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Flexible, Risk-oriented Marketing Strategies for Pinto Bean Producers

Robert P. King and Donald W. Lybecker

A model designed to identify preferred postharvest marketing strategies for pinto bean producers is presented. The model evaluates flexible strategies that use current market information to determine whether or not storage should continue. Explicit consideration is given to price uncertainty and risk preferences. The results indicate that nearly all decision makers prefer flexible strategies to fixed strategies that call for a predetermined pattern of sales. They also show that the choice of a marketing strategy is sensitive to risk preferences. Initial experiences in making the model available to producers are also discussed.

In recent years both farm managers and agricultural economists have become increasingly aware of the important impact marketing strategies have on the overall profitability of farm firms. Preharvest marketing strategies, which usually involve futures contracts or forward contracts for delivery to a local market outlet, are used primarily as tools for risk management through forward pricing. Postharvest strategies, on the other hand, are typically designed to increase revenues through storage until a time when prices have reached a more favorable level. In either case, the choice of a marketing strategy is affected by the decision maker's expectations concerning future price

levels and by his risk preferences. Storage costs and cash flow requirements also affect postharvest strategies.

In this paper a model for identifying preferred postharvest marketing strategies for Colorado pinto bean producers is presented. The pinto bean market is characterized by volatile prices that do not follow a regular seasonal pattern. Growers typically hold most of their crop in storage at a local market outlet, hoping for higher prices as the marketing year progresses. In two of the past five years, however, price levels have actually fallen in the postharvest period (Colorado Crop and Livestock Reporting Service, p. 62). Given this high degree of price uncertainty and the increasing cost of storage brought on by high interest rates, many producers are reevaluating their marketing practices.

One important feature of the model presented here is that it identifies flexible marketing strategies. While a fixed marketing strategy prescribes a predetermined set of actions at the beginning of the marketing year—for example, “sell half the crop at harvest and the other half in March”—a flexible marketing strategy continually reevaluates available market information to determine future actions. Black and Love have stressed the value of flexible strategies in the particular case of

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dry bean marketing. In a more general context, Cromarty and Myers and, more recently, Nelson have argued strongly for needed improvements in price forecasting models and for the development of more effective ways to use the information they provide. Nevertheless, many extension publications tend to emphasize fixed strategies based on long-term average price patterns—e.g., Ferris; Knox and Spencer; Good. The model presented here serves as a workable framework for incorporating repeatedly updated forecasts into the analysis of marketing alternatives.

A second noteworthy feature of the model presented in this paper is that it permits explicit consideration of risk preferences. Alternative strategies are evaluated using interval risk preferences measurements (King and Robison, 1981) and stochastic dominance with respect to a function (Meyer). As the results below indicate, risk preferences can have an important impact on preferred marketing strategies. This suggests that general marketing recommendations regarding the timing of sales may often not be appropriate, since preferred strategies can vary considerably among individuals.

In the sections which follow, the model used to identify preferred flexible marketing strategies is first described. Results of an application of the model to the analysis of postharvest marketing alternatives for pinto beans are then presented. The performance of preferred flexible strategies is compared to that of selected fixed strategies, and the impact of changes in risk preferences on preferred strategies is examined. Finally, a pilot program for making this model available to farmers is described.

The Model

The model developed for this study considers bean marketing opportunities at the beginning of each month during a marketing year that extends from the completion of harvest in early October to

the following September. To simplify the problem, marketing decisions are considered in isolation rather than in a whole farm context, and cash flow requirements are assumed not to be a constraining factor.¹ In this setting, the return to storage is a useful indicator of a marketing strategy's performance. For pinto beans, the return to storage is determined by the pattern of sales and prices received, by storage fees, and by the opportunity cost of capital. At harvest, when a marketing strategy would be selected, a return of P_1S —the product of the harvest price, P_1 (cwt), and the quantity of beans to be sold during the postharvest period, S (cwt)—would be received if the entire crop were sold immediately. The return to storage, R , associated with any other marketing strategy, is defined as the difference between discounted net revenues and this known return, as in equation 1:

$$R = \sum_{t=1}^{12} \left[\frac{[P_t - (SFEE)(t-1)]M_t}{(1+d)^{t-1}} \right] - P_1S, \quad (1)$$

where P_t is the price in month t (\$/cwt), $SFEE$ is a monthly commercial storage fee paid at the time of sale (\$/cwt), M_t is the quantity of beans sold in month t (cwt), and d is a monthly discount rate.² Since

¹ Failure to consider marketing decisions in a whole farm context can cause problems because the total risk facing the farm operator is likely to be underestimated and because tax implications are ignored. Cash flow requirements may impose constraints on a marketing strategy that would be overlooked in an isolated analysis. On the other hand, consideration of these factors makes the analysis more complex and increases the amount of farm-specific information required. See King (1982) and King and Oamek for applications of a similar marketing strategy model in a whole farm context.

² Shrink during the storage period was not considered to be important enough in this case to warrant consideration here. It may be an important factor, however, for other crops. Also, in accordance with the standard practice at commercial storage facilities in Colorado, pinto bean storage fees are assessed at the time of a sale.

the marketing year begins in October and extends to the following September, $t = 1$ in October, $t = 2$ in November, and so forth.

Prices for months beyond October cannot be known with certainty at the outset of the marketing year. Therefore, returns to storage for any strategy that does not require sale of the entire crop in October are uncertain. In an expected utility framework, the choice of marketing strategy depends, then, on the probability distribution of returns, represented by the density function $f(R)$, associated with each alternative and on the decision maker's preferences for returns to storage, as represented by the von Neumann-Morgenstern utility function $U(R)$. For any decision maker, the preferred strategy is that which maximizes the expected utility of returns to storage, EU , as defined by the expression:

$$EU = \int_{-\infty}^{\infty} U(R)f(R) dR. \quad (2)$$

The probability density function of returns to storage, $f(R)$, is determined by the joint probability distribution of postharvest prices for the months November through September and by the pattern of sales across these months.

The marketing strategies considered in this study take the form of a simple rule that makes sales in any month contingent upon current values of a set of market indicators. More specifically the quantity of beans sold in month t is defined by equation 3:

$$M_t = (V_0 + V_1Q_{t1} + V_2Q_{t2} + V_3Q_{t3} + V_4DP_t)S$$

s.t.

$$0 \leq M_t \leq S - \sum_{i=1}^{t-1} M_i \quad (3)$$

$$\sum_{i=1}^{12} M_i = S,$$

where Q_{t1} , Q_{t2} , and Q_{t3} are expected returns to one, two, and three additional months of storage; DP_t is the current

monthly percentage rate of change in price; V_0 through V_4 are parameters that determine the weight given to each market indicator; and all other variables are defined as in equation 1. The two constraints ensure that additional beans cannot be purchased, that no more than the quantity of beans currently in storage can be sold, and that all beans must be marketed during a single marketing year. This rule is termed "flexible" because it bases current actions on repeatedly updated market information. The pattern of sales it dictates cannot be known in advance, and clearly that pattern may differ considerably from one marketing year to the next.

The form of this marketing rule is not necessarily optimal. It was chosen because it is intuitively appealing and because it can be easily explained to producers, but both its form and the market indicators considered can be modified with little difficulty. Other types of marketing rules, including one which made current sales dependent on the probability of positive returns to continued storage, were also evaluated. The rule specified here performed better than any other considered.

In order to implement the marketing rule defined in equation 3, values of Q_{t1} , Q_{t2} , Q_{t3} , and DP_t must be updated on a monthly basis. At any time t , the expected return per cwt for an additional k months of storage, Q_{tk} , is defined by equation 4:

$$Q_{tk} = [\overline{PF}_{tk} - (SFEE)(k)] / (1 + d)^k - P_t; \quad k = 1, 2, 3 \quad (4)$$

where \overline{PF}_{tk} is the expected price k months in the future, and all other variables are defined as in equation 1. Values of \overline{PF}_{tk} are calculated using multiplicative expectations models of the form:

$$PF_{tk} = e^{b_{0k}} P_t^{b_{1k}} P_{t-1}^{b_{2k}} e^{u_{tk}} \quad (5)$$

where PF_{tk} is the price k months in the future; b_{0k} , b_{1k} , and b_{2k} are parameters to be estimated and u_{tk} is a stochastic distur-

bance term assumed to be normally distributed with zero mean and constant variance. To allow for seasonal variations in price movements, a distinct set of parameters for each relevant combination of t and k was estimated by ordinary least squares regression using data for the period 1964–1981.³ \overline{PF}_{tk} is defined by equation 6:

$$\overline{PF}_{tk} = e^{b_{0tk}} P_t^{b_{1tk}} P_{t-1}^{b_{2tk}} e^{-5\sigma_{tk}^2} \quad (6)$$

where b_{0tk} , b_{1tk} , and b_{2tk} are parameter estimates and $\hat{\sigma}_{tk}^2$ is the estimated variance of the disturbance term.⁴

The current percentage rate of change in the price, DP_t , is defined by equation 7:

$$DP_t = (P_t - P_{t-1})/P_{t-1}. \quad (7)$$

Given the forecasts based on equation 6 and knowledge of the current and previous months' prices, values of Q_{tk} and DP_t can be easily updated.

As the marketing rule is specified in equation 3, parameters V_1 through V_4 would be expected to have negative values, since the propensity to market in the current period would be reduced by high expected returns to further storage or rising prices. The value of V_0 , which represents an inherent propensity to sell in the

current period, can be positive or negative. The values of these parameters determine how information about current market conditions is translated into a recommended action. For example, a large, positive value for V_0 in combination with negative values of V_1 through V_4 that are small in absolute value would result in a strategy that calls for continued storage of the entire crop ($M_t = 0$) only when expected returns to continued storage and the rate of price increase are high enough to outweigh a strong propensity to sell in the current period. Conversely, negative values of all five parameters can result in a strategy that calls for sale of the entire

crop in storage ($M_t = S - \sum_{i=1}^{t-1} M_i$) only when

expected returns to continued storage and current price changes are negative. The problem of identifying a preferred marketing strategy, then, becomes one of identifying a set of parameter values that will result in a pattern of sales that maximizes the decision maker's expected utility.

Generalized risk efficient Monte Carlo programming (King and Robison, 1980; King and Oamek) was used in this study to identify the parameter values (V_0 through V_4) associated with preferred marketing strategies. This approach combines random search, Monte Carlo simulation, and evaluation of alternative strategies by the criterion of stochastic dominance with respect to a function. Sets of parameter values are generated at random, and the performance of the strategy defined by each set of parameters is simulated through a large number of sample states of nature. The resulting returns to storage values, one for each state of nature, define a sample cumulative distribution function (Barnett). Stochastic dominance with respect to a function is then used to order the alternatives considered for a decision maker or class of decision makers whose preferences conform to

³ Parameters were estimated after taking the natural logarithm of both sides of equation 5. A total of 30 sets of parameters were estimated: 11 one month forecast models ($t = 1, 2, \dots, 11; k = 1$); 10 two month forecast models ($t = 1, 2, \dots, 10; k = 2$), and 9 three month forecast models ($t = 1, 2, \dots, 9; k = 3$). Values of R^2 were above .90 for all but 4 of these 30 regression models, and all values of R^2 exceeded .83. The estimated exponent of current price, b_{1tk} , was statistically different from zero at the .05 level for 29 of the 30 forecast equations. The estimated exponent of the price lagged by one month, b_{2tk} , was statistically significant at this level in 13 of the equations.

⁴ Uncertainty due to sampling errors in estimating the model parameters had a minimal impact on forecast errors and so was ignored in this instance. Having made this simplifying assumption and noting that $\exp(u_{tk})$ has a log-normal distribution with mean $\exp(.5\sigma_{tk}^2)$, equation 6 can easily be derived.

specified lower and upper bounds on the absolute risk aversion function.⁵ This criterion divides the strategies being evaluated into two mutually exclusive sets: an efficient set, which contains all strategies that could be preferred by a decision maker whose preferences conform to the specified restrictions, and an inefficient set, which contains only strategies that no such decision maker would prefer. In effect, then, stochastic dominance is used to sort through a large number of alternatives and identify a few efficient strategies that are worthy of further consideration.

In this analysis 300 randomly selected sets of parameter values were considered. The allowable range for V_0 was from -2.0 to 2.0 , while that for V_1 through V_4 was -4.0 to 0.0 . The performance of the strategy defined by each of these 300 sets of parameter values was simulated through 50 sample states of nature—i.e., 50 hypothetical marketing years. Each state of nature was defined by a sample vector drawn from a multivariate distribution of monthly pinto bean prices based on the period 1964–1981.⁶ All strategies were simulated through the same sample states. Efficient sets were identified both for de-

cision maker classes defined by arbitrary absolute risk aversion intervals and for actual decision makers whose preferences were measured.

The model was run for conditions at the beginning of the 1982–83 marketing year. In early October 1982, the price of pinto beans in northeastern Colorado was \$12.50 per cwt. The monthly storage fee was \$0.09 per cwt, and a monthly discount factor of 1.25 percent was specified. The total quantity of beans to be marketed was assumed to be 1,000 cwt. Finally, three decision maker classes were defined by arbitrarily specified ranges of the absolute risk aversion function. The first class was assumed to be comprised of individuals whose absolute risk aversion function lies everywhere within the interval $(-.0001, .0001)$. This class would include the risk neutral decision maker, who maximizes expected returns to storage, as well as individuals who are minimally risk loving and/or risk averse. Allowable absolute risk aversion ranges assumed for the second and third classes were $(.0001, .0003)$ and $(.0003, .0006)$, respectively. Individuals with characteristics assumed in the second class can be termed moderately risk averse, while those in the third class would be highly risk averse.

⁵ The absolute risk aversion function, $r(R)$, is defined by the expression:

$$r(R) = -U''(R)/U'(R),$$

where $U'(R)$ and $U''(R)$ are the first and second derivatives of a von Neumann-Morgenstern utility function and R is return to storage. While such a utility function is unique only to a positive linear transformation, the absolute risk aversion function represents preferences uniquely.

⁶ Prices were expressed in index form, with the October price serving as the base price for each marketing year. This made all price fluctuation patterns comparable, even though harvest price levels varied considerably during this period. Procedures described in King (1979) for the generation of sample observations from multivariate distributions with correlated, non-normal marginals were used to construct the 50 sample price vectors. The resulting price index levels were then multiplied by \$12.50, the Colorado pinto bean price in early October 1982.

Results

Of the 300 flexible strategies evaluated for each of three decision maker classes, only five efficient strategies were identified, but no single strategy appeared in all three efficient sets. Summary information on the distribution of returns for these strategies is presented in Table 1 along with similar information for four representative strategies from the large set of efficient fixed strategies identified by a search of plans that call for sales in October, November, and March, the only months with non-negative expected returns to storage for the period 1964–81.

Considering the flexible strategies first,

TABLE 1. Performance of Efficient Flexible and Fixed Marketing Strategies.

Parameter	Flexible Strategies					Fixed Strategies				
	A	B	C	D	E	F	G	H	I	
V_0	-1.5	-1.9	1.1	1.8	1.4	Sell All	Sell 500 cwt in October and 500 cwt in March	Sell 500 cwt in October, 250 cwt in November, and 250 cwt in March	Sell 750 cwt in October and 250 cwt in November	
V_1	-0.7	-1.7	-0.3	-0.3	-1.8	1,000 cwt in March				
V_2	-0.5	-0.3	-3.4	-3.5	-2.5					
V_3	-1.9	-2.6	-3.6	-1.9	-1.1					
V_4	-2.9	0	-0.8	-2.9	-0.7					
Minimum Return	-2,206	-1,912	-1,616	-1,616	-1,616	-5,066	-2,533	-1,583	-478	
10th Percentile	-1,340	-1,028	-357	-300	-178	-4,502	-2,251	-1,453	-397	
30th Percentile	-668	-648	0	0	0	-2,670	-1,335	-849	-165	
50th Percentile	0	0	0	0	0	-1,411	-705	-168	-4	
70th Percentile	474	386	0	0	0	281	140	219	110	
90th Percentile	3,879	3,661	600	600	600	7,903	3,951	2,419	371	
Maximum Return	20,684	20,684	18,560	18,560	18,560	20,684	10,342	5,713	707	
Expected Return	1,596	1,560	564	561	501	378	189	125	31	
Standard Deviation	5,134	5,103	2,762	2,755	2,685	5,647	2,824	1,639	291	
Probability of a Negative Return to Storage	.44	.46	.14	.16	.14	.66	.66	.58	.50	

only A is efficient for the first class of decision makers. This is as expected, since strategy A has the highest expected return to storage and individuals in this class are assumed to be approximately risk neutral. Strategies A and B are efficient for the second class of decision makers, while strategies B, C, D, and E are efficient for the third class. Clearly, as decision makers become more risk averse, they tend to prefer strategies that are more conservative—i.e., strategies with less down-side variation and a lower probability of losses. The value of V_0 , the inherent propensity to sell in the current period, appears to be particularly sensitive to risk preferences. Individuals with low to moderate levels of risk aversion would exhibit a rather strong propensity not to sell in the current period—i.e., values of V_0 for their efficient strategies are negative. Highly risk averse individuals, on the other hand, would have a strong propensity to sell in the current period—i.e., values of V_0 for their efficient strategies are positive. Values of the other parameters do not appear to follow a definite pattern as risk aversion increases.

Among the fixed strategies, F, G, and H are efficient for the first class of decision makers. Only strategy I is efficient for the second and third classes. Once more, the portion of beans marketed at or near harvest increases as the assumed degree of risk aversion increases.

A comparison of flexible and fixed strategies indicates that the flexible strategies would be unanimously preferred to the fixed strategies by the individuals in each decision maker class. Again, this conforms with expectations, since the flexible strategies have much higher expected returns to storage and tend to have less down-side variation and a lower probability of losses than do the fixed strategies. Only at levels of absolute risk aversion above those considered here does a fixed strategy—sell all at harvest—enter the overall efficient set of strategies. In this instance the flexible

strategy model also identifies this particular fixed strategy by setting the value of V_0 at an unusually high level.

In summary, these results show that marketing strategies are sensitive to assumed risk preferences and that flexible strategies, which use market information as it becomes available, are likely to outperform fixed strategies for marketing pinto beans in Colorado. It is particularly interesting to note that, while their use differs considerably with risk preferences, forecasts based on a relatively simple expectations model have considerable value when used in a systematic decision framework.

Implementing Flexible Marketing Strategies

The results presented in the preceding section are based on arbitrary specification of risk preferences and on the assumption that 1,000 cwt of beans are to be marketed. Initial results of a pilot program for implementing the model developed for this analysis give some indication of how it may perform in an actual decision situation.

In early October 1982, an evening workshop was held for nine pinto bean producers. After some initial discussion of risk management in general and of historical price patterns for pinto beans, the price forecast model used in this study was presented. Probabilistic forecasts based on this model have been available to Colorado bean producers since April 1982. At the beginning of each month, forecasts of prices one, two, and three months in the future are made and mailed to interested producers. Sample forecasts made on October 4, 1982, are shown in Table 2. After a discussion of these forecasts and their use in calculating the approximate probability of positive returns to continued storage, risk preference measurements were made for each participant using the interval method developed by King and

TABLE 2. Probabilistic Pinto Bean Price Forecasts Made October 4, 1982.

Probability	Month ^a		
	November	December	January
	Price Range (\$/cwt) ^b		
.05	Below \$10.75	Below \$10.25	Below \$8.80
.10	\$10.75 to \$11.50	\$10.25 to \$11.30	\$8.80 to \$10.25
.35	\$11.50 to \$12.75	\$11.30 to \$13.15	\$10.25 to \$13.00
.35	\$12.75 to \$14.15	\$13.15 to \$15.35	\$13.00 to \$16.50
.10	\$14.15 to \$15.15	\$15.35 to \$16.90	\$16.50 to \$19.20
.05	Above \$15.15	Above \$16.90	Above \$19.20
Expected Price	\$12.85	\$13.40	\$13.60

^a All forecasts are for the price at the beginning of the month.

^b Price ranges are antilogs of forecast confidence interval limits for the log-log version of the price forecast model. These confidence intervals were constructed using standard econometric procedures (e.g., Pindyck and Rubinfeld, pp. 206–210). Expected prices were calculated using the expression given in equation 6. Confidence intervals are not symmetric around the mean or the median because of the multiplicative disturbance term implied by the specification of the forecast models.

Robison (1981). Finally, each participant provided information on storage costs, appropriate discount rates, and the quantity of beans to be marketed.

Risk preferences differed considerably among the nine participants. Each interval measurement included negative absolute risk aversion values at some return to storage levels. The risk aversion intervals for most participants made dramatic shifts from negative to positive ranges as return to storage levels increased from negative to positive values. This conforms with experimental results reported by Kahneman and Tversky, who observed that decision makers tend to be risk loving when confronted with losses and risk averse when confronted with gains. The quantity of beans to be marketed also varied considerably among the participants, ranging from 400 cwt to 1,600 cwt and averaging 840 cwt. All nine producers were charged a monthly commercial storage fee of \$0.09 per cwt and most found the monthly discount rate of 1.25 percent to be reasonable.

After the workshop, the model described in this paper was used to identify an efficient set of marketing strategies for each participant. The efficient sets for eight of the nine participants contained

from two to sixteen strategies. The efficient set for the ninth participant, whose absolute risk aversion interval shifted from unusually high to unusually low levels as returns to storage increased, contained twenty strategies. Efficient sets tended to be larger than those for the hypothetical decision maker classes because actual risk aversion intervals were never confined to a constant, relatively narrow range.

The composition of the efficient sets varied considerably. No single strategy appeared in all nine efficient sets. The flexible strategy that maximized expected returns to storage was included in eight of the nine efficient sets, however. Fixed strategies failed to appear in the efficient sets of eight of the nine participants. The participant whose efficient set contained 20 flexible strategies also had three fixed strategies in his efficient set, including the strategy that calls for the sale of all beans at harvest. In general, then, these results are similar to those presented in the preceding section.

As a follow-up to the workshop, recommendations based on the efficient strategies identified by the model were mailed to each individual at the beginning of each month along with the probabilistic forecasts. The recommendations and forecasts

were presented as guides for decision making; the workshop participants were in no way committed to follow them explicitly. At the end of the marketing year, however, returns to storage under the marketing strategies identified by the model will be compared to the actual returns realized by each individual. For participants who have records of past marketing patterns, the performance of the model will also be evaluated for previous years.

Concluding Remarks

The results presented here apply only for the special case of pinto beans in Colorado, though findings were similar in a recent study of preharvest hedging strategies for wheat producers (King, 1982). They provide, however, a dramatic illustration of the value of regularly updated price forecasts and of a structured framework for using them to recommend both the timing and level of sales. Despite considerable differences in risk preferences among the participants of the workshop described in the preceeding section, flexible strategies that use price forecasts clearly dominated fixed strategies for eight out of nine individuals. This suggests that more attention needs to be given by both researchers and extension personnel to price forecasting and to the dissemination of price forecasts.

The results of this study also point to the danger of using such forecasts to make "blanket" marketing recommendations. The choice of a marketing strategy was shown to be quite sensitive to risk preferences. In addition, marketing patterns are also affected by factors such as cash flow requirements and tax considerations that were not included in this analysis. This does not mean that research and extension efforts in the area of marketing management are futile. Rather, it suggests that efforts in this area should focus on the provision of relevant information on a timely basis and on the development of tools de-

signed to help producers integrate that information with information on their own attitudes and farm business situation as they analyze alternative actions.

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