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Grain Marketing Strategies Within and Across Lifetimes

Hikaru Hanawa Peterson and William G. Tomek

To reconcile the discrepancy between the efficient market hypothesis and grain marketing recommendations by advisory services and extension programs, simulated prices from an efficient market are used to compare performance of marketing practices over the long run and in individual 40-year periods. We find that an efficient market can generate diverse price behavior within finite samples, allowing for strategies that are inferior on average to perform relatively better, as frequently as half of the time in an average 40-year lifetime. Lifetime returns of strategies show considerable overlap, suggesting extremely low confidence in recommendations made based on short samples.

Key words: commodity storage model, efficient market, finite sample, grain marketing, long run, rational expectations, simulation

Introduction

Extension economists and marketing consultants have recommended a variety of strategies to farmers for marketing corn, soybeans, and wheat. They are motivated by a widespread belief that many farmers are "poor" marketers who can benefit from "improved" marketing of their crops (Anderson and Brorsen, 2005; Hagedorn et al., 2005). Presumably, such an improved strategy would reduce the variance of returns and/or increase the mean returns, but by definition, one-half of farmers will always have returns below the median, which may differ from the mean if the returns are skewed. Thus, it is sometimes not clear what consultants are promising. Nonetheless, grain marketing programs may help some farmers improve their returns relative to their past performance.

Although specific strategies differ in their details, recommended strategies fall into two broad categories: those that involve diversification of sales and those that rely on forecasts of price changes (or a combination of the two). The recommendations often take advantage of the ability of farmers to forward contract or to use futures and options markets. The existence of such markets permits some portion of the crop to be sold before harvest, and also provides longer time spans for diversifying sales and for taking advantage of forecast changes in prices. Some of the so-called "new generation" contracts (Hagedorn et al., 2003) offer producers, for a fee, an average price over a period of time. Other buyers provide a service of automating the marketing decision for farmers (Beurskens, 2000).

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The efficacy of some marketing programs is debatable. First, recommendations can be in conflict with the assumption of efficient markets; i.e., price forecasts that have economic significance are inconsistent with markets being pricing efficient, where current prices reflect current information and arbitrage opportunities do not persist (Fama, 1970). Second, it is not immediately obvious that diversification reduces the variance of returns, because the variances of grain prices are not constant over the marketing season; diversification can result in deferring sales to months with larger variances. Moreover, recommendations are sometimes derived from empirical results based on short, historical samples and data mining. The degree to which such results are applicable to future realizations of prices is unclear, and such research typically does not report confidence intervals in comparing marketing strategies.

The persistence of conflicting points of view in the literature is perhaps not surprising. Relatively small samples are used in many analyses of alternative marketing programs, partly due to the challenge of obtaining high-quality, high-frequency observations for commodities over long historical periods. Furthermore, short samples for recent periods seem desirable because they are likely more applicable to current conditions. Grain prices in particular have been subject to structural changes associated with major changes in farm programs. Consequently, it is difficult, and perhaps impossible, to measure returns or to estimate model parameters with precision (Luenberger, 1998, p. 214). With sampling errors associated with small samples, the confidence that one can place in the results from short time series is questionable.

One approach to a better understanding of different views is to analyze a large number of samples obtained by simulation from a constant market structure. Accordingly, the objective of this paper is to demonstrate how measures of returns from alternative marketing programs can be influenced by the particular (finite) sample used in the analysis, relative to the long-run comparisons, under the assumption of an efficient market. Prices used for the analysis are simulated using a model of the U.S. corn market (Peterson and Tomek, 2005). This model follows the framework of rational expectations storage models for grains (Williams and Wright, 1991), and is able to generate monthly prices that are distributed comparably to those observed in the U.S. corn market during recent decades. Tomek and Peterson (2005) reported comparisons of how selected marketing strategies perform in the long run using the prices simulated from the Peterson and Tomek model. To be clear, our objective is not to provide specific recommendations for marketing corn, but rather is to increase the depth of understanding about the diversity of outcomes that can occur over different finite periods. These simulations give a deeper appreciation of the complexities associated with making useful marketing recommendations to grain producers.

Toward that end, the simulated prices are used to compare returns received from representative, alternative marketing practices using 40-year periods, which can be viewed as a farmer's lifetime, and for the average over 10,000 lifetimes, i.e., the long run. We also illustrate the consequences of using shorter than 40-year samples in forecasting price changes, which is a common basis for recommending marketing strategies. We find, for example, that strategies with low average returns in the long run can perform relatively well in many lifetime periods, and that arbitrage opportunities identified ex post for one finite period cannot be exploited in future periods. Thus, a strategy based on analysis of a historical sample can be more profitable than a benchmark strategy within the evaluation period, but not be successful in subsequent periods. Since the prices are generated by an efficient market, such results may not be surprising, but some results run counter to conventional wisdom. Our analysis is the first to characterize return distributions for alternative strategies across repeated samples. Large overlaps of these distributions suggest that the confidence one can place in the results from typical short samples is likely to be small.

The paper is organized as follows. First, the simulation model and the nature of prices generated by it are briefly reviewed. Next, selected marketing strategies which are representative of common recommendations are simulated, and the outcomes from the long run are compared to those from 40-year periods. The concluding section provides a discussion of the implications of the large variety of outcomes that can be generated by an efficient market with a constant market structure.

Simulating Prices

A Structural Model of the U.S. Corn Market

The Peterson and Tomek (PT) model is based on the modern theory of competitive storage (Williams and Wright, 1991), which appends supply, demand, and market-clearing conditions to the intertemporal arbitrage equation of Working's (1949) classic model. Aggregate storage is restricted to be nonnegative (Gustafson, 1958), and price expectations are formed based on Muth's (1961) rational expectations hypothesis. Importantly, the model endogenizes futures prices by structurally linking their formation to the optimizing behavior of commodity stockholders, producers, and consumers, and allows decision makers to revise their price expectations given exogenous changes in their market environment.

PT incorporated considerable realism in the framework to depict the monthly U.S. corn market. Storage decisions are made based on a monthly arbitrage equation, and consumption levels are determined by monthly demand functions. In equilibrium, the crop available at the beginning of the month is either consumed or carried over to the next month. Planting decisions are made in April based on expected price at harvest. The crop is harvested from September through November. The expected crop size evolves incorporating random shocks during the growing season, and together with the information on the timing of harvest, impact storage and consumption decisions. Both consumption and planting decisions are also subject to respective random shocks.

Thus, the endogenous variables (prices, quantities consumed, storage, and crop planted) are functions of six state variables: month, demand and supply shocks, available supply, expected crop size, and harvest timing. The last three state variables depend on the endogenous variables and thus are also endogenous. The function tracing out the reduced-form relationship between the price and the state variables is determined numerically, assuming specific functional forms for the storage cost and demand functions, specifying distributional assumptions about the supply shock, the errors of the random walk process of crop size, proportions of crop harvested, and demand shocks, and calibrating the parameter values to the U.S. corn market from September 1989 to August 1998. The base period ensures the model generates values for its endogenous variables that are consistent with the recent market environment.

The model simulation proceeds forward in time. At the beginning of each month, available supply is realized as the amount carried over from the previous month plus any incoming harvest. Demand shocks are generated according to the specified probability distributions, as is a supply shock at the beginning of April. Available supply and the realized supply shock determine the size of crop planted in April. The planted crop size becomes the expected crop size and evolves as a Markov process through the beginning of November. At the beginning of August and September, the expected proportions of crop harvested in September and October are drawn from specified distributions. These values are used to compute the actual (in simulation) proportions of crop harvested in September and October. In November, the last harvest of the year takes place, determining the overall crop size for the year. The simulated values of the state variables are inserted into the cash price function to determine the price level. The price level, along with realized demand shock, determines quantity consumed, and the difference between the available supply and consumption is carried over to the next month.

December and May futures prices are simulated from initial states in months prior to their respective maturity dates. By definition of rational expectations, the basis converges to zero at contract maturity in this model. The relationship between the initial states and futures contract prices are solved numerically analogous to the cash price functions.

Once the cash and futures price functions were determined, they were used to simulate 10,000 price series of 40 years each. These simulations are described in more detail in subsequent sections. In the remainder of this section, we focus on the properties of the price series generated by such simulations. All samples are, by construction, generated from an efficient market.

Properties of Simulated Prices

For our purpose, it is sufficient that the simulated prices are plausible outcomes from a hypothetical, but realistic commodity market. In fact, the equilibrium prices generated by the model reflect distributional features observed in the U.S. corn market during recent decades. Even though the model was calibrated to the market values in the 1990s, the model can generate a wide variety of price behaviors, including one similar to the recent experience in the 2000s.

A critical distributional feature of commodity prices is seasonality, and one way of characterizing seasonal price patterns is by calculating a seasonal price index using monthly prices. Monthly price indices computed using cash bids for U.S. No. 2 yellow corn in Central Illinois from 1989/90 to 2003/04 crop years are compared to those based on the simulated prices in figures 1a and 1b.[1] The thick line represents the average, and thin lines represent plus and minus one standard deviation from the average. Both figures show that monthly prices increase on average from harvest in the fall through May, reflecting storage costs, and revert toward the harvest-time low during the growing season. At the same time, the dispersion is low after harvest, then increases throughout the following season before narrowing in August.[2]

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[1] The indices were calculated by dividing the monthly prices by the crop-year average for each crop year and averaging the ratios across crop years.

[2] The seasonal behavior is consistent with a longer history. Dhuyvetter and Kastens (2004) report a similar seasonal pattern in corn prices for Southern Central Kansas, using 31 years of data from 1973/74 to 2003/04.

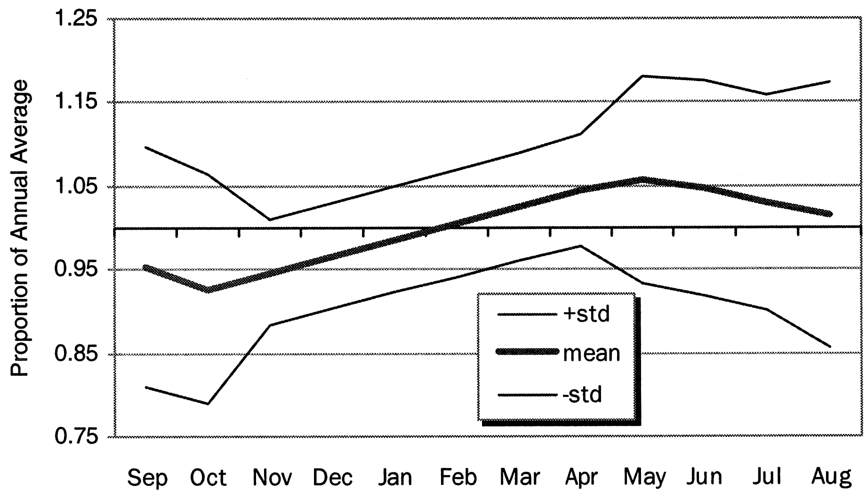

Figure 1a. Seasonal index for simulated cash prices

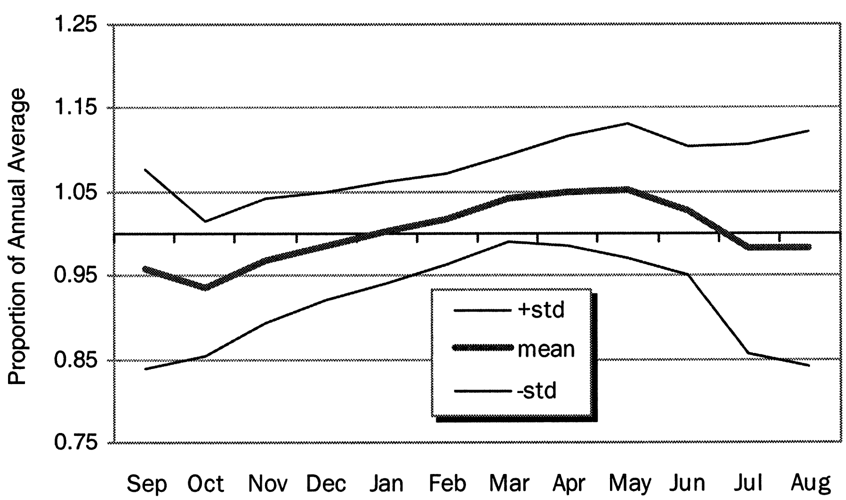

Figure 1b. Seasonal index for No. 2 yellow corn, Central Illinois (1989/90–2003/04)

The model is efficient by construction, which is confirmed by testing for efficiency using the simulated prices. In an efficient futures market, the current quote is an unbiased forecast of the price at contract maturity, assuming no risk premium. A seasonal price index, computed from the simulated pre-harvest December futures prices, illustrates the model's assumption of efficiency (figure 2a); the mean does not vary seasonally. In comparison, a seasonal price index computed from pre-harvest prices for 1989 to 2004 December corn futures contracts at the Chicago Board of Trade (figure 2b) shows that December futures prices on average were higher during February through April than in July and August preceding harvest. Given the distribution around the simulated seasonal means, however, this 16-year sample could have been generated by an efficient market like the one assumed in the simulation model.

A common model to examine pricing efficiency makes the maturity month price (F_T, or equivalently, the cash price P_T for the par location) a function of the futures price on some previous date, say i months prior to maturity:

$$P_T = \alpha + \beta F_{T-i} + e_T, \tag{1}$$

where α and β are parameters and e is a random error term. In an efficient market, the parameters take on values of $\alpha = 0$ and $\beta = 1$. Equation (1) was fitted using the simulated prices for both the December and May futures contracts for selected lag lengths to test the null hypothesis that intercept and slope parameters equal [0, 1] jointly.

Specifically, the December cash price was made a function of the December futures contract prices observed the prior February, May, and July, and the May cash price was made a function of the May futures prices observed in the preceding November, January, and March. For both contracts, the null hypothesis that the parameters equal [0, 1] could not be rejected for the three different time lags at the 5% significance level based on a sample of 400,000 years.

Evaluation of Marketing Strategies

Four groups of marketing practices are considered. All strategies are, by necessity, stylized versions of those found in the academic literature and/or recommended by marketing advisers. Clearly in all cases, farmers may alter their return distributions by enrolling in commodity programs or purchasing crop insurance or both. But, in line with our objective, we focus only on evaluating differences in returns from marketing strategies. The base case is selling the entire crop at the November cash price.[3] For the other strategies, the marketing window is assumed to extend from February preceding harvest (when December futures might be sold) through July of the following year. The strategies are summarized in table 1.

The first group involves diversification of sales, sometimes called "scale-up" strategies. A simple post-harvest, cash-only strategy is to sell one-ninth of the crop each month from November through July (strategy 1a, table 1). Alternatively, a marketing advisory service recommended pre-selling 12% and 33% of the crop by May 1 and October 1, respectively, and selling the remainder of the crop at seven points in time

[3] The benchmark is selected for convenience. As a reviewer pointed out, this base strategy itself may be regarded as a potentially optimal marketing strategy. Irwin et al. (2006) discuss suitability of benchmarks.

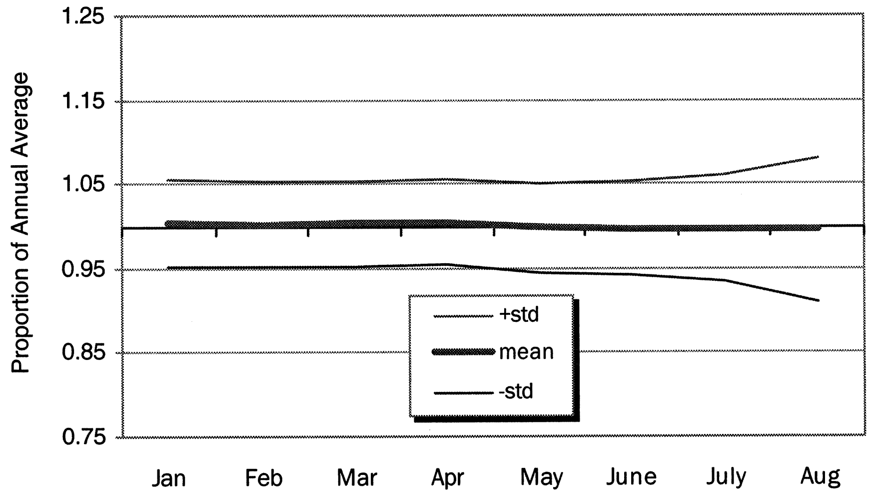

Figure 2a. Seasonal index for simulated December futures prices

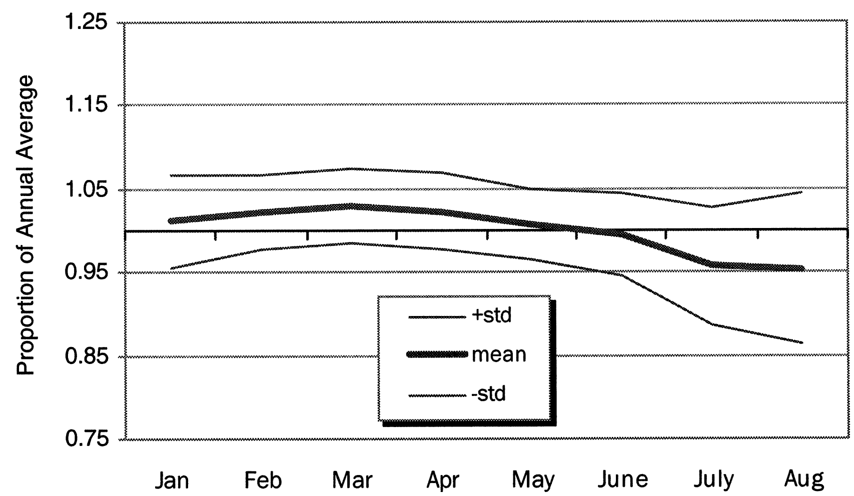

Figure 2b. Seasonal index for December corn futures contracts, Chicago Board of Trade (January–August 1989–2004)

Table 1. Description of Marketing Strategies

		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**	Aug.
	Base										Sell cash 100%									
Scale-Up	1a										Sell cash 11.1% ---------------------------------->									
Scale-Up	1b	Sell Df 10%		**Sell Df 10%**		*Sell Df 20%*						*Buy back Df 40% & sell cash 40%*		Sell cash 20%		**Sell cash 20%**			**Sell cash 20%**	
Pre-Harvest Hedge	2a				Sell Df 100%							*Buy back Df 100% & sell cash 100%*								
Pre-Harvest Hedge	2b	If A, sell Df 100%[a]			Else sell Df 100%							*Buy back Df 100% & sell cash 100%*								
Post-Harvest Storage	3a																Sell cash 100%			
Post-Harvest Storage	3b										Sell Mf 100%						Buy back Mf 100% & sell cash 100%			
Post-Harvest Storage	3c										If B, sell Mf 100%, else sell cash 100%[b]						If B, buy back Mf 100% & sell cash 100%[b]			
Speculative	4a										Sell cash 100% & if C(D), sell (buy) Mf 100%[c]						Buy (sell) back Mf 100% if C(D)[c]			
Speculative	4b										Sell cash 100% & if E(F), sell (buy) Mf 100%[d]						If E(F), buy (sell) back Mf 100%[d]			

Notes: For ease of visual alignment, plain, italic, and boldfaced text entries in table body correspond to plain, italic, and boldfaced months in column heads. "Df" and "Mf" denote December and May futures, respectively.

[a] "A" is $H_{11}^{t-1} < \Sigma_{m=9}^{12} q_m^{t-2} + \Sigma_{m=1}^{8} q_m^{t-1}$, where H_{11} is the harvested crop size and q_m is the quantity consumed in month m.

[b] "B" is $(MFP_{11} - 6k)/(1+r)^6 - b > P_{11}$, where MFP_{11} and P_{11} are the May futures price and cash price in November, respectively; k is monthly storage cost; r is the monthly interest rate; and b is the brokerage fee.

[c] "C" is $(\hat{P}_5 - 6k)/(1+r)^6 - b > MFP_{11}$, and "D" is $(\hat{P}_5 - 6k)/(1+r)^6 - b \le MFP_{11}$, where $\hat{P}_5$ is based on regressing equation (1) using the previous 10 years.

[d] "E" is $(\hat{P}_5 - 6k)/(1+r)^6 - b > MFP_{11}$, and "F" is $(\hat{P}_5 - 6k)/(1+r)^6 - b \le MFP_{11}$, where $\hat{P}_5$ is based on regressing equation (1) using the previous 10 years, and the intercept and slope coefficients in equation (1) are statistically different from [0, 1] at the 5% level.

ending the spring or summer following harvest [on average in 1995–1997; see Irwin, Good, and Jackson (2000)]. To mimic this approach, strategy 1b uses December futures to sell 10% of the expected crop in February and in April and another 20% in June. These positions are offset in December, when 40% of the crop is sold at harvest, and the remaining crop is sold in equal amounts in the cash market in February, April, and July.

The second set of strategies involves hedging with futures prior to harvest. Strategy 2a routinely sells the entire expected crop in May, using the December futures price, and completes the hedge in December when the entire crop is marketed after one month of storage. Another strategy uses a conditional hedge motivated by Wisner, Blue, and Baldwin (1998), wherein a pre-harvest hedge depends on whether the immediate past harvest is large or small relative to the previous level of consumption. Specifically, in strategy 2b, the crop to be harvested in the autumn of year t is sold in February of year t at the prevailing December futures price, if the year $t - 1$ crop was smaller than the utilization in year $t - 2$. Otherwise, the crop is sold in May of year t using December futures.[4]

The third strategy group stores the crop after harvest. Strategy 3a routinely stores the crop without hedging, while strategy 3b routinely stores and hedges in November using May futures. In both 3a and 3b, the corn is sold at the May price. Strategy 3c uses the harvest-time basis as a guide to making storage and hedging decisions. If the May futures price in November is higher than the spot price plus storage and transactions costs, the entire crop is stored, May futures are sold, and the hedge is completed at the May price; otherwise, the crop is sold immediately at the November cash price. This strategy is based on the expected basis convergence at contract maturity, and in the PT simulation model, convergence will be exact.

The fourth set of strategies is speculative. Although the simulations generate efficient futures prices, 10-year subsamples exist wherein the null hypothesis of pricing efficiency, as defined in equation (1), is rejected. A decision maker might try to use such an equation to make speculative profits. Strategy 4a is based on using a forecast made in November of the futures price in May from regression analysis of the preceding 10 years. For example, if the forecast May price, adjusted for interest rate and brokerage fees, is below the current November price of May futures, the speculator should sell May futures in November expecting to offset the position at a lower price in May. If the adjusted May price forecast exceeds the current May futures price, the speculator should buy May futures in November and sell in May at a higher price. In order to report the returns analogously to the other strategies, we assume that the entire crop is sold at harvest, and these returns are adjusted for the speculative gains or losses. Strategy 4b is equivalent to 4a, except the speculation occurs only when the two coefficients in equation (1) are statistically different from zero and one, respectively, at the 5% level based on an F-test. If the joint hypothesis is not rejected, strategy 4b is analogous to the base strategy.

All strategies were simulated for 10,000 40-year lifetimes.[5] Since the base scenario is to sell the entire crop in November, the prices received from each strategy were

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[4] Wisner, Blue, and Baldwin (1998) report that during 1975–96, the prices of December futures were, on average, higher earlier in the life of the contract than at contract maturity, which is consistent with figure 2b. The high occurred in February following a relatively small crop, and during May and July following a normal crop.

[5] The exercise simulates the returns of nine farmers who have 10,000 50-year lives, live for the same 50 years each time, and record the returns for the last 40 years. Each farmer follows one of the strategies for her whole life. The farmer following a strategy based on a regression forecast uses observations from the first 10 years to obtain her first forecast (in year 11).

standardized to represent returns per bushel in November, net of opportunity, storage, and brokerage costs. The monthly interest rate and physical storage cost were assumed to be one-twelfth of 10% and 3¢ per bushel, respectively, consistent with the simulation model specification. The brokerage cost was assumed to be 1¢ per bushel for a round-turn transaction in futures.[6] Storage costs were accumulated while the crop remained in storage and were subtracted from cash receipts when the crop was taken out of storage. The brokerage cost was incurred at the time of the initial futures transaction. All prices and costs were discounted or compounded by the interest rate to obtain the normalized November price.[7]

In interpreting the results, the reader should also remember that efficient markets cannot foresee the unexpected, and seeming "forecast errors" do not indicate irrationality or a market failure (Williams and Wright, 1991). Efficient markets can, therefore, generate prices which are seemingly irrational over finite periods, in the sense that with 20-20 hindsight, a marketing strategy can be found which provides higher returns than from the base case.

Long-Run Results

Descriptive statistics for the simulated marketing returns for 10,000 40-year lifetimes are summarized in table 2. We refer to the 40-year statistics as the *lifetime* statistics and the grand averages of the lifetime means and of the standard deviations as the *expected lifetime* means and standard deviations. For example, for the base case, the expected lifetime mean—computed from 10,000 samples—was \$2.56 per bushel with an expected lifetime standard deviation of \$0.45. To be clear, 0.45 was the average of standard deviations computed from the individual 40-observation samples, and the standard deviation of the 10,000 means was \$0.13 per bushel. Accordingly, returns generated by an efficient market for an individual lifetime, on average, were highly variable. The largest lifetime standard deviation following the base strategy for one 40-year period was \$1.28, while the smallest was \$0.20 per bushel.

The simulated performance of these strategies was largely consistent with expectations for an efficient market,[8] but diversification of cash sales (strategy 1a) lowered the expected lifetime return with little effect on the average riskiness of returns. If selling more frequently incurs additional costs, then selling the entire crop at harvest is likely a more efficient strategy. Combining pre-harvest futures sales with post-harvest cash sales (strategy 1b) reduced the expected lifetime variability of returns by 11.9¢ per

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[6] Jackson, Irwin, and Good (1998) assume \$50 per contract for round-turn futures transactions, and the contract size for corn on the Chicago Board of Trade is 5,000 bushels.

[7] For example, the price received from the routine pre-harvest hedging strategy (2a) is calculated as follows. In May, the brokerage fee (b) for a single round-turn futures transaction is incurred for selling the entire crop using a December futures contract, which is compounded by the monthly interest rate (r) for six months between May and November ($= -b(1+r)^6$). In December, the change in the December futures price from May to December ($DFP_5 - DFP_{12}$) is earned or lost from lifting the hedge, and the difference is discounted for one month ($= (DFP_5 - DFP_{12})/(1+r)$). In addition, the December price is adjusted for one month of storage ($= (P_{12} - k)/(1+r)$), where k is monthly storage cost per bushel. Since the cash and futures prices are identical at contract maturity (i.e., $DFP_{12} = P_{12}$), the receipt from strategy 2a, adjusted to November, is: $-b(1+r)^6 + (DFP_5 - k)/(1+r)$.

[8] Not surprisingly, the simulated returns from alternative strategies had different means and variances in the long run, even though prices were generated from equilibrium conditions that assumed no arbitrage. One reason is that the prices are exogenous from an individual decision maker's perspective. Further, the price received represents only a part of the return to storage, although the discussion below ignores convenience yield that can accrue to a stored crop.

Table 2. Descriptive Statistics of Simulated Marketing Returns over 10,000 40-Year Lifetimes

	Lifetime Mean				Lifetime Standard Deviation			
Strategies [a]	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.
	<------ ($/bushel) ------>				<------ ($/bushel) ------>			
Base	2.560	0.133	2.147	3.091	0.453	0.095	0.202	1.284
1a	2.530	0.138	2.132	3.095	0.429	0.098	0.183	1.286
1b	2.490	0.117	2.151	2.946	0.334	0.076	0.129	0.911
2a	2.549	0.098	2.239	2.929	0.333	0.058	0.185	0.625
2b	2.548	0.083	2.268	2.852	0.280	0.044	0.159	0.551
(% triggered) [b]	(50.2%)	(5.0%)	(32.5%)	(67.5%)				
3a	2.546	0.153	2.056	3.216	0.547	0.115	0.251	1.480
3b	2.536	0.098	2.229	2.915	0.332	0.068	0.136	0.926
3c	2.598	0.122	2.234	3.102	0.418	0.097	0.177	1.256
(% triggered) [b]	(51.4%)	(12.2%)	(7.5%)	(87.5%)				
4a	2.550	0.131	2.150	3.143	0.642	0.118	0.338	1.797
(% triggered) [c]	(22.7%)	(12.9%)	(0.0%)	(77.5%)				
4b	2.559	0.135	2.154	3.089	0.468	0.099	0.202	1.691
(% triggered) [d]	(7.3%)	(8.4%)	(0.0%)	(57.5%)				

Note: Lifetime means and standard deviations are defined over 40 years, with statistics computed from 10,000 simulations.
[a] The marketing strategies are fully described in table 1.
[b] The proportion of years within a 40-year period when the conditions were met to trigger the conditional hedging strategies.
[c] The proportion of years within a 40-year period when the May futures were bought for speculation. One minus the proportion equals the portion of years when the May futures were sold for speculation.
[d] The proportion of years within a 40-year period when the conditions were met to trigger the speculative strategies.

bushel. In light of the results for strategies 1a and 2a (to be discussed), this effect could be attributed to the pre-harvest futures sales. For strategy 1b, however, the expected lifetime return was 7¢ below the base.

Pre-harvest hedges (strategies 2a and 2b), on average, reduced risk at a cost of lower returns. The routine pre-sale of the expected crop in May using December futures (strategy 2a) reduced the expected lifetime standard deviation of returns by 12¢ per bushel relative to selling the crop at harvest. The foregoing result was driven by the seasonal and time-to-maturity behavior of the variances of futures prices, which exists in historical data (e.g., Streeter and Tomek, 1992) and was replicated by the simulated prices (figure 2a). By using futures contracts, sales were made at prices that were less variable, but there were small costs of hedging.

Similarly, the expected lifetime mean return from a conditional pre-harvest strategy (2b) was 1.2¢ per bushel lower than the base, but the expected lifetime standard deviation ($0.28) was 62% of the base. Our results are largely consistent with those of Wisner, Blue, and Baldwin (1998) where similar pre-harvest conditional hedging strategies yielded lower variability of returns than harvest sales with a small but statistically insignificant increase in the levels, despite the differences in the frequency of the hedge being triggered. The condition defined by Wisner, Blue, and Baldwin (current harvest falling short of the past year's consumption) occurred about 50% of the time in an average simulated lifetime ("% triggered" for strategy 2b); they reported a 36%

occurrence in the 1975–1996 sample. It should be noted that the comparison between strategy 2b and the work by Wisner, Blue, and Baldwin is at best crude.[9]

One could store the crop without hedging and receive 1.4¢ below the base on average (strategy 3a). However, the returns from this strategy were on average 20.8% more variable within lifetimes than the base. In contrast, a routine post-harvest hedge (strategy 3b) reduced the expected lifetime variability by 26.7% from the base at a cost of a 2.4¢ reduction in mean returns. Strategy 3c, which followed the basis signal, allowed the farmer to earn a positive return to storage when relative prices favored storage and otherwise avoid losses relative to the base. In the simulation model, there is no basis risk; thus, the return to storage was guaranteed whenever the initial basis was favorable, overstating the benefit of strategy 3c in practice. Nonetheless, comparison of these strategies supports the findings in previous research (Heifner, 1966; Kastens and Dhuyvetter, 1999), implying that the basis and its expected convergence are critical to storage decisions and that hedging is essential to assure the expected return to storage. Consistent with Heifner's evidence, when the November basis provided an incentive to store, inventory-holding without hedging (3a) incurred a loss relative to the base strategy in 44% of the years in an average lifetime.

The analysis of strategies 4a and 4b illustrates the issues associated with using statistical models based on finite samples to make speculative profits consistently in a fundamentally efficient market. On average, the returns from both strategies were similar to the base, but speculation increased the expected lifetime variability by as much as 40% (strategy 4a).

The prediction accuracy based on 10-year sample regressions was poor, as expected. When the prediction suggested buying the May futures, which was 22.7% of the time in an average lifetime ("% triggered" for strategy 4a), the speculative returns were realized 44.5% of the time; when the prediction suggested selling the May futures (occurring on average 77.3% of the time), the speculative returns were realized 55.5% of the time. Thus, the overall chance of speculative returns being realized was 52.6% ($= 0.445 \times 0.227 + 0.555 \times 0.773$). Over 10,000 lifetimes, the coefficients in equation (1) differed from [0, 1], at the 5% level, 7.3% of the time or nearly three years in an average lifetime ("% triggered" for strategy 4b).[10] Using the statistical significance of the regression-based rule helped little, increasing the overall expected chance of realizing the speculative returns to 53.2%, when the strategy was implemented.

The statistics reported in table 2 include the ranges of lifetime means and standard deviations, which help illustrate the variety of outcomes that are possible across different 40-year periods. Yet, these statistics do not provide a complete picture of this diversity, and the next section elaborates on this key point.

Lifetime Results

We report simulated distributions to demonstrate how returns from a given marketing strategy perform in different 40-year lifetimes as well as how the relative performance

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[9] Given the simulation model used, it is not feasible to replicate details of their analysis or other marketing practices such as new generation contracts. In particular, Wisner, Blue, and Baldwin (1998) computed returns that are more farm-specific including yields, costs, and basis.

[10] The probability of rejecting the null hypothesis should be 5% for tests that are done at the 5% level of type I error, but the classical test is biased for small samples from distributions that are not normally distributed. Nonetheless, we followed the convention of using the standard test.

of different strategies differs across lifetimes. The discussion centers on the mean levels and variability. These comparisons illustrate inter alia how the performance of marketing strategies in individual years, or even over a 40-year lifetime, diverges from their long-run expectations.

Mean Levels of Returns

We start by showing how frequently a particular strategy's returns equaled or exceeded the base strategy's returns. Figure 3 shows the frequency distributions of the number of years that four selected strategies yielded an equal or higher return than the base strategy (marketing the entire crop at harvest every year). For example, although diversification of sales (strategies 1a and 1b) had an expected "cost" in the long run of 3¢ to 7¢ per bushel, the distribution for 1a (1b is similar) shows that diversification yielded a higher return than the base strategy in 15 out of 40 years in about 1,500 lifetimes, i.e., 15% of all lifetimes. There were 880 lifetimes (8.8%) in which strategy 1a's returns exceeded the base return in 20 or more years. Clearly, even though diversification does not increase returns based on long-run averages, it can appear to do so quite frequently.

Returns from pre- or post-harvest hedges, such as strategy 2b (with a distribution similar to those of 2a and 3b), were higher than the base return in over half of the years in a typical lifetime. The chance that this hedge strategy would be superior to the base strategy more than 20 out of 40 years was about 0.60. Since strategy 2b would in theory yield higher returns when December futures prices were biased upward prior to harvest, the results suggest it is difficult to discriminate between an inefficient futures market with biased prices, and an efficient market where strategy 2b still had a large probability of being as good as or better than marketing the entire crop at harvest.

The distribution from storing the crop without hedging (strategy 3a) was similar to that from using regression-based forecasts routinely (strategy 4a). Both strategies provided returns that exceed the base in almost half of the years during a typical lifetime. This is a consequence of the nearly 50% probability that speculative "guess" will be correct (46.6% for 3a and 52.6% for 4a). Thus, even with a transactions cost of about 1¢, speculation can seem beneficial frequently. Strategy 4b—speculation based on significant regression results—provided returns that exceeded the base in only 1.3 years out of 40 on average, because it was implemented in less than three years out of 40 (triggered 7.3% of the time) on average. In an efficient market, speculation would be profitable, at most, half the time the strategy is used. It was nonetheless possible for conditional speculation to appear profitable in five or more years in particular 40-year periods and, as noted elsewhere, the speculative profit can be large in a single year.

The diversity of possible results using a single strategy in different lifetimes is illustrated in figure 4. It shows approximated distributions of the differences between the returns from strategy 1a and the base strategy in each of four selected lifetimes, labeled I through IV (created by SIMETAR©). Each of these distributions would be analogous to one inferred from a finite sample of historical prices. For lifetimes I and II, diversification produced returns that exceeded the base in more than half of the years. Nonetheless, the mean returns from these two 40-year periods differed; in I, diversification resulted in a mean return 4.2¢ above the base; for II, the distribution is skewed to the left, and diversification resulted in a mean return 3.4¢ below the base.

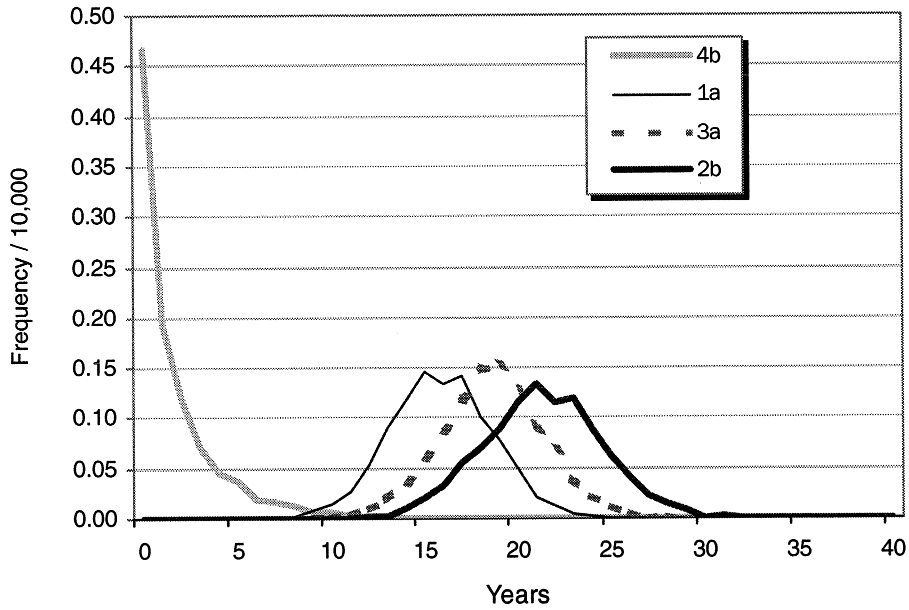


Figure 3. Distributions of the number of years per lifetime when the strategy return exceeded the base return

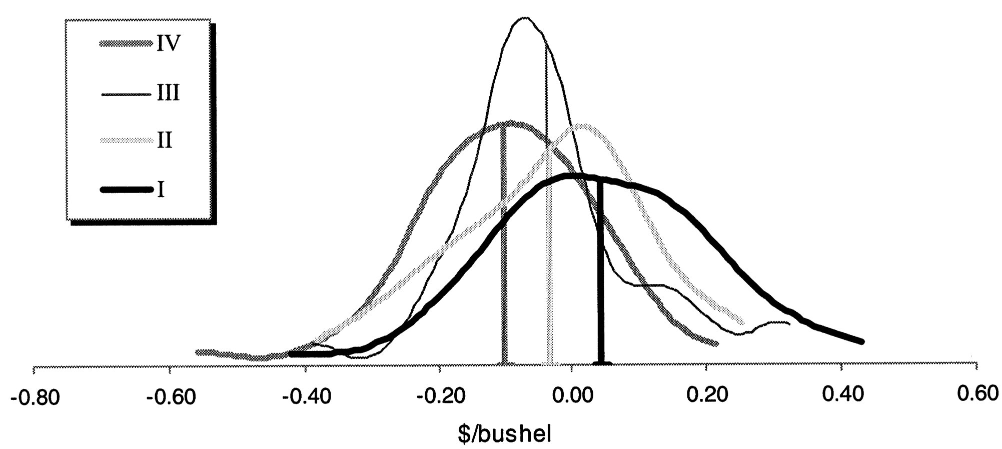


Figure 4. Distributions of differences in returns from strategy 1a and the base in selected lifetimes

In lifetimes III and IV, returns from strategy 1a exceeded the base in less than one-fourth of the years and averaged 3.7¢ and 10.2¢ below the base, respectively. The mean differences in returns for lifetimes II and III were similar, despite the differences in the number of years returns from 1a exceeded the base.

Despite the differences in means and degrees of symmetry, the distributions for the four lifetimes show considerable overlap. During lifetime I, which had returns with a relatively symmetric distribution and with a mean above the base mean, it was possible to have a year in which the return from diversification was 40¢ or more per bushel below the base. During lifetime IV, with a lifetime mean 10.2¢ below the base, it was still possible to have years with returns 15¢ or more above the base return.

Differences in Lifetime Standard Deviations

Turning to the effect of alternative strategies on the variability of returns, figure 5 plots the frequency of lifetimes against the differences in lifetime standard deviations between the base and selected strategies. Strategies with distributions centered to the left of zero are those that reduced the standard deviation in many or all lifetimes.

Hedging in futures—strategies 1b, 2a, 2b, and 3b—provided similar results across different lifetimes. Returns from hedging strategies had smaller lifetime variability than the base strategy in the vast majority (98% to 100%) of lifetimes. As illustrated in figure 5 for strategy 2a, the magnitude of reduction varied across lifetimes from more than 35¢ to exceeding the base standard deviation by more than 10¢. Another hedging strategy—3c, conditional on the harvest-time basis—had standard deviations only slightly smaller than those of the base, because the crop was stored only in selected years. Naturally, strategy 3c could be combined with 2a or 2b to reduce the variability of returns.

The diversification of cash sales (strategy 1a) lowered the variability of lifetime returns in 82% of the lifetimes, but the reduction was typically small (figure 5). Though difficult to see in the figure, there was a nonzero probability that diversification would result in a lifetime standard deviation that is more than 15¢ per bushel above the base case. If instead the farmer routinely stored the entire crop until May unhedged (3a), then the standard deviation was larger than the base in 90% of the lifetimes. This result is predictable because spot prices are more variable in May than at harvest. Nonetheless, lifetimes existed where storing the crop unhedged resulted in a lower lifetime standard deviation than that of the base, and by as much as 10¢.

Routine speculation (strategy 4a) increased the lifetime standard deviation, relative to the base, in nearly 100% of the lifetimes, but again, the difference ranged from more than 40¢ above to more than 10¢ below the corresponding base. Conditional speculation (4b) increased the lifetime standard deviation, relative to the base, in 57% of the lifetimes with a smaller range of differences from more than 20¢ above to more than 10¢ below. The additional risk is not offset by consistently positive returns. Lifetime average speculative returns ranged from -24.5¢ to 29.6¢ per bushel for strategy 4a, and from -11.9¢ to 7.2¢ for strategy 4b. The latter, smaller effect of speculation relates to the infrequency of the condition being met within a 40-year period. All of the foregoing pertains to 40-year periods, and of course the yearly returns to speculation can vary much more. Indeed, the simulated speculative return from 4a (4b) ranged from -\$3.83 (-\$3.08) to \$4.18 (\$2.45) per bushel in a given year.

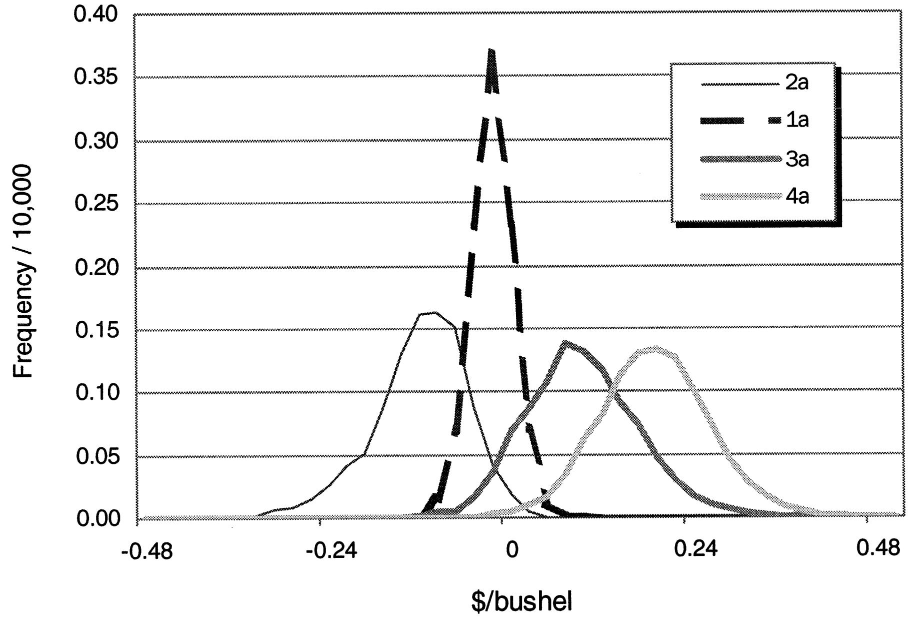


Figure 5. Histograms of the differences in lifetime standard deviations from the base

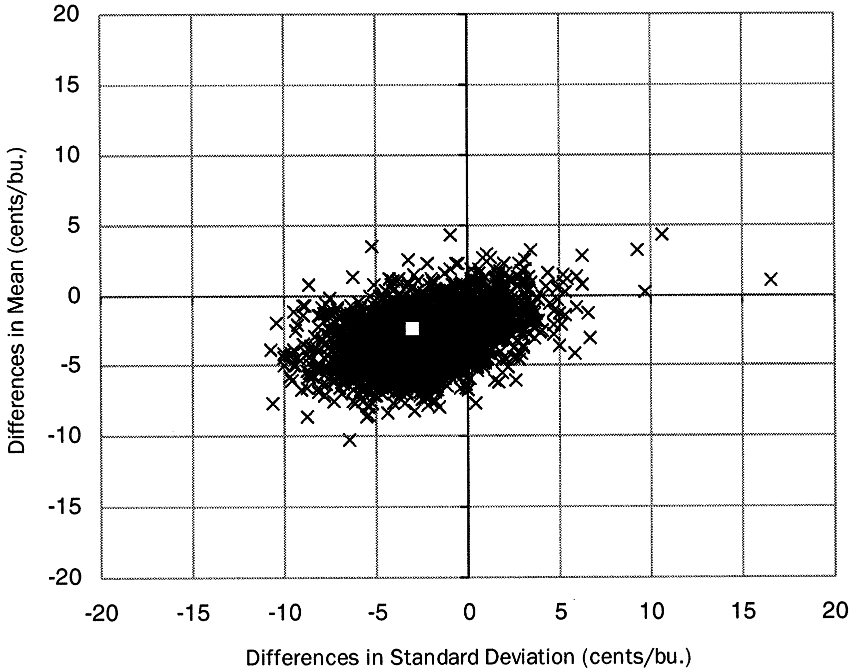
Mean and Variance

As preceding sections illustrated, performances of strategies vary considerably around the long-run expectations. Figure 6 illustrates the 10,000 differences from the base in lifetime means and standard deviations for strategy 1a, which in the long run reduces standard deviation from the base by 2.4¢ at a cost of 3¢ reduction in the mean. One can experience all sorts of lifetimes, including those where diversifying post-harvest sales can yield higher average return than the base with lower variability.

The simulations also permit comparison of the distributions of returns conditional on whether or not the strategy's variability was larger or smaller than the variability of the base returns for the identical samples. Figure 7 compares the distributions of differences in yearly returns for strategy 1a to the base for two categories of lifetimes: one with a lower and the other with a higher lifetime standard deviation than the base. The figure shows the mean of the returns from the high-variability lifetime is to the right of the low-variability lifetime returns, but the two distributions overlap considerably. A conclusion from these distributions, which is also true for other strategies, is that a farmer can be lucky or unlucky in the use of various strategies, depending upon the particular lifetime (price regime) which she or he experiences. A particular strategy might produce a combination of high returns and low variability, but also the reverse.

Concluding Remarks

An efficient grain market can generate prices that behave quite differently over different finite time periods. Consequently, the performance of alternative marketing strategies



Note: □ corresponds to the long-run average (–3.0 for the mean and –2.4 for the standard deviation).

Figure 6. Lifetime differences in mean and standard deviation plot for strategy return (1a) from the base

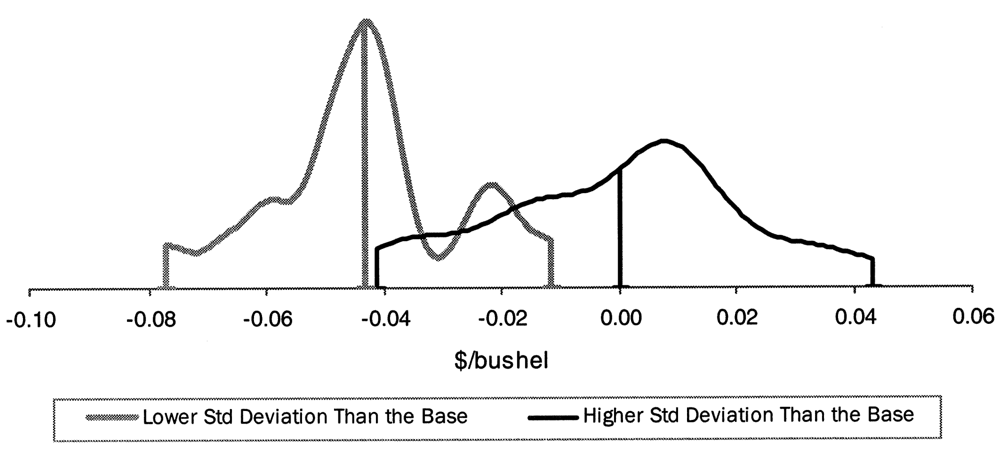


Figure 7. Distributions of differences in returns from strategy 1a and the base for lifetimes with higher and lower standard deviations than the base

can vary importantly over different samples, as our study has illustrated. While many strategies have a lower *expected* mean and standard deviation of returns than marketing at harvest time, a particular strategy can provide a higher average and a lower standard deviation of returns than the base for a finite sample. The reverse is also true. It follows that a strategy which is found to have superior performance relative to alternatives in one period may not be superior in a subsequent period. We conclude by discussing the implications of the empirical results.

First, the long-run behavior of returns is largely what could be anticipated in an efficient market, implying the simulation model indeed mimics an efficient market. Thus, there was not a strategy among those analyzed that "beat the market" by consistently raising average returns, but hedging inventory-carrying assures a return to storage in those years when relative prices at harvest time provide an incentive to store. Models to forecast basis convergence over storage intervals and to estimate the associated basis risk should be useful decision tools, which is a seemingly under-researched topic.

A possibly unexpected insight—especially for those who have not thought about the distributions of commodity prices—is that post-harvest diversification of cash sales is not particularly effective in reducing price risk, because sales are being deferred to time periods with larger price variability. If daily observations were readily available over a considerable number of years, it would be interesting to compare the distributions of returns from using various "new generation" contracts with a simple strategy like marketing at harvest. A related point is that aside from other incentives, such as delaying income for tax management purposes, deferring sales to spring was not a preferred strategy unless the inventory was hedged. It is our impression, however, that many farmers do carry unhedged inventories, perhaps in the hope of capturing the occasional spikes in prices that do occur.

Second, the results from the individual 40-year samples demonstrate the extreme care needed in drawing and qualifying conclusions about preferred marketing strategies. A strategy that is relatively inferior, on average, can perform comparatively well in particular periods, and indeed this could happen in up to 50% of the years, depending on the strategy, in an average simulated 40-year lifetime. The results also demonstrate that it is difficult to discriminate between efficient and inefficient markets using a short sample. For example, is the seeming upward bias in pre-harvest prices of December corn futures the consequence of a persistent inefficiency or the happenstance of the particular sample period? The variances of prices of a futures contract in an efficient market have time-to-maturity and seasonal components, such that it is possible for seasonal averages from a particular sample to move downward (as in figure 2b).

Estimating confidence intervals and testing for significant differences are obvious responses to the foregoing concern, but our results also suggest that such tests are not necessarily straightforward. The moments of the probability distributions of cash grain prices vary over the marketing year, and while an efficient futures market will have a constant expected mean for each contract, variances include seasonal and time-to-maturity components. If marketing strategies are based on samples shorter than the 40 years used by us, the sizes of confidence intervals associated with their estimated means and variances are likely larger than those implied by our results. Moreover, a potential problem, not analyzed here, is that data mining—searching for the preferred strategy using a fixed sample—will increase the probability of type I error. If a researcher searches for the marketing program which maximizes a farmer's returns in one period, a large probability exists that this strategy will not maximize returns in a forthcoming period.

Research and extension efforts in grain marketing relate to two areas. One is the general market behavior of prices, and the other relates more to individuals' responses in the context of existing prices. Our research addresses the former, emphasizing the consequences of price behavior in efficient markets for marketing programs, and hence has abstracted from the idiosyncratic attributes of individual farms, including their basis risks, yield risks, production costs, and tolerances for risk, among others. "Best" marketing practices likely vary from farm to farm, but grain producers do face similar price behavior (with regional and other attribute differences). Thus, grain marketing programs need to be firmly grounded in an understanding of this price behavior, which implies that distributions of returns for different marketing strategies based on finite samples will overlap substantially. Extensions of this research could build more reality into the simulations, which would presumably add to this overlap. On the other hand, it is not clear how individual transaction prices are distributed around the market-average prices, and we defer to other studies to address the effectiveness of marketing programs in helping micro-level decisions made by individual farmers in a given year.

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