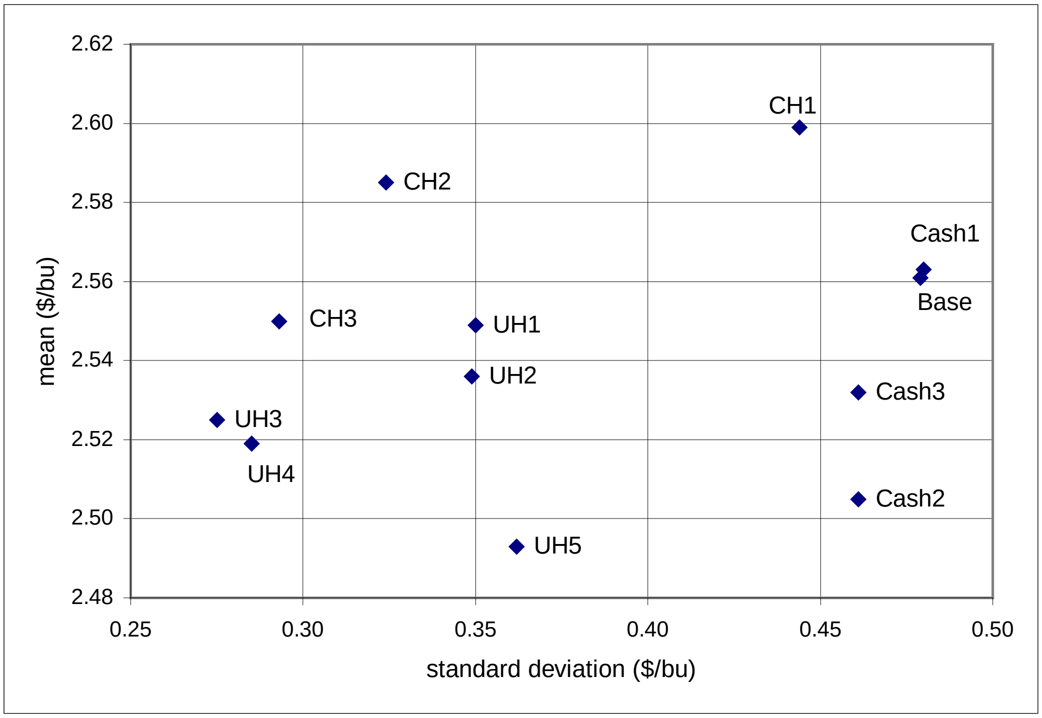


Figure 5 Mean-Variance Characteristics of Marketing Strategies

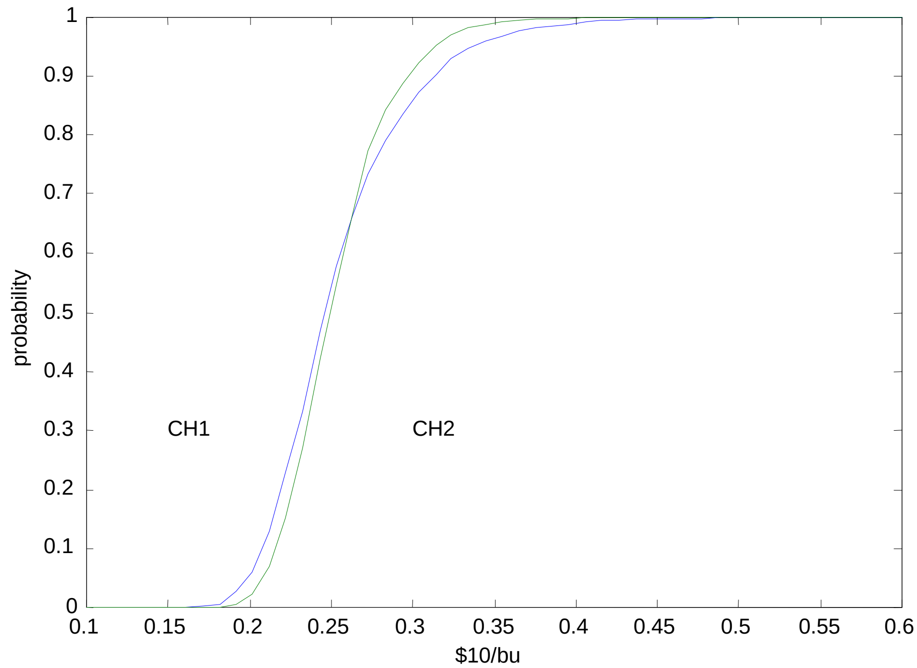


Figure 6 Cumulative Distribution Functions of the Second-Degree Stochastic Efficient Marketing Strategies

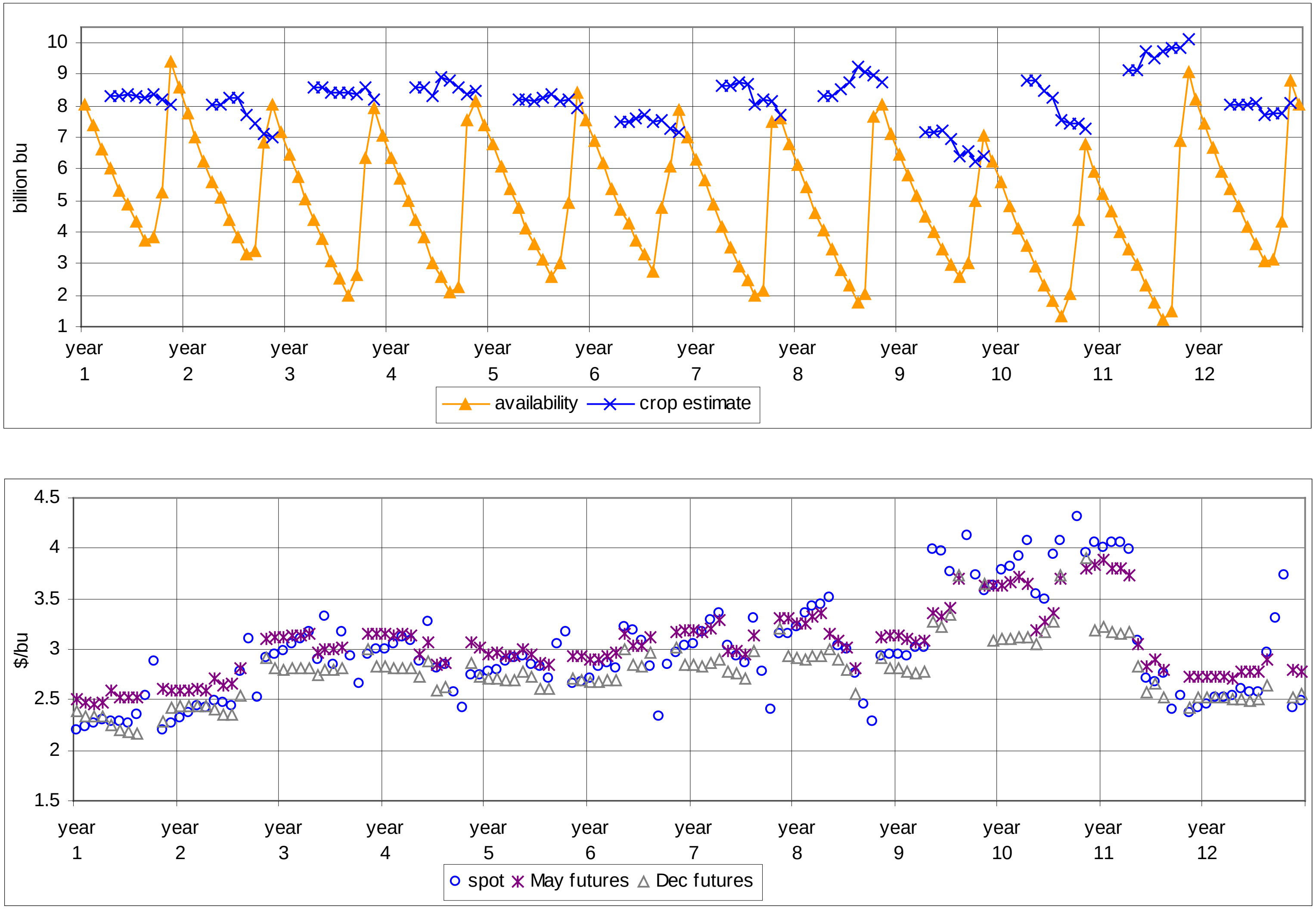


Figure 7 Time Series of the Simulated Market

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