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The relevant forecast of variance of income for marketing decisions under uncertainty

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The relevant forecast of variance of income

for marketing decisions under uncertainty

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CHAPTER 1. INTRODUCTION

Introduction

Nearly all-- if not all-- decisions by individuals are made with limited knowledge of the future conditions that will determine outcomes of decisions. Future conditions may be prices, quantities, and even the availability of a market. Innumerable factors influence future conditions; among them are government policies, other individuals' actions, and weather.

One of the roles for economists in the area of decision making under uncertainty has been to identify and provide information that would be useful to the decision makers. Economists have used their knowledge (or beliefs) of how the individuals make decisions as well as their knowledge (or beliefs) of how markets work in order to identify and to provide useful information for decision makers.

Researchers are in general agreement that an expected utility maximizer uses information on more than simply the expected return. These decision makers also use information on the riskiness of each alternative action. For the case of a mean-variance utility function, the decision maker uses the first two moments in his subjective probability distribution of returns to make decisions.

Many researchers have expressed the importance of modeling decisions under uncertainty and taking into account both the mean and the riskiness of the returns (among them, Anderson et al., 1977, Just and Hallam, 1982, Thompson and Bond, 1987, McSweeny et al., 1987, Collins and Barry, 1986). Still, much of the research does not consider the uncertainty inherent in the decisions firms must make.

Much of the agricultural marketing literature acknowledges the inherent riskiness of the returns from various marketing alternatives. However, many forecasting models developed in the literature are designed for forecasting price levels for some period of time with little or no attention to forecasting the variance of the prices. Furthermore, of the studies that have considered forecasting variance, there has not been complete agreement on how to measure the relevant variance.

Thus there is an inconsistency between what theory indicates and what researchers have done with regard to the treatment of variance for decisions under uncertainty. It is often acknowledged that a set of decision makers are expected utility maximizers and yet the forecasting models provide information useful for expected income maximizers. In addition, the measures of variance that have been included in studies are not the relevant measure of variance in that they are inconsistent with the theory.

It is a main contention of this study that the measures of variance that have been used in marketing decisions in previous work are not the relevant variance for these decisions. This study contends that the relevant variance is the momentary variance. In the limit, each moment in time is associated with a set of prices of various commodities. Therefore, for a particular month, the riskiness associated with a price of a given commodity is the uncertainty about which of those momentary prices the individual will face. With a momentary variance, it is reasonable to speak of a variance for one particular month without referring at all to prices in any previous month. Although a reasonable concept, this is not true of other measures of variance currently used.

One often-used measure of variance employs the monthly average prices for a sample period. This historical variance represents the (squared) deviations of the monthly average prices about the sample period mean (or grand mean).

Another measure of variance, as proposed by Peck (1975), is the variance of the errors made in forecasting the price level. In the case of a least squares regression of price level on the explanatory variables, this variance is the variance of the forecasted mean price.

The concern with the first measure of variance is that it is the distribution of monthly means about a grand mean. The concern with the second measure is that it represents the distribution within which the monthly mean is expected to fall. Both measures assume the individual always receives (or purchases at) the mean price in the month. Realistically, an individual can not expect to always receive the monthly mean price unless he sells a bushel of corn or a pound of beef each hour during the month. The relevant measure of riskiness for the expected utility maximizing decision maker accounts for this fact.

An example can illustrate the importance of the momentary variance in the marketing decision. Suppose that an individual has a perfect forecast of the mean price for some future month. A perfect forecast means that there is no forecast error associated with the forecast of the mean price for that month. In this example, Peck's variance would indicate that there is no uncertainty or risk associated with this price. This is clearly not the case as long as there will be more than one price observed in that future month. With the perfect forecast, the producer does not know the particular price that he will receive in the month unless somehow he can always guarantee receiving the monthly mean. He only knows the mean of the distribution of the prices that he could receive. As long as the individual can not guarantee receiving the mean price in any given month, the distribution of momentary prices -- the dispersion of which is expressed in the momentary variance -- is the relevant measure of riskiness of a price consistent with theory.

An individual interested in the expected utility of selling in some future month relative to the expected utility of selling in the current month would need be interested in the momentary variance of the possible selling prices in the future month and would also be interested in the momentary variance of the selling prices this month. This consideration is often overlooked in previous studies. Previous studies have not only assumed that the producer always receives the mean price in the future month but also that he receives the mean price in the month in which the decision was made. Not only is the momentary variance relevant for describing the riskiness of prices several months ahead, but it is relevant for describing the riskiness of prices that one will be facing this month when one makes the decisions.

Having noted the inconsistency between theory and practice, one may ask how the expected utility maximizer makes marketing decisions in the absence of the relevant information on variability. Economic theory does not address this issue directly. One may presume, as in this study, that the individual uses some rule of thumb that makes use of the information that is available.

An expected utility maximizer that is supplied with the relevant information is assumed to make the 'right' decision, where a decision is the choice of an alternative. However, when not all information is available and a rule of thumb is used, he may make the 'wrong' decision. It is quite conceivable that the wrong decision will be the same as the right decision on occasion.

With all variables continuous, i.e., no lumpiness in production or marketing, the wrong rule would in general lead to the wrong decisions if the payoff function has a unique maximum. However, in marketing soybeans or livestock or in purchasing corn or feeder cattle, there is lumpiness in purchases and sales. Therefore, the wrong rule may at times lead to the right decision.

Akerlof and Yellen (1987) indicate that agents can deviate from full optimization within a relatively wide range without incurring losses that are significant to the individual. Akerlof and Yellen refer to this as 'near-rational' behavior. Agents can follow rules of thumb in their decisions and still be nearly optimal or 'nearly rational'. This is a consequence of the envelope theorem. "...rule-of-thumb behavior typically imposes losses on its practitioners, relative to the rewards from optimizing, which are second-order" (Akerlof and Yellen, p. 139).

One of the purposes of this study is to examine the practical side of whether the wrong decision rule leads to the right decision.

The contention in this study is that the measure of variance used in previous empirical work is not the relevant variance because it is not consistent with theory. Of course there are studies that have investigated several new definitions of riskiness. This study is not in that vein. The concern in this study is not necessarily whether variance is a good or a bad measure of riskiness but rather whether the variance is measured correctly. Furthermore, this study addresses the issue that when variance is not measured correctly, does it make any difference in the decisions made. This study is confined to a discussion of variance but the ideas can apply to other definitions of riskiness also.

The overall approach of the dissertation is to suppose one has a set of farmers that make regular marketing decisions and that the mean-variance framework describes their decision making process. This study will simulate farmers with various degrees of risk aversion and vary the forecasting technique used, the response to the information provided currently. The results of the simulations will be used to analyze whether decisions made tended to differ across the representative farmers.

Objectives

There are three main objectives of this study. The first and second objectives are statistical in nature. One is concerned with the practical estimation of the relevant variance, and another is concerned with the simultaneous forecast of a price and variance during the forecast period. The third objective is concerned with the decisions made and with the outcomes from decision rules under uncertainty.

The first objective is to examine the computation of the momentary variances. Two methods by which one can arrive at an estimate of the true momentary variance are considered. This study will use daily average prices for the month in the calculation of the momentary variances. Although it is possible to compute the momentary variances from observations at very short intervals of time, e.g. each hour or each minute, this study will concentrate on calculation methods that require more readily obtainable data.

The second objective concerns the simultaneous forecasting of the mean price and the momentary variance of price within a given month. Since the decision maker must have a forecast of both and since it is likely that the errors in forecasting the price are related to the errors is forecasting the momentary variance, this study investigates the use of a systems estimation of the prices and variances needed in the simulations. Other forecasting techniques are also considered.

The typical approach is to estimate the mean return and the variance of return in separate equations and then combine them to forecast expected utility. An alternative method is to forecast expected utility directly. One would regress the expected utility of a marketing alternative on the exogenous variables in the model. For forecasting then, one can directly forecast expected utility rather than forecast means and variances of the prices independently. This alternative allows one to estimate the equations in a way that is consistent with its ultimate use, that is, to forecast expected utility. This may be important since the best forecast of a sum is not necessarily the sum of the best forecasts of the terms. In each of the alternatives, this study wishes to identify the variables that are important to forecasting price variability within a given time period.

The question that the third objective addresses may be stated as follows: would a utility maximizing farmer's decisions, and hence outcomes, differ greatly depending on whether he had an estimate of the momentary variance or not? The momentary variance of a price for a particular month describes the dispersion of the momentary prices within that month. Some studies have proposed using the variance of the forecasted mean price to represent the riskiness the decision maker faces. Other studies have used the variance of the monthly mean prices. The contention in this study is that the momentary variance is the relevant variance for a utility maximizing decision maker with a mean-variance utility. Estimates of the momentary variance are not widely available.

To achieve the third objective, one must have some answer to the question: what does a utility maximizing farmer do to compensate for the lack of certain information? This study proposes to handle this question by defining different methods by which a farmer can compensate for the lack of the momentary variance. Each of these compensation rules can be examined as the alternative to the expected utility rule.

For each utility function and compensation rule pair, one can calculate the probability that the compensation rule will lead to the same decision or at least lead to an outcome that is close enough to the outcome of the right decision.

Finally, from the results of the simulations, this study will examine the importance of considering both the momentary distribution of prices within the decision month and within the future month. Since previous studies have assumed that an individual always receives the mean price in the decision month as well as the future month, they would find that there is a certainty of a loss (gain) from a decision when in fact there may well be a positive probability of making a gain (loss). As long as this study finds that in some cases the probability of making a certain decision equals neither zero nor 1, it is important to account for the within month distribution of prices for any month in which one plans to transact business.

CHAPTER 2. ECONOMIC THEORY OF DECISION MAKING

Theory

Daniel Bernoulli, in the early 1700s, explained the Petersburg paradox by proposing that people maximize expected utility rather than simply expected return. Then, in the 1940s, John von Neumann and Oskar Morgenstern developed a set of axioms that indicated the expected utility approach described rational behavior under uncertainty. The expected utility hypothesis remains a prominent method for analyzing economic decisions under uncertainty.

Alternative risky prospects are ranked according to their expected utility. The individual has a utility $U(A_i)$ for outcome A_i where $i=1,\ldots,I$. With two possible outcomes for lottery 1, A_1 and A_2, and with the probabilities p_1 and p_2, the expected utility of lottery 1 is

$$E[U(\text{lottery } 1)] = p_1U(A_1) + p_2U(A_2)$$

The expected utility for the certain outcome A_3 is

$$E[U(A_3)] = U(A_3).$$

Whether the individual chooses the lottery 1 or the certain outcome A_3 depends then on the shape of his utility function.

For a risk averse individual, the utility function is concave downward

$$U(gA_1 + (1 - g)A_2) > gU(A_1) + (1 - g)U(A_2)$$

for all $0 < g < 1$. This individual requires that the value of a lottery be higher than the value of the certain outcome. A risk averse individual would not accept a fair gamble.

For a risk loving individual, the utility function is convex downward

$$U(gA_1 + (1 - g)A_2) < gU(A_1) + (1 - g)U(A_2)$$

for all $0 < g < 1$. This individual would accept a fair gamble since he would not require a higher expected value of the lottery compared to the certain outcome.

A utility function linear in income represents risk neutral preferences. A risk neutral individual is indifferent between a fair gamble and a certain outcome. Maximization of expected utility under risk neutrality is equivalent to the maximization of expected returns.

Arrow and Pratt independently suggested using the ratio

$$R_A(y) = \frac{-U''(y)}{U'(y)}$$

as a measure of absolute risk aversion, where y is income and $U'(\cdot)$ and $U''(\cdot)$ are the first and second derivatives of utility with respect to income. (See Hey, 1979.) The absolute risk aversion is independent of an arbitrary linear transformation of the utility function. R_A is positive, zero, or negative as the individual displays risk-aversion, -neutrality, or -loving, respectively. R_A is also larger the more risk averse an individual is.

The Arrow-Pratt measure of relative risk aversion has the properties of R_A with one addition. Relative risk aversion is defined as

$$R_R(y) = \frac{-yU''(y)}{U'(y)} = yR_A.$$

R_R is unaffected by the choice of units of y, unlike R_A.

Constant absolute risk aversion utility functions are of interest in this study. By integrating the definition of R_A (Hey, 1979, p. 49), one obtains

$$U(y) = a - b\ e^{-Ry}$$

where $R_A(y) = R$ for all y and a and b are defined by the integration. The expected utility can be written as

$$E[U(y)] = a - b\ M_y\ (-R)$$

where M_y is the moment generating function of the y distribution having mean μ and variance σ^2. If $y \sim N(\mu, \sigma^2)$, then

$$E[U(y)] = a - b\ \exp(-R\mu + (1/2)R^2\sigma^2).$$

Note that maximizing this expected utility is equivalent (for $R > 0$) to maximizing

2.1. $\mu - (1/2)R\sigma^2$

A third measure of risk aversion is the risk premium. The risk premium P is the amount of income the individual is willing to pay to change a risky choice into a certain outcome. P, then, is such that

$$U(E(y) - P) = E[U(y)]$$

where the expectations are evaluated with respect to the y distribution.

Mean-Variance Analysis

For empirical work in the area of uncertainty, one needs a utility function that is tractable. For applied work, exact utility functions are often not practical to estimate or work with. The mean-variance framework has been used extensively in applied work.

Many studies in decision making under uncertainty have used a mean-variance (or mean-standard deviation) framework for their analyses. The economic justification for the mean-variance framework lies with one of two rather restrictive conditions: (1) that the individual has a quadratic utility function or (2) that the returns are normally distributed. Under one or both of these conditions, expected utility maximization will yield the same results as the appropriate linear combination of mean and variance. The ease with which the mean-variance framework can be applied in exposition or in empirical applications explain much of this framework's popularity.

Meyer (1987) outlined another condition that, if satisfied, implies the equivalence between expected utility and the mean-standard deviation framework. Meyer refers to this condition as the location and scale condition. The condition is that "...the choice set be composed of random variables which differ from one another only by location and scale parameters" (Meyer, 1987, p. 422). The normal and uniform families are examples of two-parameter families of random variables whose members differ by only location and scale parameters. The lognormal family does not satisfy the location and scale condition. The location and scale condition specifies how all the random variables of the choice set must be related to one another. However, no restrictions are placed on the functional form of the cumulative density function of any particular random variable.

Meyer pointed out that many economic models have the property that "...a single-outcome variable depends on choice variables and parameters, one of which is random, and depends linearly on this random parameter" (Meyer, 1987, p. 423). Hence, outcome variables differ from one another by location and scale parameters. The location and scale condition is then met due to the model structure.

Meyer gave examples of previous studies that could have used the mean-standard deviation framework based on the location and scale conditions without requiring restrictions on the individual's preferences or on the cumulative density function. Meyer indicated that standard deviation should be used instead of variance, however.

An equation quadratic in, for example, income, can represent a utility function for some individual. The quadratic utility function has an advantage in its tractability. Some implications of this utility function are intuitively appealing while other implications are less so.

In general the quadratic utility function is

$$U(Y) = a + bY - cY^2$$

for b, c > 0. The expected value of utility is then

$$E[U(Y)] = a + bE[Y] - cE[Y^2]$$

Using the definition of variance, $V[Y] = E[Y^2] - \{E[Y]\}^2$, one can substitute into the equation to obtain

2.2. $$E[U(Y)] = a + bE[Y] - cV[Y] - c\{E[Y]\}^2$$

This particular utility function attains a maximum value. At some levels of income, additions to income begin reducing utility. Income levels for this utility function must be less than b/2c in order to keep marginal utility positive.

The risk aversion characteristics for this utility function follow.

The measure of absolute risk aversion is

$$R_A = \frac{-U''(Y)}{U'(Y)} = \frac{2c}{(b-2cY)}$$

and the measure of relative risk aversion is

$$R_R = \frac{-U''(y)y}{U'(y)} = \frac{2cy}{(b - 2cy)}$$

For this utility function,

$$\frac{\partial R_A}{\partial Y} = \frac{4c^2}{(b-2cY)^2} > 0$$

$$\frac{\partial R_R}{\partial Y} = R_R + \frac{4c^2 Y}{(b-2cY)^2} > 0, \quad \text{for } 0 < Y < b/(2c).$$

The quadratic utility function is intuitively appealing since expected utility is a function of both the expected income and the variance of income.

Equation (2.2) can be rearranged in order to make the mathematics somewhat easier. Subtract the constant 'a' from both sides and divide both sides by 'b'. These linear transformations do not change the preference ordering of the quadratic utility function.

2.3. $E[U(Y)] = E[Y] - L\ V[Y] - L\ \{E[Y]\}^2$

where $L = c/b$.

The quadratic utility function is not always written in its full form as in equation (2.3). An often cited quadratic utility function is of the form

2.4. $E[U(Y)] = E[Y] - L\,V[Y]$

This equation may be justified by the assumptions leading up to equation (2.1).

Studies of Utility Estimation

Officer and Halter (1968) explained three methods by which one could estimate an individual's utility function. The authors then outlined a field experiment to estimate the utility functions of five farmers by using a fodder reserve problem under uncertainty.

One method by which one can estimate an individual's utility function is using the von Neumann-Morgenstern (VNM) model. This model rests upon the continuity assumptions: if outcome A_1 is preferred to A_2 and A_2 is preferred to A_3 (that is $A_1 > A_2 > A_3$) then there exists a probability $p > 0$ such that

$$pU(A_1) + (1 - p)U(A_3) = U(A_2)$$

The utilities of A_1 and A_3 are arbitrarily set and $U(A_2)$ is computed from these utilities and from the experimental subject's value of p. Two criticisms of this model are 1) if the subject has utility or disutility for gambling, then because he is asked to indicate his preferences between the outcomes of a gamble and the outcome of a certain event, his choice of outcomes will be biased by the process which determined the outcomes, 2) if the subject does not fully understand the concept of probability or has probability preferences, then the subjective probabilities indicated by him for indifferences between the gamble and the certain event may not correspond to objective probabilities of the same numerical magnitude.

Another method by which one can estimate a utility function is the modified VNM model. The VNM model is modified by using neutral probabilities, i.e., $p = (1 - p) = 0.5$ to overcome biases due to probability preferences.

The Ramsey model is the third method by which one can estimate a utility function. This model overcomes both criticisms of the VNM model. Ethically neutral probabilities are used. Also the subject has to choose between two gambles so that there is no bias if a subject has a utility (disutility) for gambling.

Say that one wants to estimate a utility function over the range of money outcomes 'a' to 'g' where $a > g$. The questions are framed as decision problems against nature. The first game appears as follows

	Action 1	Action 2
S_1	a	b
S_2	d	c

The S_i are states of nature and outcomes a, b, c are set $a > b > c$. d is varied until the subject is indifferent between actions 1 and 2 which implies

$$U(a) + U(d) = U(b) + U(c).$$

This means that the utility interval a to b is equal to the utility interval c to d or $U(b) - U(a) = U(d) - U(c)$. The size of interval a to b is arbitrarily set.

By using a series of games, one can divide the range a to g into equal intervals of utility. The utility scale can then be used along with the monetary values to estimate the utility function. Linear, quadratic, and cubic (or higher order polynomial) equations can be fit by regression to the data.

The VNM model, the modified VNM model, and the Ramsey model were used to estimate utility functions by Officer and Halter. The study took place in Australia and the problem was phrased to farmers as a fodder reserve decision.

The five participating farmers were presented with between 10 and 19 fodder reserve programs. Three utility functions were estimated for each farmer, one for each of the three methods of utility estimation. In addition, the study estimated fodder reserve if the farmer behaved as an expected cost minimizer.

The utility functions were all estimated as polynomials. The researchers found that two of the 15 utility functions estimated were linear, 10 were quadratic, and three were cubic. The R^2s, the coefficients of determination, were greater than 0.90 for all of the equations. All of the subjects in the Officer and Halter study were found to have at least some degree of risk aversion.

For all five farmers, the estimated fodder reserve was compared to the farmer's actual fodder reserve for each fodder reserve program. The average error for each farmer was presented in the article. The results indicated that the expected cost minimization criterion selected either a plan coincident with the farmer's actual decision or selected a plan with greater variance than that selected by the farmer. The expected utility criterion derived by the modified VNM method was superior to the expected cost minimizing criterion. The VNM method for deriving utility functions performed the worst. The conclusion here was that individuals had difficulty in working with probabilities.

The second stage of the study took place one year later. The same five farmers were re-interviewed and presented with 10 of the 19 original fodder reserve programs. The modified VNM method and the Ramsey model were used to estimate utility functions. The expected cost minimizing criterion was again compared to the two utility functions in the prediction of actual fodder decisions by the farmers. The conclusions of the second stage of the study were that the Ramsey model was superior to the modified VNM and that both utility estimation methods were superior to the expected cost minimizing criterion.

Johnson (1962) tried to explain the near unanimity found in some previous studies with regard to apparent conflicts with traditional theory. Traditional theory of the firm hypothesizes firms will accept a lower certain price in the present in lieu of an uncertain future price. Five of the six studies reviewed by Johnson rejected this hypothesis. The data collection methods were very similar across the studies but the product, time period, and geographical location varied considerably. Farmers generally indicated that they would require a higher certain price in lieu of the uncertain price. This indicates that these farmers prefer uncertainty when the responses are taken on face value.

Johnson referred to the utility analysis of risk as developed by Friedman and Savage to explain the near unanimity in the studies. The

Friedman-Savage analysis considers the existence of utility functions "...that allow persons (or firms) to take what appear to be 'unfair' gambles and yet conform to other rationality criteria" (p. 200).

Johnson was concerned with two of the questions asked of farmers, (1) what is your expected price for various products? and (2) for what guaranteed price would you contract forward your output to avoid risk of the uncertain price? An unexpectedly large number of respondents indicated they would not contract unless the contract price was greater than their expected market price.

Biases may have included deliberate misrepresentation by the respondents, communication problems between the researchers and the respondents, and the gambling bias. Biases in the studies were considered minimal.

Farmers can be expected utility maximizers and there can be a range of situations where farmers apparently would choose behavior implying that they prefer risk. Friedman and Savage claim the expected utility hypothesis appears to explain best long-odds gambles and short-odds insurance.

Lin, Dean, and Moore (1974) used six case study farms in the San Joaquin Valley to test the predictive power of Bernoullian utility, lexicographic utility, and expected profit.

Theoretically, utility maximization is superior to profit maximization as an explanatory tool since "(1) it can explain why two individuals, faced with exactly the same situation, might rationally respond quite differently, and (2) it does not exclude profit maximization but rather includes it as a special case of Bernoullian utility" (p. 499).

This study used quadratic programming to derive the E-V frontiers for each farm.

The Ramsey model was used to derive the Bernoullian utility functions for the decision makers. Each decision maker played a series of nine 'games against nature'. Then by arbitrarily setting the utility levels of two of the outcomes, the authors were able to identify points on the farmer's utility function. The utility functions were then estimated by regression. Of the six subjects, two had constant marginal utility functions, three had diminishing marginal utility over the entire range, and one had diminishing marginal utility followed by a range of increasing marginal utility.

Four goals were used in the lexicographic utility. The decision makers ranked the four goals and indicated satisfactory levels of his first three.

This study concluded that the Bernoullian and lexicographic utility predict actual behavior more accurately than expected profit maximization and that the Bernoullian utility predicts more accurately than the lexicographic utility.

This study also considered the possibility that crop plans chosen in the past may not represent the plans that maximize preferences, especially in certain years. The concern was that farmers may not have been able to pick the preferred plan in a given year due to additional constraints or due to a mistake. It may also be possible that the farmer's preferences have changed. Therefore, the authors presented the farmers with the information contained in the E-V frontier so that the farmers could pick the plan that they indeed preferred -- known as direct choice behavior in the paper. The results indicated that the Bernoullian utility predicted direct choice behavior as accurately or more accurately than profit maximization in five of six cases. The lexicographic utility did not predict consistently.

Pope (1982) reviewed literature in the four areas of empirical work in uncertainty, (1) micro or firm, (2) macro or aggregate, (3) descriptive, and (4) prescriptive.

The expected utility theory has been attacked basically on its descriptive relevance. Some evidence of inconsistencies between actual behavior of people and the theory exist. Pope indicated that one typical rationalization of the expected utility theory is that the theory is useful as a normative model of a representative decision maker.

Pope stressed the importance of reviewing the deductive implications of the behavioral theory for tests and for interpretation of empirical results.

Lin and Chang (1978) investigated alternative functional forms for Bernoullian utility functions. An earlier paper by Lin, Dean, and Moore (1974) estimated a polynomial utility function. Lin and Chang indicate that researchers generally agree that a utility function should exhibit decreasing absolute risk aversion. Polynomial utility functions, however, exhibit increasing absolute risk aversion. Lin and Chang reviewed possible functional forms and estimated a Bernoullian utility function for a case-study farm. Then the authors examined to what extent the polynomial utility function may have biased the prediction of the farmer's production responses. The authors used a model with variables transformed by Box-Cox transformations.

Lin and Chang estimated the Bernoullian utility function for farm 5 of the Lin, Dean, and Moore study, using a flexible functional form. Lin and Chang then compared the optimal plan picked by each of the two functional forms. Their conclusions were that the flexible functional form could have predicted the farmer's production decisions better than the forms reported by Lin, Dean, and Moore. Lin and Chang concluded that the linear and polynomial specifications of utility functions are too restrictive. The authors also indicated that "...the tendency for the Bernoullian utility hypothesis to predict more risky behavior than that actually observed may have been due to incorrect specification of the functional form."

Buccola and French (1978) indicated that the semilog utility

$$U = d + g \ln y \;, \; g > 0$$

and the negative inverse exponential (or simply exponential) utility

$$U = K - \theta \exp[- L\, y] \quad \text{for} \quad K, \theta, L > 0$$

have not been widely applied before because these two functional forms are not associated with a quadratic (and thus more tractable) expected utility function. The authors pointed out that given exponential utility, linear in profit, and normally distributed profit, there is an expected utility model that is maximizable by using an associated quadratic function. Exponential utility and normally distributed profit $y \sim N(\mu, \sigma^2)$ produce expected utility

$$E[U(y)] = K - \Theta\exp[-L\mu + (L^2/2)\sigma^2].$$

This expression is maximized by maximizing the exponent, which is quadratic.

The authors point out, however, that fitting the exponential function to the data is not straightforward and they outlined how one might approach the estimation of the exponential coefficients. The authors illustrated their estimation method on data from two California tomato growers.

Review of Hedging Literature

The literature on hedging ratios and hedging strategies make assumptions concerning the utility of the decision maker, either explicitly or implicitly. This section will review some literature on hedging ratios and the choice of variance and also some literature on hedging strategies that have implications concerning the decision makers' utility.

Hedging ratios and variance choice

Anne Peck (1975, p. 410) pointed out that previous studies had a definition of mean and variance that imposed a 'long-run perspective' on the analysis. The mean and variance often used was of a series of monthly mean prices in past years.

Peck questioned whether it was the year-to-year price variability that was necessarily relevant. Her contention was that one could adjust production levels and adjust the mix of inputs to reduce the income variability due to the year-to-year price variability.

Peck concluded that the relevant variance was the mean-squared forecast error of the model. She concluded that this represented the price variation to which the farmer could not adjust.

Peck modeled the case where the output quantity is known in month t-i. The output quantity is mature and ready for the market in month t. The expected price at the time of the production decision was P_{t-i}^*. She defined σ_p^2 to be a measure of the uncertainty of the forecast. The expected income then is

$$E(y) = E(QP_t) = QP_{t-i}^*$$

where Q is the quantity. The forecast variance of income is

$$\begin{aligned} MSE(y) &= E(QP_t - E(QP))^2 \\ &= Q^2(E(P_t - P_{t-i}^*)^2) = Q^2\sigma_p^2 \end{aligned}$$

When the individual is considering hedging some of the production in the futures market, Peck indicated that the mean and variance to use are

$$\begin{aligned} E(y) &= E(QP_t + Q_H(F_{t-i} - (P_t + B_t))) \\ &= QP_{t-i}^* + Q_H(F_{t-i} - P_{t-i}^* - B_{t-i}^*) \end{aligned}$$

$$\begin{aligned} MSE(y) &= E(y - E(y))^2 \\ &= (Q - Q_H)^2\sigma_p^2 + Q_H^2\sigma_b^2 - 2Q_H(Q - Q_H)\sigma_{pb}. \end{aligned}$$

where Q_H is the quantity hedged, F_{t-i} is the price of the futures contract, B_t is the basis, and B_{t-i}^* is an expected basis. σ_p^2 is the variance of price, σ_b^2 is the variance of the basis, and σ_{pb} is the covariance of price and basis. With the objective function

$$\text{Max } W = E(y) + L\ MSE(y),$$

where L is a risk aversion parameter, the optimal hedge ratio is

$$\frac{Q_H}{Q} = \frac{\sigma_p^2 + \sigma_{pb}}{\sigma_p^2 + \sigma_b^2 + 2\sigma_{pb}} - \frac{F_{t-i} - P_{t-i}^* - B_{t-i}^*}{2Q\ L\ (\sigma_p^2 + \sigma_b^2 + 2\sigma_{pb})}$$

Kandice Kahl (1983) re-examined previous studies in order to draw some general conclusions about the optimal futures and cash positions.

Kahl concluded that the work done by Heifner (1972, 1973) was consistent with the solution of Johnson (1960) and Ward and Fletcher (1971). Kahl also compared Heifner's results to Telser's model of expected profit maximization subject to the probability of a disastrous level of profits constrained to be less than a given probability level.

For each of these models, the optimal cash and futures positions depended upon the risk parameter in the objective function. However, for each of these models, the ratio of the optimal futures position to the optimal cash position is not a function of the risk parameter.

Kahl indicated that since Peck had assumed a fixed cash position, Peck's equation for the ratio of the optimal futures position to the given cash position was a function of the risk parameter.

Hedging strategies

Many studies have examined hedging strategies for livestock and grain farmers. The studies were concerned with identifying hedging signals that the farmer could use to increase average income or reduce the variance of income over a specified time period. A great number of strategies have been identified by these studies as being superior to the routine cash strategy and to the routine hedge strategy.

Gorman, Schuneman, Catlett, Urquhart, and Southward (1982) simulated various hedging strategies for 747 pens of fat cattle over a six and a half year period. The data were from a commercial feed lot. This study contended that other studies had assumed several variables constant when, in fact, variations in these variables may have been quite important. Some of these variables were 1) the mismatch between pen size and futures contract size, 2) the differences between pens in feeding efficiency, and 3) the effects of cattle weights, grades, and sex. Six hedging strategies were tested. There were two routine strategies (cash and hedging) and four selective strategies. Signals in the selective hedges included breakeven price, moving averages, downtrend signal, and profitability.

Spahr and Sawaya (1981) outlined prehedging strategies. These strategies called for selectively hedging the major inputs -- feed, feeder cattle -- and the output -- slaughter cattle. The prehedge was made if the estimated profit from hedging exceeded some predetermined target profit.

Purcell and Riffe (1980) examined how selective hedging strategies affect the cattle feeder's cash flow. The authors stated that studies that presented results in terms of mean and variance of the net returns per head for feeding periods or longer analysis periods were missing some of the risk exposure the operator may encounter.

The authors reported on their set of selective hedging strategies. "The strategies were analyzed in terms of 30-day flows from the cash, futures, and combined cash-futures operations to generate a picture of the financial position of the simulated feeding operation within the feeding or other analysis period."

At the beginning of each month, one lot of cattle was sold, one lot was purchased, and feed was purchased for the new lot. The prices in the first week of the month were used. A quarterly price forecasting model and a technical trading system were used to signal hedges.

Some statistics supplied in the paper for each strategy were mean 30-day cash balances, the standard deviation of 30-day balances, mean 30-day negative balances, the number of 30-day negative balances, and the range of 30-day balances.

Previous studies on hedging have not considered that the producer can not always guarantee receiving the monthly mean in the future sales month. Previous studies have also not considered that the distribution of prices in the current month may be important in determining which marketing alternative yields the highest expected utility.

Chapter 3 will discuss the inconsistency between what economic theory indicates is important for decision makers and what is typically provided to them. Chapter 3 will examine the measures of variance currently used and contrast these with the momentary variance. Chapter 4 will present the marketing decision that will be used to investigate the importance of using an irrelevant variance in decision making.

CHAPTER 3. INCONSISTENCY BETWEEN THE THEORETICAL AND THE PRACTICAL MEASURE OF VARIANCE

Chapter 2 outlined some economic theory and literature that is useful background for this study. This chapter will describe in more detail the inconsistency between the theoretical and the practical measure of variance in marketing decisions. This chapter turns first to the discussion of the inconsistency and provides a definition of the momentary variance and two other commonly used variances.

The second section of this chapter discusses how individuals respond to inadequate information. Very little economic theory addresses this issue so this section outlines some plausible responses on the part of decision makers when the variance measure provided is not the relevant measure.

The last section of this chapter discusses an issue often ignored in other studies but that will be addressed in this study. This issue concerns the randomness of prices in the current month. Ignoring the randomness by using only monthly mean prices prompts previous studies to conclude that there is a certainty of a loss (gain) from a decision when in fact there may well be a nonzero probability of a gain (loss).

The Inconsistency in Variance Definitions

Economic researchers by and large agree that the decision makers consider the riskiness of a return as well as the expected return (Brandt and Bessler, 1981; Thompson and Bond, 1987; Anderson et al., 1977; McSweeny et al., 1987; Just and Hallam, 1982; among others).

Collins and Barry cite the need for "...new approaches in measuring and analyzing risks that may enhance empirical analysis and improve the quality and generality of decision information" (1986, p. 152).

In contrast however, much of the forecasting literature is concerned with forecasting price levels alone. Brandt and Bessler, e.g., introduced a discussion on composite forecasting by saying "Producers, processors, and distributors of agricultural commodities make decisions in a risky environment. Uncertain production and relatively low price elasticities of demand provide the setting for rather large fluctuations in commodity prices" (1981, p. 135). Yet their forecasts were of price levels alone.

There have been studies that have addressed the issues of variability in price in their analyses. Some previous work has used an historical measure of variance to represent the relevant variance for within-year decisions. Others have followed Peck and have used the variance of the forecasted mean price as the relevant variance (Peck, 1975; McSweeny et al., 1987; Thompson and Bond, 1987; Young, 1984; Rolfo, 1980).

Peck argues that year to year variation in price is not the relevant variance to consider for within year marketing decisions. Peck stated that with year to year variation in price, one can respond by adjusting production level and inputs. Peck continued "the crucial variance remaining, however, is that which surrounds the accuracy of the producers' forecasts, the mean squared error of the forecasts" (p. 411).

An example of a general marketing problem can be used to identify the relevant variance. A farmer has a quantity of a commodity in time t that he can sell now in month t or he can wait and sell in month t+1. All of the possible selling prices in time t, the current month, are not known for certain. The individual will not know which price he will receive until he transacts business in the market. Likewise the farmer does not know the selling price he would receive if he waited and sold in month t+1. The farmer does have some idea of the distribution of the prices both this month and in month t+1. The distributions of concern for the farmer are the distribution of all possible selling prices within month t (the current month) and the distribution of all possible selling prices within month t+1.

Say that in the above example the producer had a perfect forecast of both the mean price in month t and the mean price in month t+1. Peck's measure of the risk in this case indicates that there is no uncertainty in the two selling prices since the variance of the forecasted mean price with a perfect forecast is zero. Clearly, however, the producer would still be facing an uncertain price in both months unless the producer could guarantee receiving the monthly mean price in both months.

This study maintains that there is an inconsistency between theory and practice with regard to the relevant variance. Theory indicates that (expected utility maximizing) decision makers are interested in the riskiness of returns and that the relevant variance of the returns to use is the second moment of the decision maker's subjective probability distribution of returns. This study contends that the relevant variance for the marketing decisions, the variance consistent with theory, is the momentary variance.

The mean price for a certain time period is probably the most common type of information made available to decision makers. Forecasts provided are of mean prices and possibly an interval within which the forecasted mean price is expected to fall. Expected utility theory indicates that a risk neutral individual needs only the mean to make decisions. Nonrisk-neutral individuals -- both risk averse and risk seeking -- need to develop a subjective notion of the distribution of prices. Nonrisk-neutral individuals form a notion of the likely return they could receive as a result of the decision as well as a notion of the riskiness of the return. For the quadratic utility function, the measure of riskiness is simply the variance.

Work has been done on forecasting the variance of the futures prices as input to option pricing models (see Hauser and Andersen, 1987 or Glauber and Heifner, 1986). These variances are of percent change in futures price and are not directly applicable in an expected utility context where price levels are relevant. Most marketing situations where the riskiness of the alternatives will be considered will require forecasting more than just the variability of the futures price.

This section now turns to the three definitions of variance of price with which this study is concerned. The first definition is the momentary variance, believed in this study to be the relevant variance in the marketing decisions. The second two definitions are variances that have been used in previous studies.

Momentary variance

Unless an individual sells some of his production at each moment during the month, he cannot always expect to sell at the monthly mean. The decision maker is interested in the riskiness of selling within a particular month. The individual will sell at one price within that month and so is interested in the dispersion of all possible selling prices within that month.

One can view a price received (or paid) as a point in a more-or-less continuous series of prices. At the limit, each moment of time has a price associated with it. Thus, we denote the relevant variance as the momentary variance within a given month. The momentary variance can be ideally calculated as

$$V(P_i) = \int_{-\infty}^{+\infty} (P_i - \bar{P}_i)^2 f(P) dP$$

where the P_i denote prices at each moment during the given month i, $\bar{P}_i$ is the monthly mean price for month i, and $V(P_i)$ is the momentary variance of price within month i.

Figure 3.1 relates the significance of the momentary variance by plotting two hypothetical time series of prices that share the same monthly mean price for the months M_1, M_2, and M_3. Define the dashed line the price series from market A and the solid line the price series from market B. The variance of the monthly mean prices is the same between the two markets but market A clearly has a higher momentary variance (the within month variance of the momentary prices). A risk

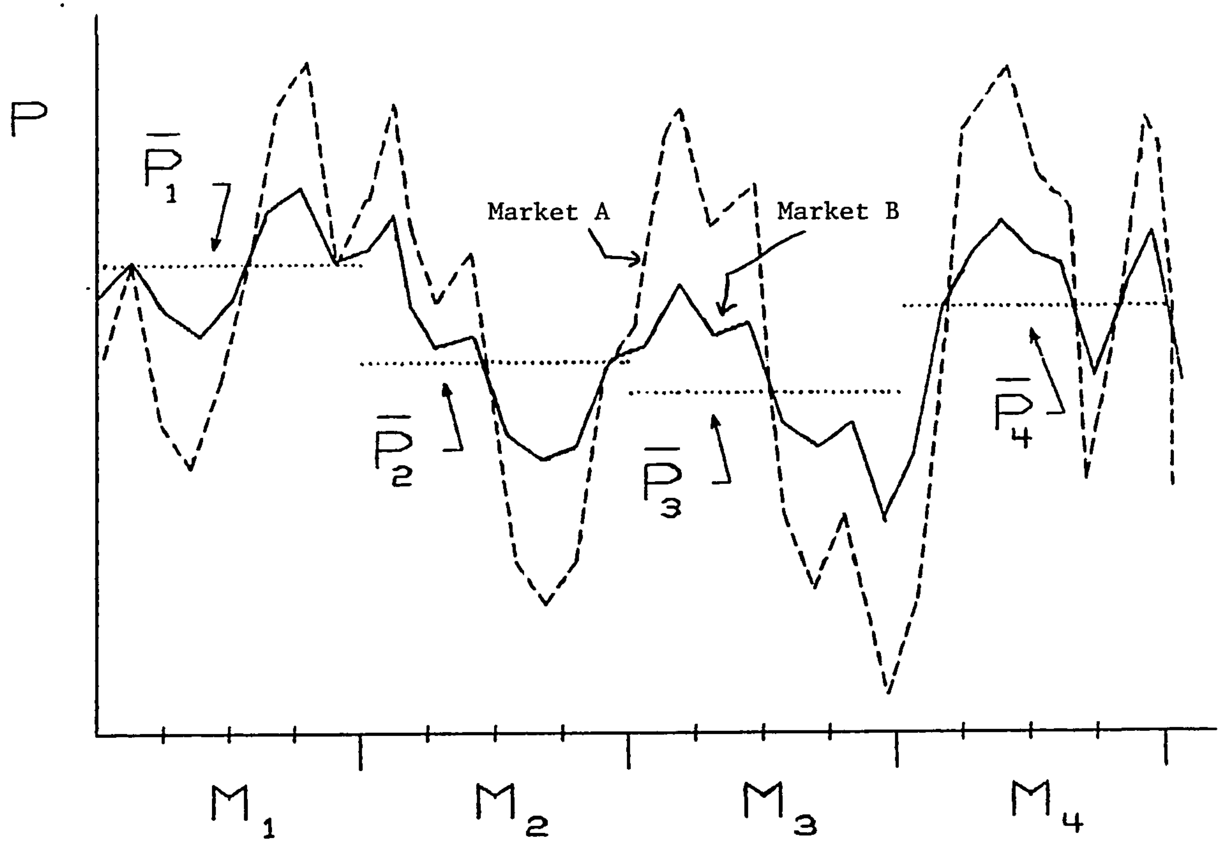

Figure 3.1. Two Hypothetical Time Series that Share Monthly Means but that Differ in Variability

averse individual or a risk seeking individual would not consider the risk of selling in market A to be comparable to selling in market B since the mean prices are the same but the within month variance differs between the two markets.

Our approach differs from other approaches in that our measure of variance describes the distribution of possible selling prices for the decision maker within the month in question. Other approaches measure the distribution of monthly means.

Variance of monthly mean prices

This variance will also be called the historical variance since one traditional procedure is to use the variance of a series of past prices about the mean of the past prices. For example, if monthly data were used, the h month ahead forecast of the variance in month F would be

$$V(\bar{P}_F) = \sum_{i-1}^{F-h} (\bar{P}_i - \bar{\bar{P}})^2/(F-h-1)$$

The $\bar{P}_i$ are the monthly mean prices and $\bar{\bar{P}}$ is the mean of the $\bar{P}_i$ for i = 1,..., F-h. This approach uses the past as the best forecast of mean and variance for month F. If an individual were interested in an estimate of the variance in price next month (say it is May) and the individual had monthly data over the past five years, this method provides two ways to approximate that variance. One way is to use the past two years of data and calculate the variance above using h = 1 and F = 25. Another way would be to pick out the data for the particular calendar month in question (May) over the past five years. So h = 1 again and F = 6.

This variance is not appropriate for intrayear marketing decisions. This variance implies that the distribution of possible future selling prices is made up of the monthly means from the preceding sample period and that the concern is how these monthly means are dispersed about a sample period mean. Hence the estimate of the variance in prices next month (for F=13, h=1) is the sum of the squared deviations of the 12 monthly means of the past year from the past year's mean. This measure of variance sheds no light on what the distribution of possible selling prices next month will be. The distribution marked II on Figure 3.2 represents the distribution of the monthly mean prices.

Variance of the forecasted mean price

Peck proposed an alternative definition of variance that would be relevant for intrayear marketing decisions. Peck proposed that the variance of the forecast was the relevant variance. Form the regression

$$\bar{P}_i = X_i B + e_i \quad , \ i=1,\ldots,F-h$$

where $\bar{P}_i$ is again the monthly mean price for month i, X_i is a vector of exogenous variables, B is a vector of coefficients, and e_i is the error. The variance of the forecast for the forecast $\bar{P}_F$ given the set of exogenous variables X_F is

$$V(\bar{P}_F) = \sigma_e^2[1 + X_F'(X'X)^{-1}X_F]$$

where σ_e^2 is the variance of the errors and X is the matrix of exogenous variables in the sample period. The variance of the forecasted mean price accounts for the dispersion of e and of B.

The distribution marked III in Figure 3.2 represents part of the distribution used in Peck's variance of the forecasted mean price. The

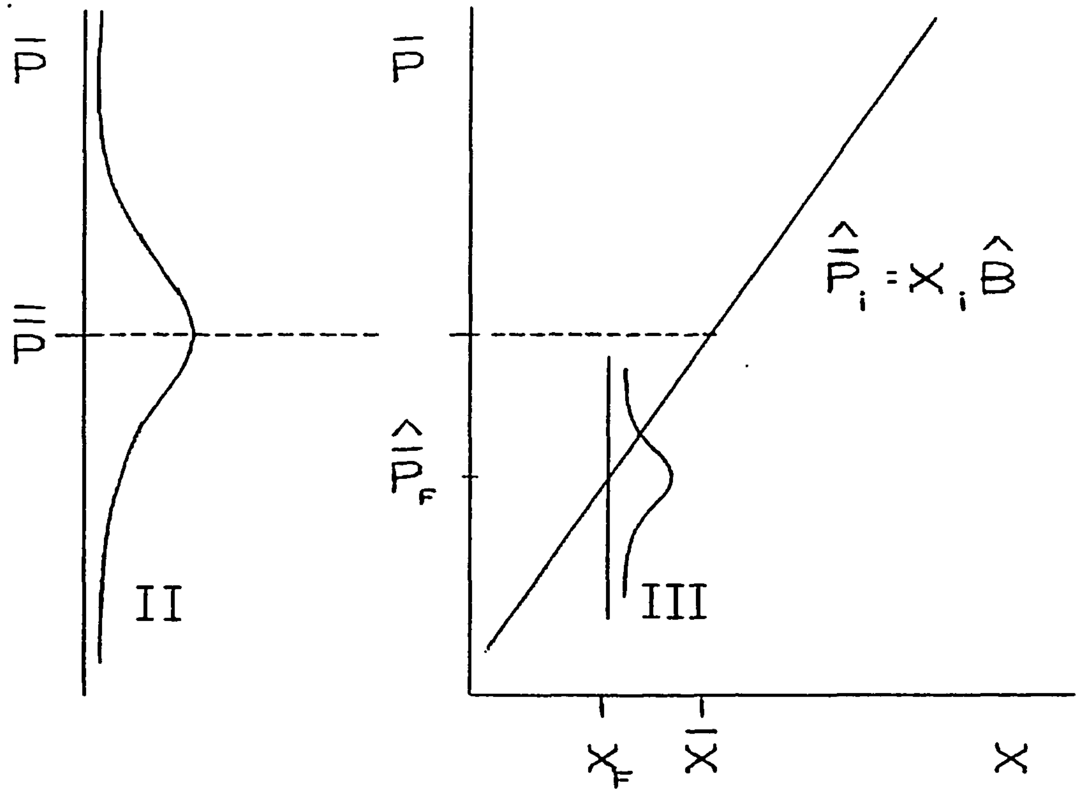

Figure 3.2. The Distribution of Monthly Mean Prices and the Distribution of the Errors form a Regression Equation that Uses Monthly Data

distribution shown is the distribution of the errors at X_F and has a variance of σ_e^2. Note that the dashed horizontal line shows the relationship between the two halves of Figure 3.2.

The variance of the forecasted mean price, as a distribution of the possible monthly means for the forecast month, implies that the individual can always receive the monthly mean price. Clearly, the only way an individual can be assured of the monthly mean price is to sell a bushel of corn or a pound of beef every hour during the sales month. The variance of the forecasted mean price then is not relevant for marketing decisions within the year.

For the general marketing decision discussed previously, the price (or return) distributions of interest are the possible selling prices for the two markets within the month in question. The farmer can not, in all likelihood, expect to receive the monthly mean price in month t -- not unless he markets his production continuously over that month.

Under any of the three variance measures, the best forecast of the price the individual will receive is the monthly mean price. However, the best forecast of the variability in the possible selling prices is the momentary variance.

The concept of a momentary variance is not limited to this one measure of riskiness. Although not dealt with explicitly in this study, note that the concept can also be extended to a momentary semivariance. The momentary deviations below the target would be squared, summed, and divided by the total number of 'moments' in the month. If the individual is concerned about the downside risk in the sales month, it is clear that the within month deviations in price that are below the target are relevant. The number of monthly mean prices from previous months that are below the target price is not relevant for this individual's decisions.

Plausible Compensation Rules

Although much has been written on the expected utility theory of decision making, some areas of the theory are, as yet, undeveloped. Present theory states that an individual forms a subjective notion of what the distribution of payoffs looks like. Economic forecasts help decision makers form their notion of the subjective distribution. Economic theory does not address satisfactorily how individuals use economic data or forecasts that do not fully meet their data requirements. How do individuals compensate for a lack of information on certain variables of interest? In this study in particular, how do individuals compensate for the lack of an appropriate measure of variance?

Expected utility maximization says that an individual develops a subjective notion of the distribution of returns. The individual of course has facility with probabilities and is able to update his subjective notion of the distribution with Baye's theorem when provided new information. Therefore new information can not lower utility although it does not necessarily raise utility. The individual can in essence ignore useless information.

There is little work in economics on how people actually update their subjective notion of a random variable. From a psychological perspective, some studies have looked at the expected utility theory assumptions regarding peoples' ability to update their subjective notions (Gardner, 1985; Martin, 1985; and Arrow, 1982). These studies suggest that people tend not to update with new information in the way expected utility theory indicates. People do not seem to use Bayes' theorem correctly and when they change a probability, the change is influenced by factors such as the phrasing of the problem, their interest in the outcome, their memory of what they believed before, among other factors. People do not necessarily use all of the information with which they are presented either.

How does the individual make decisions if some of the information he requires in not available to him? Ladd (undated lecture notes) and Meyer (1987) proposed that when a producer does not have information on the distribution of a characteristic within an input, he may assume there is no distribution of the characteristic, i.e., the amount of the characteristic is a given number. This individual then does not maximize expected profit, but instead maximizes anticipated profits. He maximizes profits from the anticipated level of the characteristic. This would be true of a utility maximizer also. Instead of maximizing expected utility, the individual maximizes anticipated utility.

Currently, expected utility maximizing decision makers are not being supplied with the relevant variance. The question then is how do individuals compensate for this lack of information? One could imagine myriad possible responses to a lack of information. Some of the responses may be erroneous in that the individual is wrong about the relationship between two variables. The individual may believe that, for example, the variance of the forecast is related to the momentary variance. The individual, however, may be able to identify the correct relationship between two variables. Following are listed six possible responses to a lack of information on the momentary variance. Presume that the individual currently obtains forecasts of the returns and of the variances of the forecasts of the returns of the marketing alternatives.

Case 1: The individual may feel that neither the variance of the forecasted mean price nor the variance of the monthly mean prices is the relevant variance for his marketing decisions. The individual may however have no basis for believing that the relevant variance can be forecasted with the information that has been supplied to him. In case 1, then, suppose the individual uses his perception of what the relevant variance was last year as his forecast of the relevant variance for this year. The individual uses his perception of the average monthly momentary variance for the last marketing year as the best forecast of the variance of prices in time t_1 and t_2 of the current marketing year.

To avoid the additional complication of specifying how this individual arrives at his subjective notion of the average monthly momentary variance, one could pick the case where the individual is correct about his estimate of this variance in the past year. A more complicated (or more realistic) specification of how this individual arrives at his estimate is beyond the scope of this study.

Case 2: This case is a variation on case 1. Here the individual again feels that neither the variance of the forecasted mean price nor the variance of the monthly mean prices is the relevant variance for his marketing decisions. In case 2, the individual has a perception or subjective notion of what the average momentary variance has been for a particular calendar month over say the past three years. For example, when the individual is forecasting the relevant variance of a price for month t_1 of the current marketing year, he uses his notion of the average monthly momentary variance for the month t_1 over the past three years.

Again it is beyond the scope of the study to model how the individual arrives at his subjective notions of the momentary variance in the past. One could consider the case where the individual was correct about his notion of the average of the monthly momentary variance for a particular calendar month over the past three years.

Case 3: This case is straightforward. The individual believes that the variance of the forecasted mean price that he receives is the relevant variance for his marketing decisions. This individual uses this variance measure then in calculating the expected utilities of the various marketing alternatives.

Case 4: This case is the same as case 3 except that instead of receiving the variance of the forecasted mean price, he receives the variance of the monthly mean prices. In this case, the individual believes that this is the relevant variance for his marketing decisions. This measure of variance is then used in calculating the expected utilities of the decisions.

Case 5: The final case considered in this study is the case where the individual receives one of the two irrelevant measures of variance but he uses neither. The individual realizes that neither the variance of the forecasted mean price nor the variance of the monthly mean prices provide information on the momentary variance. This individual uses only the forecasted price in making his marketing decisions and thus acts as if he were an expected profit maximizer.

In all five cases above, there is the presumption that the individual would prefer to obtain the forecasts of the return and of the momentary variance for each marketing alternative. Given that they do not have access to the momentary variance, they respond in different ways.

In a practical setting, where there is lumpiness in purchases, production, and sales, different decision rules may lead to the same decision. Stated differently, even though an individual does not have the specific information required for a certain decision rule, that individual may still make the 'right' decision by using another decision rule.

This study will examine how often using the wrong decision rule leads to the right decision. A sample period will be chosen over which marketing decisions will be simulated using the various decision rules.

There is one decision rule that will be considered the 'right' rule and thus will lead to the 'right' decision. The right rule is the mean-variance utility function with the momentary measure of variance. The wrong rules --or compensation rules -- are rules that approximate how the individual might make decisions in the absence of the momentary variance.

Random Selection of Current Prices

Previous studies have typically ignored the distribution of prices within the decision month just as they have ignored the distribution of prices within the future month. Previous studies have assumed that the individual always receives the monthly mean price in the decision month and in the future month. The typical approach then ignores the fact that the marketing alternative that maximizes expected utility depends in part on the particular momentary price the individual faces when he transacts business in the decision month. The typical approach would conclude that a particular marketing alternative either maximizes expected utility or it does not for a given decision month. This dissertation however will consider the distribution of prices within the decision month and hence can state what the probability is that a particular alternative maximizes expected utility for that decision month. If this probability is neither 0 nor 1 for the decision month, the results of studies where only monthly mean prices are used will be incomplete.

Ignoring the distribution of prices within the decision month has yet another implication. When researchers examine the outcomes or the incomes received from the various decision rules they are testing, the distribution of prices within the decision month together with the distribution of prices within the future month are important. Previous studies would conclude that there is a certainty of a loss (gain) for a particular decision because these studies only use the monthly mean price in the decision month and the monthly mean price in the future month. In actuality, there may well be a nonzero probability of a gain (loss) with that decision because of the particular momentary prices at which the individual transacts business.

This dissertation uses daily average prices in the cash market and daily closing prices in the futures market in order to examine the importance of considering the within month distribution of prices for both the decision month and for the future month. When the hypothetical producer in the simulations in this study examines the marketing alternatives, there is approximately a 1 in 22 chance of receiving any particular price in the decision month (assuming about 22 business days per month). Since the individual could have transacted business at any of the approximately 22 prices in the decision month and any of the approximately 22 prices in the future month, when one evaluates the income received from a particular decision, one must consider about 484 combinations of current month prices and future month prices to calculate the possible incomes.

CHAPTER 4. METHOD OF ANALYSIS FOR THIS STUDY

Chapter 3 outlined the inconsistency between the theory and practice in regard to the choice of the relevant variance of income. Theory indicates one definition of variance that individuals use in making decisions, but in practice, either another variance is given or none is given. Therefore, possible responses by the individual to the currently provided variance were presented also. These responses were called compensation rules since they represented rules of thumb the individual could use to compensate for the lack of the relevant variance.

Chapter 4 outlines the method by which one can examine the closeness of two decision rules. If, during a certain period of time, an individual made the same marketing decisions using the old information (variance) as he would have made had he used the new information (momentary variance), then the new information was not of much use to this individual. How often does an 'incorrect' decision rule yield the same marketing decisions as the 'correct' decision rule?

The known quadratic utility function is used to yield the maximum expected utility for the correct and the incorrect decision rules. The correct decision rule uses the momentary variance for the measure of variance. The incorrect decision rule uses one of the variance measures of the compensation rules from Chapter 3.

This study will examine whether a utility maximizing farmer's decisions differ greatly depending on whether he had an estimate of the momentary variance or not by selecting a group of farmers hypothetically. There are three main characteristics of the hypothetical farmers that are important in this study. So this study will select a representative farmer from each possible combination of these characteristics. By simulating the marketing decisions of these representative farmers, one can identify how decisions differ depending on each of the three characteristics.

First, these three characteristics are outlined. Second, there will be an outline of a farm marketing decision and how it can be simulated in this study. Third, there will be an explanation of how the simulation results will be evaluated.

Characteristics of the Hypothetical Farmers

The three characteristics are the risk aversion, the forecasting technique used, and the compensation rule followed (which includes the definition of variance currently received).

Levels of risk aversion L are used to identify the affect of risk aversion on the decisions during the sample period. The expected utility function will take the form

$$EU(y) = E(y) + L\ V(y)$$

where y is the return, U(.) is the utility, E is the expectations operator and V(.) is the variance.

The compensation rules outlined in Chapter 3 are used to describe how individuals make decisions without a measure of the momentary variance. The simulations in this study will be conducted using the variance alternatives specified in compensation rules 3 and 5 of Chapter 3. Compensation rule 3 maintains that the farmer uses the variance of the forecasted mean price currently. Compensation rule 5 maintains that the farmer uses a variance of zero in response to the lack of the relevant variance. Results from these rules are compared with results obtained by using the predicted momentary variance.

There may be differences in the decisions made depending on which forecasting technique the individual has access to. The individual does not necessarily have to do the forecasting himself but must at least have access to forecasts made from the particular technique.

Nature of a Soybean Marketing Decision

This study will simulate a farmer's marketing decisions over a period of time in order to evaluate the importance of the relevant definition of variance to the farmer. Although there are many marketing decisions that could be simulated, this section discusses soybean hedging decisions for a farmer throughout the year.

In this section, this study examines the marketing decisions of a soybean farmer. The farmer is willing to use the futures market to hedge his eventual cash sales. This farmer examines his marketing alternatives beginning in the spring but marketing decisions at this time do not alter production. The farmer also re-examines his marketing alternatives at harvest. The latest that the farmer will sell his crop is the spring following its harvest.

The spring set of marketing alternatives includes (1) hedged until harvest and (2) unhedged until harvest. The fall set of alternatives includes (1) hedged storage through the winter, (2) unhedged storage through the winter, and (3) cash sales now (in the fall). Any hedges placed in the past spring must be offset in the fall since the contract used matures in the fall. Likewise, any hedges placed in the fall must be offset in the following spring since the contract used matures in the spring.

The spring decision

In the spring (time t_0), after the planting decisions are made, the farmer has the option of hedging some or all of his expected harvest using a futures contract that matures in month t_1. This is known as a preharvest hedge or an anticipatory hedge. Presume that the farmer will either hedge all of his production, Q_0, or none of it.

At time t_0, the farmer compares the expected utility of hedging and the expected utility of remaining with a cash position until the fall, time t_1. The expected utility function is

$$EU(yQ_0) = Q_0EU(y) = Q_0Ey + LQ_0^2V(y)$$

where E is the expectations operator, V(.) is the measure of variance, and y represents the per unit return from the particular decision. Since the expected utility is defined up to a linear transformation, one can divide through by the assumed constant Q_0 to yield

$$EU(y) = Ey + LQ_0V(y)$$

This is the form that all expected utility comparisons that follow will take.

<u>Expected utility of being hedged until harvest</u>   Hedging in t_0 would involve selling futures contracts that mature in time t_1 totaling Q_0. The expected return per bushel to hedging is the expected localized futures price denoted $\hat{y}_H$ where

4.1. $\hat{y}_H = (F_{01} - \hat{B}_{11}) - hc.$

F_{01} is the current price of the futures contract that matures in t_1. $\hat{B}_{11}$ is the forecasted mean basis on the contract that matures in t_1 (futures price F_{11} minus cash price P_1) observed in time t_1. HC is the total hedging costs which include broker fees and interest on the margin and $hc = HC/Q_0$ is the per bushel hedging cost.

The variance of the return to hedging (on a per bushel basis) is the variance of the localized futures price or

$$\hat{V}(y_H) = Q\hat{V}(B_{11})$$

since F_{01} and hc are assumed known to the farmer at time t_0.

The expected utility of hedging in t_0 then can be calculated as

4.2. $EU(y_H) = (F_{01} - \hat{B}_{11}) - hc + LQ_0\hat{V}(B_{11}).$

<u>Expected utility of remaining unhedged until harvest</u>   The farmer also calculates the expected utility of remaining with a cash position alone until fall, time t_1. The expected return from this alternative is simply

4.3. $\hat{y}_N = \hat{P}_1.$

where $\hat{P}_1$ is the forecasted mean cash price in month t_1. The variance of the return from this alternative (on a per bushel basis) is

$$\hat{V}(y_H) = Q\hat{V}(P_1).$$

The expected utility of this cash market alternative is

4.4. $EU(y_N) = \hat{P}_1 + LQ_0\hat{V}(P_1).$

So, in t_0, the farmer either hedges with expected utility $EU(y_H)$ or does not hedge with expected utility $EU(y_N)$, depending on which expected utility is higher. One knows then that this farmer will choose the hedging alternative when the following expression is positive

4.5.
$$\begin{aligned} EU(y_H) - EU(y_N) &= F_{01} - \hat{B}_{11} - hc + LQ_0\hat{V}(B_{11}) \\ &\quad - [\hat{P}_1 + LQ_0\hat{V}(P_1)] \\ &= F_{01} - (\hat{P}_1 + \hat{B}_{11}) + LQ_0\hat{V}(B_{11}) \\ &\quad - LQ_0\hat{V}(P_1) - hc \\ &= F_{01} - \hat{F}_{11} + LQ_0\hat{V}(B_{11}) - LQ_0\hat{V}(P_1) - hc. \end{aligned}$$

The fall decision

In the fall, time t_1, the marketing alternatives open to the farmer are essentially the same whether he decided to hedge or not to hedge last spring. The farmer has three alternatives in time t_1. He can offset any current futures position and (1) store and place a new hedge using a more distant contract (one that matures in time t_2), or (2) store the crop unhedged until time t_2, or (3) sell the crop in the cash market in month t_1. Note that the farmer must offset his current futures position (if he has one) regardless of his marketing decision in t_1. Assume the transportation costs involved in delivering on the contract are high enough so the individual does not deliver in lieu of offsetting the hedge. The farmer chooses among the three alternatives based on their expected utilities.

Expected utility of hedged storage through the winter With no current futures position this is a straightforward hedge. This alternative is referred to as rolling a hedge forward if one does have a current futures position. Placing the new hedge involves buying back any futures contracts that mature in t_1 and selling futures contracts (amounting to Q_0) that mature in t_2. The current price on the t_1 contracts is F_{11} and the current price on the t_2 contracts is F_{12}. In the following spring, the farmer would offset the hedge and sell his soybeans in the cash market. The expected return from placing the new hedge is the localized futures price $\hat{y}_H$

4.6. $\hat{y}_H = F_{12} - \hat{B}_{22} - hc$

where $\hat{B}_{22}$ is the forecasted mean basis for the contract that matures in t_2 observed in time t_2 and other variables are as defined before. Note that '$- F_{11}$' has been deleted from equation (4.6). The reason is that the difference in the expected utilities of the alternatives does not depend on the value of F_{11} (due to cancellation). Equation (4.6) then is valid whether a hedge was placed in time t_0 or not.

The variance of the return to placing the new hedge (on a per bushel basis) is

$$\hat{V}(y_H) = Q_0\hat{V}(B_{22}).$$

Then the expected utility of placing the new hedge is

4.7. $EU(y_H) = F_{12} - \hat{B}_{22} - hc + LQ_0\hat{V}(B_{22}).$

Expected utility of unhedged storage through the winter This alternative calls for the purchase of any futures contracts that were sold in time t_0. The farmer then maintains only a cash position until he sells the cash commodity in time t_2.

The expected return from this alternative is simply the expected price to be received in time t_2,

4.8. $\hat{y}_N = \hat{P}_2$.

$\hat{P}_2$ is the forecasted mean cash price in time t_2. Note that the term '$- F_{11}$' is again deleted for the same reason given earlier. The variance of the return to remaining unhedged until time t_2 (on a per bushel basis) is

$$\hat{V}(y_N) = Q_0\hat{V}(P_2).$$

The expected utility of this alternative is

4.9. $EU(y_N) = \hat{P}_2 + LQ_0\hat{V}(P_2)$.

<u>Expected utility of cash sales in month t_1</u> This alternative involves offsetting any current futures position and simultaneously selling the crop in time t_1. The return from this alternative is

$$y_S = fP_1$$

where P_1 is the (known) current price of the commodity. f is the factor $(1+i)^7$ which converts the current income into the future value for an interest rate i. This allows one to compare current income to income that will be received in seven months. Again, the term '$- F_{11}$' has been deleted. There is no variance of return with this alternative so the expected utility can be stated

4.10. $EU(y_S) = fP_1$.

The farmer will choose the hedged storage alternative if the following two expressions are positive:

4.11. $EU(y_H) - EU(y_N) = F_{12} - \hat{B}_{22} - hc + LQ_0\hat{V}(B_{22}) - [\hat{P}_2 + LQ_0\hat{V}(P_2)]$

4.12. $EU(y_H) - EU(y_S) = F_{12} - \hat{B}_{22} - hc + LQ_0\hat{V}(B_{22}) - fP_1$.

The farmer will choose the unhedged storage alternative if equation

(4.11) is negative and the following equation is positive:

$$4.13. \quad EU(y_N) - EU(y_S) = \hat{P}_2 + LQ_0\hat{V}(P_2) - fP_1.$$

The farmer will choose to sell the commodity on the cash market in time t_1 if equation (4.12) and equation (4.13) are both negative.

Simulation of Marketing Decisions

Simulations of the marketing decisions will be performed in order to identify whether decision making would improve if the individual had access to the relevant variance, the momentary variance. Decision making is not improved in this study when the use of the relevant variance does not result in decisions significantly different from what would have been made otherwise. What is 'significantly different' varies from individual to individual and so any cut-off point used in this study can only be rather arbitrary. Intuitively, one may suppose that using a different decision rule (the same equation but with a different measure of variance) will at times lead one to make the right decision. The right decision is the decision that is made using the known utility function and the relevant variance. One result of the simulations that will be important is the percent of the time a 'wrong' decision rule leads to the 'right' decision. If this percentage is 'large', one can conclude that even without the relevant variance, the individual is making the right decision much of the time.

There is another aspect to how close the right and the wrong rules are to one another. When the two rules yield different decisions, it is possible that their respective outcomes are quite similar. This is possible for two reasons. The first reason is that the two decision rules are optimizing different equations just as the expected profit maximization rule differs from the expected utility maximization rule. One should not be surprised that on average an expected profit maximizer has higher profits than an expected utility maximizer. The same can be true when one is discussing two expected utility maximizing rules. One expected utility rule may yield a higher average profit than another. The second reason is that the outcome from one decision rule can be greater than its average while the outcome from the other decision rule is less than its average and so the outcome from a right decision rule can be less than the outcome from the wrong decision rule.

Therefore, this study is also interested in what percent of the time did the following two events occur together: (1) the decision rules yielded different decisions and (2) the difference between the outcome of the right rule and the outcome of the wrong rule was no more than e. This information will be gleaned from the simulations.

One can then combine into one number (1) the percent of the time the decisions from the right and wrong rules were the same and (2) the percent of the time the outcomes from the right and wrong rules differed, but this difference did not exceed e. Call the first percentage Pr1 and call the second Pr2. One can then make the statement that (Pr1 + Pr2) percent of the time, using the wrong rule led to the right decision or at least to an outcome that is close enough to the right outcome. Differences in outcomes of less than e are considered 'insignificant' by the individual. The choice of e is rather arbitrary.

The simulations of the marketing decisions discussed will be performed over a period of seven years. Several different simulations will be conducted, each with different farmer characteristics. The characteristics that will be varied are (1) the farmer's risk aversion, (2) the farmer's response to insufficient information, (3) the forecasting technique used. Various levels of risk aversion L within a range will be used in the simulation. There will be two responses to insufficient information (compensation rules 3 and 5 of Chapter 3) and there will be two forecasting techniques from which to choose.

The values of L that will be chosen are based in part on implied results of previous studies and in part on possible magnitudes of the risk effect in this study. This discussion is saved for the chapter on the choice of risk aversion.

Evaluation of Simulations

A more detailed description of the simulations follows. The spring decision and the fall decision are discussed separately here, though the approaches are essentially the same.

An important consideration in all the simulations is the difference between the prices that the farmer faces in the decision month and the prices that this study uses. The concept of the momentary variance applies to the distribution of prices faced in the current month as well as it does to the distribution of prices one will face in the future. The farmer can not be assured of receiving the monthly average price in the current month just as he can not be assured of receiving the monthly average price in the future month.

This study presumes that the farmer makes his marketing decision on one day during the decision month and that the current price he faces is that day's average price. This study assumes the farmer has no strategy to select the day within the month to make his decision. Likewise, once the decision is made either to hedge or not to hedge on that day, no changes are made until the next decision period (either t_1 or t_2). So how does the researcher determine which set of daily average prices the farmer is facing when the decision is made?

There are approximately 22 business days in a month and the daily mean prices are considered in this study. This study will, in essence, conduct the simulated decision 22 times that month and aggregate the results to calculate the probability of certain decisions being made. For exposition, use the two decision rules--one, the correct rule and the other, the incorrect rule. The individual makes his decision using the correct rule by comparing the expected utility of the two marketing alternatives being considered. The individual makes his decision using the incorrect rule by comparing the expected utility also but in this case, the incorrect or irrelevant information was used to calculate the expected utilities.

Spring simulation evaluation

Consider the spring decision. One uses equation (4.5) to compare expected utilities of the alternatives. Add a new subscript that identifies the decision rule used. So $EU_1(y_H)$ is the expected utility of hedging when decision rule 1, the correct rule, is used. $EU_2(y_H)$ is the expected utility of hedging when decision rule 2, the incorrect rule, is used. Therefore, referring to equation (4.5), one knows that the individual chooses the hedging alternative over the nonhedging alternative as

$$EU_i(y_H) - EU_i(y_N) > 0$$

for decision rule i (i=1,2).

Note from equation (4.5) that once the forecasts of F_{11}, $V(B_{11})$, and $V(P_1)$ are made for a given decision rule, the only term that can yet influence the decision made is the term F_{01}, the current price of the futures contract. The other terms are already known in the sense that their forecasts are known. Therefore, one can combine these 'fixed' terms into one. For decision rule 1, define

$$G_1 = \hat{F}_{11} - LQ_0\hat{V}_1(B_{11}) + LQ_0\hat{V}_1(P_1) + hc$$

where the forecasted prices and variances are the relevant forecasts. The variances have been subscripted with a 1 now to indicate that they are the relevant variances. The relevant forecast of the variance is the forecasted momentary variance of price. For decision rule 2, define

$$G_2 = \hat{F}_{11} - LQ_0\hat{V}_2(B_{11}) + LQ_0\hat{V}_2(P_1) + hc$$

where the forecasted prices and variances are not the relevant forecasts. The variances here have been subscripted with a 2 to indicate that they are not the relevant forecasts of variances. The irrelevant forecasts of variance of price include the variance of the forecasted mean price and the variance of the monthly mean prices.

So the decision made using rule 1 depends on the sign of

$$EU_1(y_H) - EU_1(y_N) = F_{01} - G_1$$

and the decision made using rule 2 depends on the sign of

$$EU_2(y_H) - EU_2(y_N) = F_{01} - G_2.$$

Recall that the researcher does not know on which day the individual made his decision but since the researcher knows the daily closing futures prices for the decision month, he can calculate the probability that a certain decision was made. Figure 4.1 can be used to gain some insights on the closeness of the two decision rules.

The center line of Figure 4.1 represents the array of the futures price F_{01} from its decision month low, F_{01}^{low}, to its decision month high, F_{01}^{high}. G_1 and G_2 are as defined earlier and the case $G_1 < G_2$ is depicted in the figure. The top half of Figure 4.1 indicates the ranges of F_{01} where rule 1, the correct rule, yields a no hedge decision and a hedge decision given the value of G_1. Likewise, the bottom half of Figure 4.1 indicates the ranges of F_{01} where rule 2, the incorrect rule, yields a no hedge decision and a hedge decision given the value of G_2.

It is clear that there are two ranges of F_{01} where the two decision rules make the same decision: below $\min(G_1, G_2)$ and above $\max(G_1, G_2)$. For F_{01} between G_1 and G_2 the decision rules differ. Since the researcher knows the daily closing futures prices F_{01} in this month, the researcher can calculate the probability that F_{01} was such that the two decision rules led to different actions. The probability in the month that F_{01} was either less than $\min(G_1, G_2)$ or greater than $\max(G_1, G_2)$ equals the probability that the decisions from the right and wrong rules were the same. This probability has been already defined as Pr1 in the introduction to this section. This probability is a measure of how

```
Rule 1                        no hedge          hedge
                           <-----------> <--------------->
                                        G1
Array of prices:  F01low I------------I-----I---------I F01high
                                              G2
                           <----------------> <--------->
Rule 2                         no hedge          hedge
```

Figure 4.1. Ranges of Futures Price F_{01} Where the Two Decision Rules Yield the Various Marketing Alternatives for $G_1 < G_2$

close the two decision rules are to one another. If Prl is quite large, one can say that the decision rules for this month were closer than for another month where Prl was quite small.

The probability Prl can be calculated as one minus the probability that the two decision rules will yield different decisions. So

$$Prl = 1 - Pr(\min(G_1, G_2) < F_{01} < \max(G_1, G_2))$$

Prl will be calculated by finding the percent of the time that daily closing futures price F_{01} was either less than $\min(G_1, G_2)$ or greater than $\max(G_1, G_2)$ for the decision month.

The other measure of closeness of the right and the wrong decision rules that will be examined takes into account that even though the actions of two decision rules are different, their respective outcomes may be quite similar as far as this individual is concerned. In the range $\min(G_1, G_2)$ to $\max(G_1, G_2)$, the two decision rules yield different decisions. This study will set an arbitrary level e such that when the difference between the return from the optimal rule and the return from the suboptimal rule is no more than e, the individual considers this difference insignificant. The outcomes of the decision rules can then be thought of as being close enough to one another.

By way of example, consider the case where $G_2 > G_1$ for the particular decision month. Within the range G_1 to G_2 then, rule 1 (the optimal rule) yields a hedge and rule 2 (the suboptimal rule) yields a no hedge decision. The cost of following the suboptimal rule, calculated after any futures position is offset and the cash commodity is sold, is

$$\begin{aligned} C_{HN} &= y_H - y_N \\ &= F_{01} - B_{11} - P_1 - hc \\ &= F_{01} - F_{11} - hc \end{aligned}$$

where C_{HN} is the ex post cost of not hedging when hedging was the correct decision. The per bushel hedging costs hc are included in the calculations.

For the case $G_1 > G_2$, the optimal decision is to remain unhedged and the suboptimal decision is to hedge within the range $G_2 < F_{01} < G_1$. Therefore the cost of the suboptimal decision in this case can be defined as

$$\begin{aligned} C_{NH} &= y_N - y_H \\ &= P_1 - F_{01} + B_{11} + hc \\ &= F_{11} - F_{01} + hc \end{aligned}$$

which is simply the negative of C_{HN}.

Note that the same problem arises here as earlier. That is, the researcher does not know on which of the approximately 22 days the farmer actually offset his futures position and sold the cash crop. Again this study will assume that the farmer picks one day in the month to transact business but that he has no strategy to pick that day. The researcher uses the daily closing futures prices F_{11} to identify the probability that a certain outcome is received.

The researcher has to consider both the F_{01} that the farmer faced and the F_{11} that he faced. For all combinations of (F_{01}, F_{11}) where $\min(G_1, G_2) < F_{01} < \max(G_1, G_2)$, there will be a nonzero cost to following the suboptimal rule. This study will calculate the probability that the cost of the suboptimal decision is less than e when the decisions differed between the two rules. This probability, Pr2, is a joint probability: the probability that $\min(G_1, G_2) < F_{01} < \max(G_1, G_2)$ and that C_{HN} or C_{NH}, whichever is appropriate, is less than e. For $G_1 < G_2$, this probability is

$$Pr2 = Pr(G_1 < F_{01} < G_2\ ,\ F_{01} - F_{11} - hc < e)$$

For the case $G_1 > G_2$, this probability Pr2 is

$$Pr2 = Pr(G_2 < F_{01} < G_1\ ,\ F_{11} - F_{01} + hc < e)$$

This probability will be calculated in this study by calculating the cost of the suboptimal rule using the actual daily closing futures prices F_{01} such that $\min(G_1, G_2) < F_{01} < \max(G_1, G_2)$ and all of the actual daily closing futures prices F_{11}. The probability equals the number of the combinations of $\min(G_1, G_2) < F_{01} < \max(G_1, G_2)$ and F_{11} where the cost is less than e divided by the total number of the combinations of $\min(G_1, G_2) < F_{01} < \max(G_1, G_2)$ and F_{11} all multiplied by the percent of the F_{01} within the range $\min(G_1, G_2) < F_{01} < \max(G_1, G_2)$.

As mentioned in the introduction to this section, one can state that the probability is Pr = (Pr1 + Pr2) that using the wrong rule will lead to the right decision or at least to an outcome that is close enough to the right outcome. This figure is of course for the particular spring decision period, the period from the decision month t_0 to the final transaction month t_1, but could easily be combined with the probabilities in other decision periods to indicate over time how close two decision rules are to one another.

So for the spring decision, this study will calculate the probabilities Pr1 and Pr2 as measures of how close the optimal and suboptimal decision rules are to one another. These same two measures of closeness of two decision rules (Pr1 and Pr2) can be calculated for the fall set of marketing decisions also. The analysis is an extension of the spring decision case but is somewhat more complicated.

<u>Fall simulation evaluation</u>

Again the expected utilities of the alternatives (in this case three) are compared and the alternative with the highest expected utility is chosen. As is the case with the spring decision, decision rule 1 is the correct rule (the optimal rule) and decision rule 2 is the incorrect rule (the suboptimal rule). Equations (4.11), (4.12) and (4.13) can then be amended by adding the decision rule subscript as $EU_i(.)$ for decision rule i (i=1,2).

Note that in equations (4.11), (4.12) and (4.13), some of the terms are known in the sense that their forecasts are known. The forecasted terms known to the researcher (and the farmer) include $\hat{B}_{22}$, $\hat{P}_2$, $\hat{V}(B_{22})$, and $\hat{V}(P_2)$. The researcher again does not know the current price facing the farmer. There are approximately 22 daily closing futures prices, F_{12}, and the same number of bases, B_{12}, that the farmer could be faced with in this decision month. So, just as before, this study defines some 'knowns' for the two decision rules. Group the terms in equation (4.11) as

$$EU_i(y_H) - EU_i(y_N) = F_{12} - [\hat{B}_{22} + \hat{P}_2 - LQ_0\hat{V}_i(B_{22}) + LQ_0\hat{V}_i(P_2) + hc]$$

and define

$$G_{iHN} = \hat{B}_{22} + \hat{P}_2 - LQ_0\hat{V}_i(B_{22}) + LQ_0\hat{V}_i(P_2) + hc$$

where subscript H represents 'hedged storage', subscript N represents 'unhedged storage'. Just as for the spring decision, the subscript i has been added to the variances to indicate which forecast of the variance is used: a 1 indicating the relevant forecasts and a 2 indicating the irrelevant forecasts. The variable hc is again the per bushel hedging costs. Group the terms in equation (4.12) as

$$\begin{aligned} EU_i(y_H) - EU_i(y_S) &= F_{12} - fP_1 - [\hat{B}_{22} - LQ_0\hat{V}_i(B_{22}) + hc] \\ &= F_{12} + fB_{12} - fF_{12} \\ &\quad - [\hat{B}_{22} - LQ_0\hat{V}_i(B_{22}) + hc] \\ &= (1-f)F_{12} + fB_{12} \\ &\quad - [\hat{B}_{22} - LQ_0\hat{V}_i(B_{22}) + hc] \end{aligned}$$

and define

$$G_{iHS} = \hat{B}_{22} - LQ_0\hat{V}_i(B_{22}) + hc.$$

Where subscript S represents 'sale this month'. Group the terms in equation (4.13) as

$$\begin{aligned} EU_i(y_N) - EU_i(y_S) &= \hat{P}_2 + LQ_0\hat{V}_i(P_2) - fP_1 \\ &= - fP_1 + [\hat{P}_2 + LQ_0\hat{V}_i(P_2)] \\ &= - fF_{12} + fB_{12} + [\hat{P}_2 + LQ_0\hat{V}_i(P_2)] \end{aligned}$$

and define

$$G_{iNS} = \hat{P}_2 + LQ_0\hat{V}_i(P_2).$$

Therefore, instead of referring to equations (4.11), (4.12) and (4.13), one can refer to the following set of three equations to evaluate under what conditions decision rule i will yield hedged storage, unhedged storage, and sales this month.

4.14. $EU_i(y_H) - EU_i(y_N) = F_{12} - G_{iHN}$

4.15. $EU_i(y_H) - EU_i(y_S) = (1-f)F_{12} + fB_{12} - G_{iHS}$

4.16. $EU_i(y_N) - EU_i(y_S) = - fF_{12} + fB_{12} + G_{iNS}$

Note also the identity $G_{iHN} = G_{iNS} + G_{iHS}$.

The three equations (4.14), (4.15), and (4.16) are all expressed in terms of F_{12} and B_{12}. Which F_{12} and B_{12} face the individual are not known to the researcher but the researcher does know the daily closing values of F_{12} and B_{12} in the decision month. Table 4.1 can be used to identify the probability that the right and wrong decision rules will yield the same decision.

For all possible values of G_{iHN}, G_{iNS}, and G_{iHS}, $i = 1, 2$, that satisfy the identity $G_{iHN} = G_{iNS} + G_{iHS}$, Table 4.1 defines areas or regions in (F_{12}, B_{12}) space. For each of the six regions in Table 4.1, the action of the two decision rules, the defining inequalities, and the

Table 4.1. Actions of the Decision Rules, The Defining Inequalities, and the Probability to be Calculated in the Associated Region for the General Case

Region	Action	Defining Inequalities	Probability to be Calculated
I	Rule 1: sales now Rule 2: sales now	$fF_{12} \geq fB_{12} + \max(G_{1NS}, G_{2NS})$ and $(1-f)F_{12} \leq -fB_{12} + \min(G_{1HS}, G_{2HS})$	Pr_{S1}
IIa	For $G_{1HS} < G_{2HS}$: Rule 1: hedged storage Rule 2: sales now	$F_{12} > G_{1HN}$, $fF_{12} > fB_{12} + G_{2NS}$, and $-fB_{12} + G_{1HS} < (1-f)F_{12} < -fB_{12} + G_{2HS}$	Pr_{HS2}
IIb	For $G_{1HS} > G_{2HS}$: Rule 1: sales now Rule 2: hedged storage	$F_{12} > G_{2HN}$, $fF_{12} > fB_{12} + G_{1NS}$, and $-fB_{12} + G_{2HS} < (1-f)F_{12} < -fB_{12} + G_{1HS}$	Pr_{SH2}
III	Rule 1: hedged storage Rule 2: hedged storage	$F_{12} \geq \max(G_{1HN}, G_{2HN})$ and $(1-f)F_{12} \geq -fB_{12} + \max(G_{1HS}, G_{2HS})$	Pr_{H1}

IVa	For $G_{1NS} > G_{2NS}$: Rule 1: unhedged storage Rule 2: sales now	$fB_{12} + G_{2NS} < fF_{12} < fB_{12} + G_{1NS}$, $(1-f)F_{12} < -fB_{12} + G_{2HS}$ and $F_{12} < G_{1HN}$	Pr_{NS2}
IVb	For $G_{1NS} < G_{2NS}$: Rule 1: sales now Rule 2: unhedged storage	$fB_{12} + G_{1NS} < fF_{12} < fB_{12} + G_{2NS}$, $F_{12} < G_{2HN}$, and $(1-f)F_{12} < -fB_{12} + G_{1HS}$	Pr_{SN2}
Va	For $G_{1HN} > G_{2HN}$: Rule 1: unhedged storage Rule 2: hedged storage	$G_{2HN} < F_{12} < G_{1HN}$, $(1-f)F_{12} > -fB_{12} + G_{2HS}$, and $fF_{12} < fB_{12} + G_{1NS}$	Pr_{NH2}
Vb	For $G_{1HN} < G_{2HN}$: Rule 1: hedged storage Rule 2: unhedged storage	$G_{1HN} < F_{12} < G_{2HN}$, $(1-f)F_{12} > -fB_{12} + G_{1HS}$, and $fF_{12} < fB_{12} + G_{2NS}$	Pr_{HN2}
VI	Rule 1: unhedged storage Rule 2: unhedged storage	$F_{12} \leq \min(G_{1HN}, G_{2HN})$ and $fF_{12} \leq fB_{12} + \min(G_{1NS}, G_{2NS})$	Pr_{N1}

associated probability to be calculated are identified.

The regions defined in Table 4.1 were identified using equations (4.14), (4.15), and (4.16). From the equations, one knows that rule i yields hedged storage when $F_{12} > G_{iHN}$ and $(1-f)F_{12} > -fB_{12} + G_{iHS}$. Rule i yields unhedged storage when $F_{12} < G_{iHN}$ and $fF_{12} < fB_{12} + G_{iNS}$. Rule i yields cash sales now when $(1-f)F_{12} < -fB_{12} + G_{iHS}$ and $fF_{12} > fB_{12} + G_{iNS}$. The exact boundaries of the six regions identified in Table 4.1 depend on the size of G_{1HN} relative to G_{2HN}, the size of G_{1HS} relative to G_{2HS}, and the size of G_{1NS} relative to G_{2NS}. The defining inequalities then use the notation min(.,.) and max(.,.) so that the most restrictive inequality defines the appropriate boundary.

Note that decision rules 1 and 2 yield the same decision for (F_{12}, B_{12}) points in areas I, III, and VI. Decisions are not the same for points in areas II, IV, and V.

The researcher knows the daily closing futures prices F_{12} and B_{12} in the decision month so the researcher can calculate the probability Pr1 that the decisions from the two rules were the same. The probability Pr1 equals the probability that both rules yield hedged storage, PrH1 (area III), plus the probability that both rules yield unhedged storage, PrN1 (area VI), plus the probability that both rules yield cash sales this month, PrS1 (area I). Then Pr1 = PrH1 + PrN1 + PrS1 where each of the probabilities is calculated as the percent of the daily closing F_{12} and B_{12} that actually fell within the specified regions.

A figure analogous to Figure 4.1 can be drawn, except that in the fall there are three marketing alternatives instead of two as in the spring. There are six possible shapes of the six regions defined in Table 4.1 where the difference in shapes is a function of the magnitude of G_{1HS} relative to G_{2HS}, of G_{1NS} relative to G_{2NS}, and of G_{1HN} relative to G_{2HN}. In this chapter, however, only one of the six cases is presented in Figure 4.2. All six cases are presented in Appendix A. Note that all lines in Figure 4.2 are continuous but only the segments that represent important boundaries have been drawn.

Area (IIa + III) in Figure 4.2 represents the combinations of F_{12} and B_{12} where rule 1 yields hedged storage. Area (IVa + Va + VI) indicates where rule 1 yields unhedged storage. Area I indicates where rule 1 yields cash sales now. Likewise for rule 2, area (III + Va) indicates where rule 2 yields hedged storage, area (VI) indicates where rule 2 yields unhedged storage, and (I + IIa + IVa) indicates where rule 2 yields cash sales now.

The second measure of closeness of two decision rules is calculated after the outcomes of the decisions are known to the farmer. From the outcomes, one can calculate the cost of using the wrong decision rule. There are six ways in total that an individual can be wrong about a decision given the values of G_{1HN}, G_{1NS}, G_{1HS}, G_{2HN}, G_{2NS}, and G_{2HS} and the identity $G_{iHN} = G_{iNS} + G_{iHS}$. The individual could have chosen (1) cash sales this month when he should have chosen hedged storage (area IIa of Figure 4.2), (2) cash sales this month when he should have chosen unhedged storage (area IVa of Figure 4.2), (3) hedged storage when he should have chosen unhedged storage (area Va of Figure 4.2), (4)

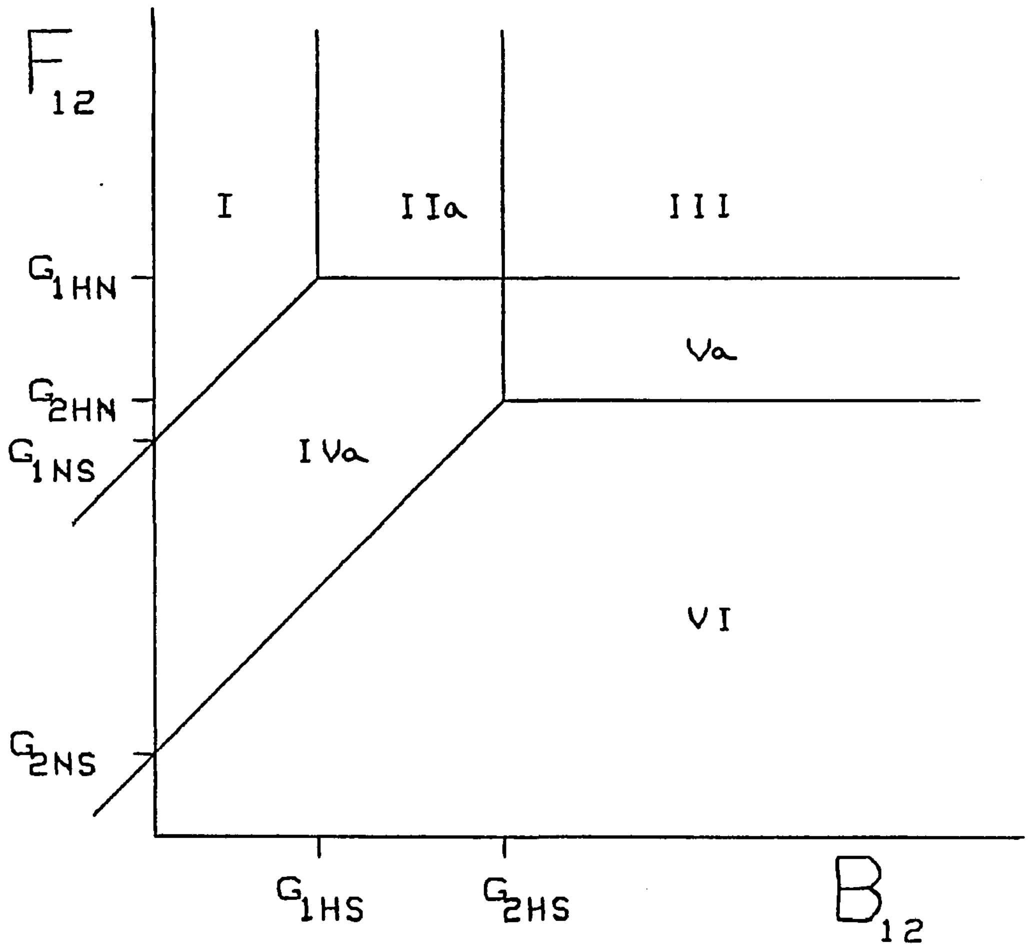

Figure 4.2. Combination of Futures Price and Basis Where the Decisions from Two Decision Rules Coincide Given that $G_{1HN} > G_{2HN}$, $G_{1NS} > G_{2NS}$, and $G_{1HS} < G_{2HS}$

unhedged storage when he should have stored hedged, (5) hedged storage when he should have sold cash this month, and (6) unhedged storage when he should have chosen cash sales this month. For any given set of G_{iHN}, G_{iNS}, and G_{iHS}, $i = 1, 2$, only a set of three of the six errors listed will be possible. Given the case depicted in Figure 4.2, only the first three of these errors are possible. The cost of following the suboptimal rule in the first error (area IIa of Figure 4.2) is

4.17. $$\begin{aligned} C_{HS} &= y_H - y_S \\ &= F_{12} - B_{22} - F_{11} - fP_1 + F_{11} - hc \\ &= F_{12} - B_{22} - fP_1 - hc \\ &= fB_{12} - B_{22} + (1-f)F_{12} - hc \end{aligned}$$

The cost of following the suboptimal rule in the second error (area IVa of Figure 4.2) is

4.18. $$\begin{aligned} C_{NS} &= y_N - y_S \\ &= - F_{11} + P_2 - [fP_1 - F_{11}] \\ &= P_2 - fP_1 \\ &= F_{22} - B_{22} - fF_{12} + fB_{12} \end{aligned}$$

The cost of following the suboptimal rule in the third error (area Va of Figure 4.2) is

4.19. $$\begin{aligned} C_{NH} &= y_N - y_H \\ &= - F_{11} + P_2 - [F_{12} - F_{11} - B_{22}] + hc \\ &= F_{22} - F_{12} + hc \end{aligned}$$

Note that the future value of the return to the sell-now alternative is the relevant outcome to compare with the other outcomes. The factor that is used to calculate the costs here is different from the factor used by the individual to compare the expected utilities. The factor used in the expected utility comparison is based on the November interest rate on T-Bills in order to represent the expected rate of interest. The factor used in the cost calculations is based on the average interest rate on T-Bills in December and March in order to represent the actual return the individual would have received.

The researcher does not know which F_{11}, F_{22}, B_{12}, B_{22}, P_1, and P_2 the individual actually faced but the researcher does know the daily closing futures prices and daily average cash prices in the relevant months. From the information known to the researcher, one can compute the probability that the cost, in terms of outcome, of following the suboptimal rule is less than e when the decisions differed between the decision rules. Recall that this probability has been defined as Pr2.

The probability Pr2 for the case depicted in Figure 4.2 is calculated in three parts, each corresponding to one of the three costs. Define PrHS2 as the probability that C_{HS} is less than or equal to e when the decisions differed (in area IIa). Likewise, define PrNS2 corresponding to C_{NS} (in area IVa) and PrNH2 corresponding to C_{NH} (in area Va). So, Pr2 = PrHS2 + PrNS2 + PrNH2.

PrHS2 for Figure 4.2 can be calculated, for example, by first identifying all the days during the decision month whose closing daily futures price F_{12} and associated basis B_{12} fall in the region IIa marked in Figure 4.2. Once these (F_{12}, B_{12}) points are identified, each point is paired with all of the closing daily futures prices F_{22} and associated bases B_{22} in order to calculate C_{HS}. This pairing is necessary since if in the period t_1 the individual transacted at an F_{12} and B_{12} that are within region IIa, he may pick any of the approximately 22 days in period t_2 to transact in the futures and cash markets again. Finally one can calculate the percent of all pairings of (F_{12}, B_{12}) in region IIa with (F_{22}, B_{22}) such that $C_{HS} < e$. This percent is the probability PrHS2. The probabilities PrNS2 and PrNH2 are calculated in a similar manner.

So for the fall decisions, one can compute the probability (Pr1 + Pr2) that using the wrong rule will lead to the right decision or at least to an outcome that is close enough to the right outcome. As with the results of the spring decision, one can combine Pr1 and Pr2 over a period of time to measure how close the outcomes of decision rule 1 and decision rule 2 are to one another.

CHAPTER 5. FORECASTING CONSIDERATIONS

In June (the spring decision), the producer forecasts the cash price for November and the basis (of the November contract) for November. In addition, the producer forecasts the variance of the cash price and the variance of the basis, both for November. The forecasts in November (for the fall decision) are of cash price, basis (using the July contract), and the variance of price and basis for the coming July.

This chapter reviews some forecasting issues to be considered in this dissertation. The first section of this chapter presents explanatory variables that have been used in previous studies. Results from previous literature and other forecasting considerations will determine the possible explanatory variables this study will use in the forecasting equations. The second section discusses the data and timing issues. In a forecasting context, one must consider how far in the future forecasts are made. Data availability is closely linked with the timing of forecasts and the number of months ahead the forecasts are made.

Previous Literature

Weymar (1966) reviewed the theory of supply of storage. He presented the supply of storage function $f_h(I_t)$ for an interval of h time units

$$5.1. \qquad \frac{P_t{}^{*h} - P_t}{h} = f_h(I_t)$$

which states that the expected price change over some finite interval is only a function of the current inventory level I_t.

Weymar questioned this supply of storage function on empirical and theoretical grounds. Weymar wrote the general supply of storage function for a specific horizon as

$$5.2. \quad \frac{P_t{*h} - P_t}{h} = \frac{1}{h} \int_0^h f_h(I_t{*h})dh$$

Here the expected price change over the interval is a function of the expected inventory behavior over the interval. Weymar pointed out that equation (5.1) is a special case of equation (5.2): a case where the harvest is highly lumpy and where, after harvest, inventory declines continuously until the next harvest.

Weymar also discussed the spot price function. From one model, Weymar concluded that if "(a) in arriving at their expectations people assume that expected behavior is generated by the same equation system that they feel generates actual behavior ..., and (b) people behave as if their expectations were certain to come true ..., then the current rent price is a function of the current inventory level alone" (Weymar, 1966, p. 1226).

Westcott and Hull (1985) discussed the relationship between quarterly grain prices and quarterly ending stocks. Westcott and Hull, without explanation, chose the hyperbolic functional form to relate quarterly wheat and corn cash prices with their own quarterly ending inventory level.

The hyperbolic functional form specifies

$$(P - a)(S - d) = c$$

where P is the quarterly cash price, S is the quarterly ending stocks of the grain, and a, c and d are parameters. It was assumed that d = 0. Solving for price then

$$P = a + cS^{-1}$$

Westcott and Hull included a lagged price in the equation also to reflect "stickiness" of prices and to circumvent the issue of choosing a price deflator. The following equation was estimated

$$P = a + b\,\text{Lag}(P) + \sum_{i=1}^{4} c_i\, D_i\, (S/U)^{-1}$$

where the D_i are dummy variables equal to 1 in quarter i and zero otherwise. The lag in price was one quarter. The quarters were as follows: i = 1 is January-March, i = 2 is April-May, i = 3 is June-September, and i = 4 is October-December. The stock variable is adjusted in the equation by the "scale of activity" or utilization U which was necessary due to the growth in the industry over time. The coefficient on the stocks-to-utilization ratio was allowed to differ over the quarters.

Garcia and Good (1983) examined factors that influence the Illinois corn basis. The relationship between cash and futures price is based on the theory of carrying charges. Basis is a function of storage, transportation costs and the consumption demand. Garcia and Good stated that the supply and demand for storage are presumably determined by the size of stocks, the rate of flow of the commodity to market, and the demand for shipment.

Garcia and Good indicated that the most variable component of ownership or storage cost is the interest on the stored commodity. Transportation costs such as barge rates influence the basis also.

In addition to cost factors, Garcia and Good examined the influence of stock factors on basis. Not only is the size of the stocks of the particular commodity of importance, but also the stocks of other commodities that compete for space. To represent this stock factor in the analysis, Garcia and Good suggested using the ratio of storage capacity-to-stocks. This standardization allows comparison across years.

Yet another influence on basis is flow factors. Garcia and Good discussed two types of flow factors: (1) the rate at which producers deliver corn to the market and (2) the rate at which the market is consuming corn.

To examine the influence of these factors on the corn basis in Illinois, Garcia and Good used time series and cross-section data for the period 1971-1981 and for the Market News Service price reporting areas of the state. They specified the basis for month j, region i for crop year t as

$$\begin{aligned} \text{Basis}_{jit} = f(&\text{ILLSTO}_{jt}, \text{TPRST}_{it}, \text{TRAN}_{jt}, \text{REGDV}_{it}, \text{INC}_{jit}, \\ &\text{CP}_{jit}, \text{TREND}_t, \text{MDV}_j, \text{DV}_{jt}) \end{aligned}$$

ILLSTO is the ending stocks of corn and soybeans in the state relative to storage capacity. TPRST is total production of corn and soybeans relative to storage capacity. TRAN is the average barge rate. REGDV is a set of regional dummy variables. INC is the interest charge in cents per bushel. CP is the monthly average cash price. TREND is a trend variable for the years. MDV and DV are dummy variables, the first for the months and the second for specific pricing aberrations.

For estimation, the bases were grouped into three seasonal time periods: Harvest (October-December), Post-Harvest (January-April), and Distant-Harvest (May-July). Garcia and Good included all explanatory variables in the equations for the preliminary estimation. Variables with t-values less than 1.0 were dropped and the equation re-estimated. The transportation variable TRAN was dropped from the Harvest period equation and the variable $TPRST_{it}$ (total production of corn and soybeans relative to permanent commercial storage capacity in region i for year t) was dropped from both the Post-Harvest and the Distant-Harvest equations. Other noneconomic variables were dropped from the three equations also.

Options are yet another source of information on forecasting the important variables in this dissertation. Since the introduction of options on the futures of some commodities, there has been some work on forecasting the variance of the underlying futures price of the option. The price of an option is a function of the variability in the futures price with which it is associated. The option pricing literature then is a possible source of information on explanatory variables for variance of cash price.

Samuelson (1965, 1976) proposed that futures price volatility increases as the contract nears maturity. Rutledge (1976) did not find that volatility increased in this way. Anderson (1985) tested

Samuelson's hypothesis for several commodities. His results indicated that seasonality in the flow of information was the main determinant in price volatility.

Anderson and Danthine (1983) constructed a model of hedging behavior and found that futures price variability was a function of the information flowing into the market. Months in which there is a lot of uncertainty would have more volatility in price than months in which there is less uncertainty.

Glauber and Heifner (1986) forecasted futures price variability. Their dependent variable was the variance of the percent daily change in closing futures prices for contract i during month j. Independent variables were the seasonal pattern, the average daily futures price for contract i during month j, the interest rate, and the total supply available for consumption in the next quarter. All nonbinary variables were entered in the equation as logs so that the coefficients could be interpreted as elasticities. The elasticity on the futures price was significant but the elasticities on the interest rate and supply were not.

Glauber (1984) and Glauber and Heifner (1986) indicated that stocks and production should be negatively related to the variance of the futures price. They found a negative relationship between carryover stocks and their variance for four of six contract months studied. None of the coefficients on the carryover stocks were significant at the 10 percent level however.

Anderson (1985) and Kenyon et al. (1987) also investigated factors that affect the variance of the futures price. Anderson investigated the Samuelson hypothesis and also the hypothesis that volatility will be relatively high during times when significant amounts of supply and demand uncertainty are resolved. Both hypotheses were largely tested by examining seasonality in the variance of the futures prices. Kenyon et al. examined economic and noneconomic variables that may explain changes in futures price volatility.

The options pricing literature has examined the relationship between the variance of the futures price and the stock and production variables. There is some question, however, as to the correct sign on the stock and production variables in the momentary variance of the cash price equation.

The identity cash price (P) equals futures price (FP) minus the basis (B) yields ambiguous results on the relationship between futures price variability and cash price variability. Taking the variance of both sides of this identity yields

$$V(P) = V(FP) + V(B) - 2Cov(FP,B).$$

If the variance of FP, V(FP), is negatively related to a variable X (say stock level), one must know how the variance of the basis, V(B), and how the covariance between futures price and basis Cov(FP,B) are related to X before one can say how the variability of cash price is related to X. The options pricing literature on volatility of the futures price then does not shed much light on the volatility of the cash price.

One could hypothesize that local market conditions such as transportation or storage problems or local supply and demand pressures likely have a large impact on the volatility of cash price. Unfortunately, it is not feasible in this study to forecast when the Missouri River will freeze or where and when there will be transportation bottle necks six months in the future. This study must hypothesize the relationship between the variance of the cash price and variables that are known at the time the forecasts are made.

To identify the sign on the stock and production coefficients in the variance of the cash price equation, this study relies on hypotheses regarding the movement of grain through the marketing system.

One could hypothesize that the volatility of price would be relatively low when the marketing channels are running at or below capacity. If the marketing system is running near capacity, there is less flexibility in the transportation and storage system to deal with, e.g., transportation bottlenecks, especially in a year with a bumper crop being harvested or peak exports. Although it is not hypothesized that higher stocks or higher production alone will mean relatively more variable prices, these conditions make it more likely for prices to have relatively higher volatility within a month.

A similar hypothesis could be stated for low stocks and low production. When the marketing system is greatly underutilized, there is a minimum level of labor and/or capital employed below which grain marketing companies do not wish to operate. This minimum level is made up of fixed facilities and core labor which can not be laid off without affecting the companies' ability to rebound once market conditions have changed. When the industry is operating near this minimum, the marketing system has less flexibility to deal with changing market conditions within a month.

This hypothesis would predict a positive relationship between the stocks and the production variables and the variance of cash price. This study will accept positive coefficients on the stock and production variables as representing a valid relationship between these variables and the momentary variance of cash price.

The hypothesis regarding the movement of grain through the marketing system can also be used to identify the correct sign on the stock and production variables in the variance of the basis equation. When the marketing system is operating at or above capacity, the demand pressures and bottlenecks with the storage and transportation functions can be hypothesized to increase the volatility of the basis. The hypothesis is not that high production or high stocks alone would mean higher variability in the basis but that it means the system is less flexible in response to transportation or storage bottlenecks. This lack of flexibility would increase the volatility. Therefore, it is hypothesized that the stock and production variables would be positively related to the variance of the basis.

Data and Timing Considerations

This section will first review the availability of the variables to be used in the forecasting equations. An important aspect of the availability of data is the time when the data become available. The second part of this section will then discuss the variables that may be important in the forecasting equations.

Daily closing cash soybean prices are available for the six crop reporting districts in Iowa since August 1974. These prices represent the average daily price prevailing in each district after the futures market has closed for the day. Cash prices for shorter time intervals than a day, for example hourly, do not appear to be widely available. The crop reporting district selected for analysis in this study is the Southeast district. This district has access to barge loading facilities for transportation to the Gulf. These daily cash prices are available from the Market News Service in Des Moines, Iowa.

Daily soybean futures prices are available over the period that the daily cash prices are available. The daily prices selected are the daily closing prices rather than the daily average prices since the closing prices are more widely reported and more widely used by decision makers. The futures contracts that are assumed to be used by the hypothetical decision makers in this study are the November contract for the summer hedge and the July contract for the winter-storage hedge. The daily futures price data are available from the Wall Street Journal.

The momentary variance of the cash price within a month and the momentary variance of the basis within a month are calculated using the daily cash and futures prices.

Stock data are available for soybeans and corn four times per year. For soybeans, national and state stocks for all positions are published for January 1, April 1, June 1, and September 1. These data are available through the 1986/87 crop year. From 1984 to 1986, both the

January 1 and December 1 stocks were reported as the transition to the December 1 date was made. There was also a transition from the April 1 date to March 1 during these two years. State stock data for corn for all positions are published for December 1, March 1, June 1, and October 1 during the 1974 through 1987 period. Insufficient monthly data are available to make more than a rough calculation of the monthly stocks for these two commodities. National stock data on soybeans are available from various issues of Fats and Oils Situation (USDA, 1978d-1980d), Fats and Oils Outlook and Situation (USDA, 1981b-1983b), and Oil Crops Outlook and Situation Report (USDA, 1984c-1987c). State stock data on soybeans and corn are available from various issues of the USDA publication entitled Grain Stocks (USDA, 1973f-1987f). This publication also contains the grain storage capacity for Iowa.

Soybean production figures are for the crop year beginning September 1. In addition to the total U.S. production, total utilization of the U.S. crop is available. Utilization includes domestic crush, exports and a residual amount used for seed. Data on the production of soybeans in Brazil and Argentina, two major competitors of the U.S., are also available. Domestic soybean production and utilization data are available from various issues of Fats and Oils Outlook and Situation (USDA, 1981b-1983b) and Oil Crops Outlook and Situation Report (USDA, 1984c-1987c). Production from Brazil and Argentina are available from various issues of Oil Crops Outlook and Situation Report (USDA, 1984c-1987c).

It is assumed that in November, the U.S. crop size or a good forecast of crop size is known to the decision maker. This is reasonable since by November, much of the uncertainty concerning crop size will have been resolved.

In the spring when the decision maker is forecasting the November cash price and basis, the U.S. crop size must be forecast. Projected U.S. production can be calculated in June by using the prospective plantings data that are available in February, March, or April. Projected production in this study is calculated as the prospective planted acres multiplied by the average of the yields in the past two years. The prospective acres-planted data are available from the February, March or April issues of Prospective Plantings (USDA, 1973g-1987g). The past years' yield data are available from Agricultural Statistics (USDA, 1973a-1986a).

In November, the decision maker must evaluate three marketing alternatives where the outcome of one of the alternatives is received significantly earlier than the outcomes of the other two alternatives. Therefore, an interest rate is needed to bring the return from this alternative (the cash sales now alternative) to the same time when the outcomes from the other two alternatives are received. Two interest rates are used, one for the expected utility evaluation and the other for the comparison of the outcomes of the decisions expost. The forecast of the interest rate by the decision maker in November is assumed to be the 91-day T-bill rate for November. The actual interest rate received is the average of the December and the March 91-day T-bill rate. These interest rates are chosen since they represent a fairly riskless interest rate and it is assumed that all of the hypothetical decision makers in this study are risk averse. The future value factor for the cash price alternative is then $(1 + i)^7$ where i is the November interest rate when making the decision and i is the average of the December and March interest rates when evaluating outcomes. The 91-day T-bill rate data are available from various issues of Business Conditions Digest (U.S. Dept. of Commerce, 1985-1987).

From the above data, one can form the variables that theory and previous studies suggest are relevant and important in the forecasting. Many of the variables may be important in more than one equation in the model.

One can calculate four stock variables. The first stock variable can be stated as the ratio of April soybean stocks in Iowa to total domestic utilization. The second stock definition is the ratio of soybean and corn stocks in Iowa in April to the total domestic utilization. A third stock definition is the ratio of Iowa soybean stocks in April to the total storage capacity in Iowa that year. The fourth definition specifies the Iowa soybean and corn stocks in April relative to the total storage capacity in Iowa. From theory and previous results, one expects that these stock variables are negatively related to cash price and positively related to basis.

Domestic production level and projected production level may be used to form other variables also. It may be that prices and bases respond more to the excess of production over utilization than to the level of either production or projected production. Therefore, one could use the ratio of production to utilization or projected production to utilization. The production and projected production measures are expected to be negatively related to cash price and positively related to basis.

Previous studies have found that coefficients of the regression equations vary over the course of the year. Therefore, when modeling with monthly data, one needs to allow the coefficients to vary between blocks of months, if not for each month in the calendar year. In this study, few variables are available on a monthly basis. The various stock variables discussed, for example, are only available four times per year. The production and annual utilization variables by their nature are observed once per year.

This study is interested in forecasting the November cash price and basis from June of that year and forecasting the July cash price and basis from November of the previous calendar year. Forecasting this far ahead means that this study is unable to use some exogenous variables that may be important in shorter term forecasting. In addition, the data series for the estimation of the forecasting equations is very short. Only one observation per year is available for each of the forecasting exercises. Consequently, the values of R^2 will be relatively low as the equations do not contain seasonal dummy variables that account for variation of monthly prices about the annual mean price.

CHAPTER 6. STATISTICAL METHODS

Economic theory tells one that forecasting the price level as well as the price variability within a given time period is important for expected utility maximizing individuals. Yet typically, studies have built models to forecast the level of a variable while only acknowledging the importance of its variability about the forecasted mean to a decision maker. Previous studies have not dealt with the issue of simultaneous forecasts of mean and variance for use in expected utility analysis. This study will consider the simultaneous forecast of cash price, basis, momentary variance of cash price and the momentary variance of basis for particular months.

The previous chapters have outlined the economic considerations of this study. The statistical considerations are covered in this chapter. The first section of this chapter will discuss the calculation of the three measures of variance considered in this study: the momentary variance, the variance of the monthly mean prices, and the variance of the forecasted mean price. The second main section of this chapter assimilates the forecasting considerations of the last chapter and the statistical considerations of this chapter to arrive at an appropriate systems estimation method. Estimation methods such as generalized least squares, two- and three-stage least squares, and seemingly unrelated regression are some of estimation methods from which to choose in the estimation of a set of equations. The third section of this chapter examines in more detail the systems estimation method finally selected in the second section. The fourth main section of this chapter will examine an alternative estimation and forecasting technique. This technique calls for the direct estimation and forecast of expected utility rather than the estimation and forecast of the components of expected utility separately.

Calculation of Variance Measures

This study contends that the momentary variance is the relevant variance for decision making under many of the cases considered by previous studies. This study will calculate the variance measures discussed in Chapter 3 for each month during a sample period. The sample period is broken down into two periods: the first is the estimation period from which the initial forecasting equations will be estimated, and the second is the period (one year) over which simulations will be conducted. The forecasting equations will be updated each year so the sample period from which the equations will be estimated will add the newest year's data as the simulations progress through time.

In this section, methods by which one can calculate the momentary variance, the variance of the monthly mean prices, and the variance of the forecasted mean price are discussed.

Momentary variance

Ideally, one would need price data measured at momentary intervals to calculate the momentary variance for a month. Some futures price data come close to meeting these criteria with the time-and-sales data.

These data are observations on each transaction that takes place. This amounts to a great volume of data. In addition, cash prices are not typically available on such a continuous basis. Therefore, two approaches to calculating momentary variance are outlined here that do not require the use of momentary prices.

The first method for calculating the monthly momentary variance uses the daily mean prices. The straightforward variance calculation is

$$6.1. \quad \sigma^2 = \frac{1}{(n-1)} \sum_{i=1}^{n} (\bar{P}_i - \bar{P})^2$$

where n is the number of business days in the month and $\bar{P}_i$ is the mean price for day i and $\bar{P}$ is the mean $\bar{P}_i$. This choice is completely justified if one assumes that a person receives the average price for the day on whatever day he markets.

This calculation, because it uses the daily mean prices, underestimates the true momentary variance since the individual can not guarantee receiving the daily average. One can verify this fact by decomposing the true momentary variance into two parts.

The true momentary variance can be written as

$$\frac{\sum_i \sum_j (y_{ij} - \bar{y}_{..})^2}{NM - 1}$$

where y_{ij} is the observation on the ith minute of day j of the particular month and $\bar{y}_{..}$ is the overall mean for the month. There are N total days and M minutes (or moments) per day. One can decompose the numerator of the true momentary variance into

$$\sum_j \sum_i (y_{ij} - \bar{y}_{..})^2 = M \sum_j (\bar{y}_{.j} - \bar{y}_{..})^2 + \sum_j \sum_i (y_{ij} - \bar{y}_{.j})^2$$

by using the fact that

$$\sum_i (\bar{y}_{.j} - y_{ij}) = 0 \quad \text{and} \quad \sum_j (\bar{y}_{.j} - \bar{y}_{..}) = 0.$$

The first of the two terms in the decomposition of the numerator is M times the numerator of equation (6.1). The second term represents the variance of the momentary prices y_{ij} about the daily mean $\bar{y}_{.j}$. Since this term is positive, it is clear that the calculation using the daily means underestimates the true momentary variance. Unfortunately, without the momentary prices, it is not possible to estimate the magnitude of the underestimation.

The second method of calculating the momentary variance uses the month's high, low and mean. One can form the $(1-\alpha)$ percent prediction interval about the month's mean price as

$$\bar{P} \pm \sigma Z_{\alpha/2}$$

where $\bar{P}$ is the month's sample mean price, $Z_{\alpha/2}$ is the Z-value for the given significance level α and σ is the momentary standard deviation for the month.

The prediction interval can be thought to yield the month's high and low prices when α is set at some level. One can write

$$P_L = \bar{P} - \sigma Z_{\alpha/2}$$

$$P_H = \bar{P} + \sigma Z_{\alpha/2}$$

where P_L and P_H are the low and high prices, respectively, for the month. Each of these equations can be solved for σ:

$$\sigma = \frac{\bar{P} - P_L}{Z_{\alpha/2}}$$

$$\sigma = \frac{P_H - \bar{P}}{Z_{\alpha/2}}$$

These two estimates of the momentary standard deviation are not necessarily equal so an estimate of the momentary variance for this month can be

$$6.2. \quad \sigma^2 = \frac{1}{2}\left[\left(\frac{\bar{P} - P_L}{Z_{\alpha/2}}\right)^2 + \left(\frac{P_H - \bar{P}}{Z_{\alpha/2}}\right)^2\right].$$

With this second method of calculating the momentary variances comes the problem of how to select the appropriate α (and hence Z). One method by which α can be selected accounts for the fact that the first calculation of the momentary variance underestimates the true momentary variance.

For each month in the sample period, one can find the $Z_{\alpha/2}{}^*$ such that the estimates of the momentary variance are equal between equation (6.1) and (6.2). One equates (6.1) and (6.2) and solves for $Z_{\alpha/2}$.

$$6.3. \quad Z_{\alpha/2}{}^* = \left[\frac{(P_H - \bar{P})^2 + (\bar{P} - P_L)^2}{2\sigma^2}\right]^{1/2}$$

Where σ^2 is the variance calculated using the daily means for the particular month.

Since the true momentary variance is at least as great as that estimated in equation (6.1), one selects the lowest calculated $Z_{\alpha/2}{}^*$ in the sample period. This method of finding α gives one an estimate of the momentary variance that is greater than the variance calculated using daily means. It is unclear how close the variance calculated from the prediction interval approach is to the true momentary variance.

If one had access to prices observed at 'momentary' intervals, one could better judge the accuracy of the prediction interval approach. It may be that this approach would provide an easy-to-calculate estimate of the true momentary variance since only the month's high, low, and mean are required once α is selected.

Without the specific momentary data, it is reasonable to use as the estimate of the true momentary variance the variance calculated from daily means. At least one knows a priori in which direction errors in estimation are made.

Appendix B presents graphs comparing the momentary variance calculated from daily means and the momentary variance calculated using only monthly high, low, and average price and basis. These graphs indicate that $0.05 < \alpha < 0.10$ provide the best estimate of the momentary variance calculated with daily means.

<u>Variance of monthly mean prices</u>

The calculation of this variance is straightforward. There are two ways of representing this variance, however. The first way uses the monthly mean prices for all months during the chosen sample period. The other method selects the monthly mean prices from certain calendar months from the sample period. Both ways of representing the variance of the monthly mean prices are discussed further here.

The first representation treats all calendar months alike in that seasonal patterns in the variance measure is ignored. For a sample period of 5 years, for example, this variance is calculated using the monthly mean price for each month in those 5 years. The variance is calculated in a standard way, i.e., the weighted sum of the squared deviation of the monthly mean prices from the grand mean of the sample period.

The second representation of the variance of the monthly mean prices is calculated by selecting certain months from the sample period to calculate the variance. An example might be to select the monthly mean prices from June, July, and August in each of the sample period. This variance, using these prices, then represents an historical summer variance. Similar calculations can be made for other sets of months.

This method of calculating variance will not be pursued further in this dissertation. The following commonly used measure of variance will be used further in the analysis of this study.

<u>Variance of the forecasted mean price</u>

Peck (1975) proposed the use of the variance of the forecasted mean price as the relevant variance in marketing decisions. The variance of the forecasted mean price in this study will be calculated from a regression equation. The regression equation will be specified with monthly mean price as a function of a set of exogenous variables,

$$\bar{P}_i = X_i'B + e_i \ , \quad i = 1, \ldots, F\text{-}h.$$

$\bar{P}_i$ now denotes the mean price in month i, X_i is the vector of exogenous variables, B is the vector of coefficients, and e_i is the random error.

The data used are monthly data and the equation is estimated over the sample period month 1 through month F-h. The single equation can be estimated by ordinary least squares or by generalized least squares.

The forecast of $\bar{P}_F$ is made given a set of exogenous variables X_F. The variance of the forecasted mean price of $\bar{P}_F$ (often referred to as the square of the standard error of the forecast) is simply

$$V(\bar{P}_F) = \sigma_e^2[1 + X_F'(X'X)^{-1}X_F]$$

where σ_e^2 is the variance of the disturbance e and X is the matrix of exogenous variables.

This variance can be calculated for any month by selecting the appropriate vector X_F. The forecasting equation can be updated each year by adding the recent observations to the problem.

Selection of an Estimation Method

Previous work reviewed in the Forecasting Considerations Chapter indicates that the cash price can be specified as a function of a set of exogenous or predetermined variables and that the basis can be specified as a function of a set of exogenous or predetermined variables as well as the current cash price. It is reasonable to specify the (momentary) variances of cash price and of basis as a function of a set of the exogenous variables discussed as well as lagged variances.

Results of previous studies of the cash price and basis and the intuition concerning the variability of cash price and basis indicates that the system can be specified as a recursive set of equations. One can either estimate this recursive system or one can estimate the reduced form of the system. Both approaches are possible in this study but the estimation of the reduced form is more appealing on statistical and forecasting grounds.

If one wishes to estimate the system of equations as a recursive system, there are at least two estimation methods available: generalized least squares and three-stage least squares. One can estimate each equation separately from the other equations with the generalized least squares (GLS) method. This method generalizes the variance-covariance matrix of the residuals to allow it to be nonscalar-diagonal, as would be the case with first order autocorrelated residuals. The GLS estimator applied to each equation separately does not suffer from the problem of the simultaneous equations bias as long as the system is recursive. To see this point, take a simple example of two equations that form a recursive set of equations where $Ee_1e_2 = 0$.

$$y_1 = X'A_1 + e_1$$

$$y_2 = X'A_2 + y_1B + e_2$$

The endogenous variable y_1 is independent of the error e_2 since y_1 is determined independently from y_2, as can be seen from the first equation.

The second method of estimating the recursive system accounts for the possible contemporaneous correlation in the residuals across equations. Both three-stage least squares (3SLS) and Zellner's seemingly unrelated regression (SUR) estimation method account for this contemporaneous correlation. However, three stage least squares would need to be employed in this case. Zellner's SUR would be inappropriate for use on a recursive system. Using the previous simple example, if one estimated that system of equations with Zellner's SUR and the errors from the two equations are correlated with one another, y_1 in the second equation would be correlated with the residual e_2. This correlation between the right hand side endogenous variable and the residual in that equation causes the simultaneous equations bias in the estimation of the parameters of the second equation. 3SLS purges the right hand side endogenous variable of its correlation with the residual of that equation.

One need not estimate the recursive model in this study to arrive at the forecasts of cash price, basis, and the momentary variances of cash price and basis. Instead a reduced form model can be estimated and 3SLS can be eliminated as an estimation method. A reduced form model can be used since, to forecast, one does not need the structural coefficients. In fact, the forecasts from the recursive model are made by first finding the reduced form in the four endogenous variables. The variance of the forecasted mean price from the reduced form equation yields as much information as the variance of the forecasted mean price from the recursive model for the calculation of Peck's variance measure for price and basis.

Estimating the reduced form instead of the recursive system can also be justified on two other counts. The first concern is that the 3SLS estimator is sensitive to specification error. It is clear from a review of the literature that one can not be sure one is using the true specification of the system of equations. The concern that the 3SLS estimator is more sensitive to specification error than simple estimators can lead to the conclusion that the simple estimation methods are better is this study. The second concern regards the relevance of the asymptotic characteristics of 3SLS with a small sample size. This study must work with a small sample size, and therefore the concern arises whether one can rely on the desirable asymptotic characteristics of a sophisticated technique such as 3SLS. In other words, one can not be sure of achieving an improvement in the consistency or efficiency of the estimates compared to a simple technique when there is a small sample.

The reduced form model can be estimated by either the GLS applied to each equation separately or by Zellner's SUR.

In this study, the reduced form of the system of equations will be estimated using Zellner's SUR method. The contemporaneous correlation of the errors will be accounted for and the system is already in the correct form for forecasting the four variables of interest.

There will be two specifications of the system of equations used in forecasting the variables of interest. The first system is the full system of four equations where the cash price, basis, and the momentary variances of cash price and basis are the endogenous variables. The second system is a two equation model where only cash price and basis are endogenous. This set of two equations represents the information available to the decision makers currently. Currently, only forecasts of the cash price and basis are available along with the variance of the forecasted mean price and basis (Peck's variance measure). These forecasts are available from this set of two equations. The cash price and the basis equations will be estimated using Zellner's SUR for the same reasons given previously for the full four equation specification.

There is a final consideration for the estimation of the system of equations. The nature of the momentary variance of cash price or of basis -- that being it is always greater than zero -- suggests that a transformation of the variance is in order for the purpose of estimation. A reasonable transformation to consider is the natural logarithm. In this way, the truncated distribution of the dependent variable is converted into a distribution that is not truncated at zero. The antilogarithm of the forecasts of the transformed momentary variances will be the forecasts of the momentary variances.

Estimation of a Set of Equations

Ordinary least squares (OLS) assumes that the variance-covariance matrix is a scalar diagonal matrix. This study will ignore possible heteroscedasticity but will leave open the possibility of first-order autocorrelated errors within an equation and contemporaneous correlation among errors in different equations. Therefore, OLS is not appropriate and instead, the technique used is generalized least squares (GLS), one version of which is Zellner's seemingly unrelated regression (SUR).

GLS for a single equation

For a single equation where the errors may have first-order autocorrelation but where there is no contemporaneous correlation among the errors across equations, define

6.4. $y_i = X_i B_i + e_i$, $i = 1, \ldots, m$

where y_i is an (nxl) vector of the ith dependent variable, X_i is the (nxk_i) matrix of independent variables, B_i is the ($k_i$xl) vector of regression coefficients and n is the number of observations. e_i is the (nxl) vector of errors such that $E(e_i) = 0$ and $E(e_i e_i') = S_i$. The (nxn) variance-covariance matrix S_i is scalar diagonal and $S_i = \sigma_{ei}^2 I$ when there is no first-order autocorrelation in the ith equation. Some off-diagonal elements of S_i are nonzero in the presence of autocorrelated errors in the ith equation (see Johnston, 1984).

In the case of first-order autocorrelated errors in the ith equation, the GLS estimator of B_i is

6.5. $\hat{B}_i = (X_i' S_i^{-1} X_i)^{-1} X_i' S_i^{-1} y_i$

One can calculate that $E(\hat{B}_i) = B_i$ and that the variance-covariance matrix of $\hat{B}_i$ is

6.6. $E[(\hat{B}_i - B_i)(\hat{B}_i - B_i)'] = (X_i' S_i^{-1} X_i)^{-1}$.

By the Gauss-Markov theorem, $\hat{B}_i$ is the best linear unbiased estimator for the model in equation (6.4).

If S_i is not known and must be estimated, then the estimate of B_i from estimated generalized least squares (EGLS) is not best linear unbiased. It is difficult to know whether EGLS will yield better results than OLS.

The Durbin-Watson statistic can be used to test for first-order autocorrelated errors. The test statistic is

$$d = \frac{\sum_{t=2}^{n} (e_{it} - e_{it-1})^2}{\sum_{t=1}^{n} e_{it}^2}$$

The null hypothesis is H_0: $p_i = 0$ and the alternative is H_A: $p_i \neq 0$.

Some specifications of the model have a lagged dependent variable as an explanatory variable in order to correct for autocorrelated errors. For example, the basis in the current period is a function of lagged basis, among other variables. The Durbin-Watson test was derived assuming the X_i matrix was nonstochastic. This assumption is violated with lagged dependent variables in the equation. This study will therefore require a method other than the standard Durbin-Watson statistic for testing for the presence of autocorrelated errors in some equations.

Johnston (1984) described Durbin's asymptotic test for this case. Take the case of an equation with a lagged dependent variable and first-order autocorrelated errors

$$e_t = \phi e_{t-1} + v_t \quad \text{where} \quad v_t \sim N(0, \sigma_v^2 I).$$

The null hypothesis of the Durbin test is H_0: $\phi = 0$. The test statistic is

$$h = r \left[\frac{n}{1 - \text{var}(b_3)} \right]^{1/2} \sim AN(0, 1)$$

where n is the sample size, $\text{var}(b_3)$ is the estimated sampling variance of the coefficient of y_{t-1} in the OLS regression and

$$r = \frac{\sum_{t=2}^{n} \hat{v}_t \hat{v}_{t-1}}{\sum_{t=2}^{n} \hat{v}_{t-1}^2}$$

is the correlation coefficient between the OLS residuals $\hat{v}_t$ and $\hat{v}_{t-1}$. The one-sided test for positive first-order autocorrelation rejects the null hypothesis at $\alpha = .05$ for $h > 1.645$. The one-sided test for negative first-order autocorrelation rejects the null hypothesis at $\alpha = .05$ for $h < -1.645$. Note that the Durbin test is valid only for var(b_3) < 1.

The variance of the forecasted mean y_i (the square of the standard error of the forecast) is not calculated from the estimated single equations in this study. This variance is calculated from the set of equations that is estimated by GLS (Zellner's seemingly unrelated regressions).

GLS for a set of equations

The notation used to describe the GLS procedure for a single equation is used to describe the GLS procedure where there is contemporaneous correlation among the errors across equations. The equations in this study do not require transformations to correct for autocorrelation since including the lagged dependent variable accounted for the autocorrelation. Had this study required transformations, the procedures outlined in Johnston (1984) and Guilkey and Schmidt (1973) would have been used. This study will refer to GLS applied to a set of equations as SUR after Zellner's seemingly unrelated regression.

The m equations defined in equation 6.4 are stacked to form

$$y = Z\ B + e$$

where y is the (mnx1) vector of endogenous variables, Z is the (mnxK) matrix of exogenous variables where $K = k_1 + \ldots + k_m$, and B is (Kx1). The (mnxmn) variance-covariance matrix of e, E(ee') equals S where

$$S = \begin{bmatrix} S_1 & & \cdots & & S_{1m} \\ \cdot & S_2 & & & \cdot \\ \cdot & & \cdot & & \cdot \\ \cdot & & & \cdot & \cdot \\ & & & \cdot & \\ S_{m1} & & \cdots & & S_m \end{bmatrix}$$

S is scalar diagonal when there is neither first-order autocorrelation nor contemporaneous correlation across the m equations. This dissertation, however considers the case where the off diagonal elements of S, which represent the contemporaneous covariances among the errors across the m equations, are nonzero.

With these definitions, the SUR estimator for the m equations in the system is $\hat{B} = (Z'\ S^{-1}\ Z)^{-1}\ Z'\ S^{-1}\ y$. The square of the standard error of $\hat{B}$ is $E(\hat{B} - B)(\hat{B} - B) = (Z'\ S^{-1}\ Z)^{-1}$. The variance of the forecasted mean $\hat{y}_F$, where the subscript identifies that the forecast is for month F, is calculated as

$$6.7. \quad E(\hat{y}_F - y_F)(\hat{y}_F - y_F)' = E[Z_F'(\hat{B} - B) - e_F][Z_F'(\hat{B} - B) - e_F]'$$
$$= Z_F'\ (Z'\ S^{-1}\ Z)^{-1}\ Z_F\ +\ S$$

$\hat{y}_F$ is an (mx1) vector of forecasts and Z_F is an (mxK) vector of exogenous variables for month F. The variance defined by equation (6.7) represents the measure of variance recommended by Peck as the relevant variance for decisions under uncertainty.

The SUR estimator would not lead to a gain in efficiency when S is diagonal (no contemporaneous correlation among errors in different equations). The SUR estimator will also not lead to a gain in efficiency when the exogenous variables entering the m equations are all identical.

Kmenta and Gilbert (1968) compared the estimation results of OLS and joint generalized least squares (or Zellner's SUR) with a small sample size. They examined the case of contemporaneously uncorrelated errors and the case of other misspecifications on the estimates from OLS and SUR. They found that SUR (or ZEF for Zellner's asymptotically efficient estimator in their paper) was superior to OLS except in cases in which the disturbances were uncorrelated across equations. The SUR estimator was superior under all other misspecifications considered in their study. Kmenta and Gilbert indicated that their results favored the use of SUR over OLS since SUR was only a little worse than OLS with contemporaneously uncorrelated errors but SUR was considerably better than OLS in most of other cases (pp. 1192-1195).

Direct Estimation and Forecast of Expected Utility

In some cases it may be worth while to integrate the final use of the model into the estimation stage. In this study, the final purpose of the model is to forecast the expected utility of various marketing alternatives. The procedures discussed so far have been in the context of forecasting the components of expected utility (price, basis, and variance variables) and then combining these components to calculate the expected utility. The direct forecast of expected utility approaches the forecasting exercise in a different way. Instead of forecasting the components of expected utility, one forecasts the variable of ultimate interest, expected utility. One can calculate the expected utility of the marketing alternatives over the sample period using actual prices and momentary variances to form the endogenous variable to be used in the estimation. The direct forecasting approach will provide interesting comparisons with the typical approach of forecasting the components of expected utility.

Rahn (1973) discussed the issue of incorporating the final use of the model into the estimation stage. In his study, he weighted each equation in an econometric model by the weights used to combine the endogenous variables in the final forecast. Ladd (1976) discussed assigning weights to equations in an econometric model. The weights used in the estimation stage are associated with the relative importance of each equation in the model. Ladd examined the case of a set of seemingly unrelated regression equations.

In this dissertation, the several month ahead forecast of cash price, basis, momentary variance of cash price and the momentary variance of basis are combined linearly to estimate the expected utilities of the alternatives.

In this section, the direct estimation of an equation for expected utility of the marketing alternatives will be outlined. In this way, the final purpose of the model is incorporated into the estimation method.

There are m (where m = 4) equations in the econometric model considered in this chapter. The final purpose of the model is to forecast expected utility of marketing alternative a. U_a, the (nxl) vector of expected utilities from the sample period, is

6.8. $$U_a = w_{1a}y_1 + w_{2a}y_2 + \dots + w_{ma}y_m.$$

The w_{ia} are scalars and represent the weight on the ith endogenous variable of the econometric model discussed previously. From the Method of Analysis Chapter, recall that the expected utility of a marketing alternative was equal to a linear combination of the four endogenous variables (the y_i) in this study: cash price, basis, momentary variance of cash price and momentary variance of basis. The w_{ia} will be equal to zero, one, or Q_0L (the product of the quantity and the risk aversion coefficient).

This estimation method of the reduced form model is referred to as weighted generalized least squares (WGLS). This estimation method takes into account the final purpose of the model. The system of equations is solved for the reduced form in the endogenous variables, the y_i. These reduced forms are substituted into equation (6.8) to arrive at the single equation to be estimated for the particular marketing alternative. Recall from equation (6.4) that $y_i = XB_i + e_i$.

If there are no jointly dependent variables on the right hand sides in the system of equations, then the equation to estimate appears as

$$U_a = w_{1a} X_1 B_1 + \dots + w_{ma} X_m B_m + w_{1a}e_1 + \dots + w_{ma}e_m$$

or in matrix notation

$$U_a = X\ D + u$$

where X is a (nxK^*) vector of the exogenous variables in the system and K^* is the number of exogenous variables in the system. Every exogenous variable from the X_i is represented in X so $K/m = K^*$ only if $X_i = X_j$ for all i and j. The (K^*x1) coefficient vector D is related to B by the weighted sum of the relevant coefficients of the B_i. The (nxl) vector of residuals $u' = [e_1w_{1a} \quad e_2w_{2a} \cdots e_mw_{ma}]$. The GLS estimator of D is

$$\tilde{D} = (X'\ \mathcal{S}^{-1}\ X)^{-1}\ X'\ \mathcal{S}^{-1}\ U_a$$

where

$$\mathcal{S} = (W_a \otimes I_n)\ S \quad (W_a \otimes I_n)'.$$

Therefore, $\mathcal{S}$ is a weighted sum of the matrices that make up S.

The endogenous variable U_a, the expected utility of the a^{th} marketing alternative, is calculated for the sample period with the actual cash prices, bases, momentary variances and risk aversion level, and quantity marketed. Recall from the Method of Analysis Chapter that the expected utility of hedging was a function of the futures price in the decision month and the forecasts of basis and variance of basis in the future month. Since the futures price in the decision month is known to the producer at the time of his decision and since the futures price he observes depends on the day in which he transacts business, this futures price is not included in the calculation of the expected utility of hedging variable. Since the same is true for the fall cash price, the expected utility of selling in the cash market in the fall is not calculated. All terms in the expected utility of not hedging are forecasts of variables in the future month so the dependent variable that is calculated for this marketing alternative is the complete expected utility of not hedging. Several different levels of risk aversion will be used in this study but only two will be selected to estimate the direct expected utility equations.

One can estimate this single equation by GLS. Note that even though one knows the weights for each equation, the w_i, this information does not help in the estimation of the D. The weights are only used to calculate the endogenous variables used in the estimation stage.

Next, this section demonstrates that the forecast of U_{aF} from the direct approach does not equal the weighted sum of the $\hat{y}_i$ from the typical approach. The forecast of U_{aF} by the typical approach is

$$\hat{U}_{aF} = W_a \hat{y}_F$$

where the (mxl) vector $\hat{y}_F = Z_F\hat{B}$ and $W_a = [w_{1a}\ w_{2a} \cdots w_{ma}]$. By substituting in for $\hat{y}_F$, one finds

$$\hat{U}_{aF} = W_a Z_F (Z' S^{-1} Z)^{-1} Z' S^{-1} y.$$

The forecast of U_{aF} from the direct expected utility approach is

$$\begin{aligned} \tilde{U}_{aF} &= X_F \tilde{D} \\ &= X_F (X' \$^{-1} X)^{-1} X' \$^{-1} U_a \\ &= X_F (X' \$^{-1} X)^{-1} X' \$^{-1} (W_a \otimes I_n) y \end{aligned}$$

The forecast of U_{aF} by the typical approach differs from the forecast of U_{aF} from the direct expected utility approach.

CHAPTER 7. SELECTION OF RISK AVERSION LEVELS

Chapter 2 stated that the risk aversion levels chosen in this study would be taken from past studies of utility estimation. The utility estimation studies cited in this dissertation estimated utility as a polynomial of some degree. Their estimates of the coefficients of the utility function are not estimates of the risk aversion coefficient needed in this study. This chapter determines the relationship between the estimated coefficients of the previous studies and the coefficient needed in this dissertation.

Theoretical Considerations

The expected utility function used in this dissertation is

7.1. $EU(y) = Ey + L\ V(y)$

which is from a constant absolute risk aversion utility function. Equation (7.1) is justified by the assumptions leading up to equation (2.1) of Chapter 2. From the constant absolute risk aversion utility function

7.2. $U(y) = a - b\ e^{-Ry}$

where R is the absolute risk aversion for all y and a and b are defined by the integration. The expected utility can be written as

7.3. $EU(y) = a - b\ M_y\ (-R)$

where M_y is the moment generating function of the y distribution having mean μ and variance σ^2. It was assumed that $y \sim N(\mu, \sigma^2)$ so that

7.4. $EU(y) = a - b \exp(-R\mu + (1/2)R^2\sigma^2)$.

Maximizing equation (7.4) is the same as maximizing

7.5. $EU(y) = \mu - (1/2)R\sigma^2$

or by defining $L = -(1/2)R$ and $V(y) = \sigma^2$

7.6. $EU(y) = \mu + L\ V(y)$.

The marginal utility of income in the case depicted in equations (7.1) through (7.6) is

7.7. $-2\ b\ L\ \exp(2yL)$

For all risk aversion levels L less than zero, the marginal utility of income is positive. This indicates that there is no lower bound on L (no upper bound in absolute value).

One can calculate the risk aversion coefficient needed in this study by finding the implied absolute risk aversion from the utility equations estimated in other studies. For a true quadratic utility function

$$U(y) = a + by - cy^2\ ,\ b,\ c > 0,$$

the absolute risk aversion measure is

7.8. $$R_A = \frac{2c}{b - 2cy}$$

Implied Results From Previous Studies

Officer and Halter (1968) estimated the utility of individual farmers in order to understand how fodder reserve decisions were made. In that study, they estimated the 'disutility' of various levels of fodder reserve. Utility of these costs is the negative of disutility of these costs. One can calculate the utility of income from the disutility functions presented in Officer and Halter. Begin with the disutility DU of costs x, $DU = bx + cx^2$. The disutility of income (negative costs) is then $DU = b(-y) + c(-y)^2$ which can then be written as $DU = -by + cy^2$. Multiply by -1 to arrive at an equation for utility of income: $U = by - cy^2$ where b and c are positive.

The estimated disutility equations presented in the Officer and Halter paper were used to identify the parameters b and c needed to calculate the absolute risk aversion measure. Officer and Halter provided the range of costs that the farmers were to consider in their fodder reserve decisions. It is assumed in this dissertation that the implied utility equations derived are relevant for income in the same range as the costs. In other words, the costs ranged from $A812 to $A1631 and it is assumed that income would range from $A812 to $A1631 (at the time $A1 = $2.25).

Table 7.1 presents the implied absolute risk aversion measure from equation (7.8) for some of the quadratic utility equations that were estimated in Officer and Halter. There were 5 subjects in their study and there were three models used to estimate the utility equations. In addition, there were two stages to their study. Therefore, the equations in the table are identified by the subject, the model, and the stage. The R_A was calculated for the low income (812) and for the high income (1631). The table also presents the implied L for the equation.

Lin, Dean and Moore (1974) also estimated utility functions for individuals. The decisions were larger in scale than those considered in the Officer and Halter study. Expected outcomes ranged from about $20,000 to $700,000, depending on the farm. Six farmer's utility

Table 7.1. Implied Absolute Risk Aversion and L from Equations Presented in Officer and Halter

Subj/Mod/Stg[a]	R_A		L^b	
	low y	high y	low y	high y
1/2/1	0.005049	0.0008609	-0.0025245	-0.0004305
3/1/1	0.0164	-0.001319	-0.0082	na
4/2/1	0.0001678	0.0001945	-0.0000839	-0.00009725
5/2/1	-0.00179856	-0.0007272	na	na
5/3/1	0.00101398	-0.0059805	-0.0005070	na
1/3/2	0.0004883	0.0008139	-0.0002442	-0.0004069
2/3/2	0.00034628	0.0004834	-0.0001731	-0.0002417
3/2/2	-0.001234	-0.0006138	na	na
3/3/2	-0.0012744	-0.000624	na	na
5/2/2	-0.0023577	-0.000804	na	na
5/3/2	-0.0119837	-0.001108	na	na

[a]Identifies the subject, model, and stage in Officer and Halter.

[b]na indicates not applicable due to negative R_A.

functions were estimated by several methods. The equations of interest in this dissertation are the quadratic Bernoullian utility equations estimated for each farm. In the Lin, Dean and Moore study, the range of income considered for each farmer was presented along with the estimated equations. The incomes marked 'actual' and 'Bernoullian' in their study were selected from the data supplied for each farmer to derive the values of L to be used in this dissertation. The income marked 'actual' in the Lin, Dean and Moore study represented the expected income of the actual alternative selected by the farmer. The income marked 'Bernoullian' in that study represented the expected income of the alternative selected by the Bernoullian method for estimating utility.

Table 7.2 presents the absolute risk aversion measure for the two selected incomes for some of the farmers in the Lin, Dean and Moore study.

To compare the estimates of L from the Officer and Halter study with the estimates of L from the Lin, Dean, and Moore study, Table 7.3 arranges all of the applicable values of L in order from smallest in absolute value (most nearly risk neutral) to the largest in absolute value (most risk averse).

To investigate what impact this set of risk aversion coefficients has on the hedging decision in this dissertation, a table is generated that presents three differences between the momentary variance of price and the momentary variance of basis $[V(P_1) - V(B_{11})]$ and three risk aversion coefficients (selected from the two previous studies) along with the associated effect on decisions. Recall that the individual hedges when

7.12. $EU(y_H) - EU(y_N) = F_{01} - F_{11} + L\,QV(B_{11}) - L\,QV(P_1) > 0$

which says the individual hedges when

7.13. $F_{01} - F_{11} > L\,Q[V(P_1) - V(B_{11})]$.

If the individual was risk neutral, then equation (7.13) would simply be written as $F_{01} \geq F_{11}$ (hedge when the selling price is greater than the buying price). To see the impact on the hedging decision with different levels of L, one can calculate the dollar amount on the right hand side of equation (7.13). Table 7.4 can give one an idea of a 'reasonable' value of L.

The difference between the monthly momentary variance of price and

Table 7.2. Implied Absolute Risk Aversion and L from Equations Presented in Lin, Dean and Moore

	R_A		L^a	
Farm No.	low y	high y	low y	high y
1	0.02041	0.111236	-0.010205	-0.055618
3	0.0055605	0.0064583	-0.0027803	-0.0032292
6	-0.0101587	-0.006737	na	na

[a]na Indicates not applicable due to negative R_A.

Table 7.3. List of Computed L from Officer and Halter (OH) and Lin, Dean, and Moore (LDM) in Order from Smallest in Absolute Value to Highest in Absolute Value

Study	Computed L
OH	-0.0000839
OH	-0.00009725
OH	-0.00017314
OH	-0.00024168
OH	-0.00024415
OH	-0.0004069
OH	-0.0004305
OH	-0.00050699
OH	-0.0025245
LDM	-0.00278025
LDM	-0.00322915
OH	-0.0082
LDM	-0.010205
LDM	-0.055618

Table 7.4. Effect on Hedging Decision of a Given Difference in the Momentary Variance of Price and of Basis and a Given L

$[V(P_1) - V(B_{11})]$	L	$LQ[V(P_1) - V(B_{11})]$
-0.08014	-0.00024168	0.0968
-0.08014	-0.00278025	1.114
-0.08014	-0.055618	22.286
0.03383	-0.00024168	-0.0409
0.03383	-0.00278025	-0.470
0.03383	-0.055618	-9.408
0.1478	-0.00024168	-0.179
0.1478	-0.00278025	-2.055
0.1478	-0.055618	-41.102

the monthly momentary variance of basis was calculated from the actual sample period data (1974-1987). The mean was 0.03383, the mean minus 2σ was -0.08014, and the mean plus 2σ was 0.1478. Q is set equal to 5,000 bushels.

Risk Aversion Levels Selected

This study chooses a set of risk aversion coefficients to be used in this dissertation by selecting a wide range of L that would take values from both the Officer and Halter and the Lin, Dean, and Moore studies. More weight is given to implied risk aversion coefficients from the Lin, Dean and Moore study since one is able to match the estimated equation of farmer i to the range of expected income that is applicable to farmer i.

This dissertation will select a set of five values of L to be used in the simulations. A reasonable set of values is the following:

$$
\begin{aligned}
L1 &= -0.0001 \\
L2 &= -0.0005 \\
L3 &= -0.001 \\
L4 &= -0.005 \\
L5 &= -0.01
\end{aligned}
$$

L1 represents the most risk neutral producer and L5 represents the most risk averse producer in this study. The smallest of these values is not the smallest of the implied results of the two previous studies. Likewise, the largest is not the largest of the two previous studies. However, these values should provide some insight into the marketing behavior of very risk averse individuals and nearly risk neutral individuals as well as a good mixture of intermediate risk preferences.

CHAPTER 8. ESTIMATED SPRING SYSTEMS OF EQUATIONS

The spring forecast, which is made in June, is used to decide between hedging the soybean crop over the growing season and remaining unhedged over this time. It is assumed that the farmer will offset any spring hedge in November. Therefore, the relevant cash price to forecast in June is the November price. The futures contract used is the November contract. Therefore, the basis of the November contract in November is the relevant basis to forecast.

The estimation methods for the spring forecasting equations were discussed in the Forecasting Considerations Chapter and the Statistical Methods Chapter. This chapter discusses the results of the estimation of the system of equations by ordinary least squares (OLS) and Zellner's seemingly unrelated regression (SUR) estimation for the spring forecasting exercise. As stated previously, there are two systems of equations for the spring forecast that need to be estimated. One is the set of four equations for: the November cash price, the November basis (November contract), the momentary variance of the cash price in November and the momentary variance of the November basis. These four equations yield the forecasts that an individual would have access to if the momentary variance were provided by forecasters. The second set of equations consist of only two variables: the cash price in November and the November basis. This set of equations yields the forecasts that are typically available to the decision makers. The measures of riskiness that these individuals are provided from this set of two equations are

Peck's measure of variance, that being the variance of the forecasted mean price and the variance of the forecasted mean basis.

Chapter 9 is concerned with the systems estimation results for the fall forecasting exercise. Chapter 10 then presents the results of the direct expected utility estimation for both the spring and the fall forecast.

Table 8.1 presents the notation for the four endogenous variables used in the spring forecast for this study. Table 8.2 presents the notation used for the exogenous variables in the spring forecasting equations. Not all exogenous variables are used in each of the four equations, however.

Ordinary Least Squares Estimations

Estimation results from ordinary least squares (OLS) for two time periods are discussed: the 1975 through 1980 period and the 1975 through 1987 period. It is desirable to identify a set of variables that perform reasonably well in the forecast equations over the entire simulation period which will be from 1981 through 1987 for the spring forecast exercise.

The OLS regressions used either one or two variables as regressors due to the low degrees of freedom. Coefficients were considered statistically significant at the $\alpha = 0.10$ level. Equations were judged based on the significance of the coefficients, the significance of the regression for the case of two regressors, the signs of coefficients, the mean squared error (MSE), and the R^2. The Durbin-Watson statistic

Table 8.1. Definitions of the Endogenous Variables for the Spring Forecasting Equations

Endogenous variables	Variable definition
SE	Cash price of soybeans in southeast Iowa in November. Calculated as the monthly average of daily average closing prices.
NSB	November soybean basis in southeast Iowa in November. Calculated as the monthly average of the difference between the daily closing futures prices and the daily average closing cash prices.
TVSE	Natural logarithm of the momentary variance of soybean cash price SE in November. Calculated from daily average SE.
TVNSB	Natural logarithm of the momentary variance of November soybean basis NSB in November. Calculated from daily average SE and daily closing futures prices.

Table 8.2. Definitions of the Exogenous and Predetermined Variables for the Spring Forecasting Equations

Exogenous variables	Variable definition
MAYSE	May SE.
MAYNSB	May NSB.
TMVSE	May TVSE.
TMVNSB	May TVNSB.
SU1	April Soybean stocks (all positions in Mill. bu.) in Iowa divided by crop-year utilization of soybeans.
SU2	April Soybean stocks and Corn stocks (all positions in Mill. bu.) in Iowa divided by the crop-year utilization of soybeans.
SC1	April Soybean stocks (all positions in Mill. bu.) in Iowa divided by Iowa storage capacity.
SC2	April Soybean stocks and Corn stocks (all positions in Mill. bu.) in Iowa divided by Iowa storage capacity.
PPROD	Projected production. Prospective acres planted multiplied by average of past two years' yield.
PPROUT	PPROD divided by crop-year utilization of soybeans.
MAYEXP	Soybean exports for the month of May.

was used to test for the presence of autocorrelated errors in each equation.

The November cash price equation

The sign of the coefficient on SU1 was negative as expected. Several coefficients in this regression had unexpected signs. The coefficients on the stock variables SU2, SC1, and SC2 were expected to be negative. Higher stocks in April tend to mean higher carryout stocks at crop-year's end which should reduce cash price in November. The only stock variable coefficient that was significant at the 10 percent level (SC2) had the incorrect sign.

The coefficient on projected production also had an unexpected sign and was nonsignificant at the 10 percent level. One would expect that higher projected production would lead to lower cash price in November. Although the coefficient on the other production variable (PPROUT) had the anticipated sign, it also was nonsignificant. The coefficient on the May export variable MAYEXP was significant at the 10 percent level and had the anticipated sign.

The coefficient of May cash price level (MAYSE) was not significant. The regression with both the projected production-to-utilization variable and the stock variable SU1 had the correct signs but the F-statistic indicated that one could not reject the hypothesis that both coefficients equalled zero.

Of the regressions with the correct signs on coefficients, the lowest MSE and the highest R^2 were in the equation with May exports as the explanatory variable. The regression with the SC2 had both a higher

R^2 and a lower MSE but the coefficient sign was not as anticipated.

The Durbin-Watson statistic indicated that one either failed to reject the null hypothesis of no first-order autocorrelation or that the test was inconclusive at the 5 percent level of significance for all of the November cash price equations.

These OLS regressions of the cash price equation were also run with the same set of variables but this time using the longer sample period, 1975-1987. The results of the longer sample period revealed unexpected signs on three coefficients in the single variable models: SC1, SC2, and PPROD. These three variables had unexpected signs for the short sample period also. The coefficient on PPROD was significant at the 10 percent level however. The coefficient on SU2 changed sign and in the longer sample period was of the correct sign, although still nonsignificant.

Four regressions were estimated that had two exogenous variables. The coefficients of these equations were all of the expected signs except for the coefficient on PPROD in the regression with PPROD and SU1. This coefficient was not statistically significant at the 10 percent level. Only one of the equations containing two exogenous variables had a statistically significant coefficient that was of the expected sign. The F-statistic indicated however that the hypothesis that both coefficients were equal to zero could not be rejected at the 10 percent level. The equation with the lowest MSE specified November cash price as a function of projected production. The coefficient was of the wrong sign however.

The Durbin-Watson statistic indicated that one either failed to reject the null hypothesis of no autocorrelation or that the test was inconclusive at the 5 percent level of significance for all of the equations.

The regression with May exports had a reasonably low MSE and a high R^2 relative to the other equations. The coefficient on MAYEXP was not significant at the 10 percent level but the sign was correct. None of the equations in the longer sample period were particularly good so the equation with May exports was selected as the best model for this period. Recall that this model was also considered best of the regressions discussed for the shorter sample period.

<u>The November basis equation</u>

The same pool of exogenous variables was used here as for the November cash price although it was expected that different variables would be selected in the best model for the basis.

One of the coefficients of the single variable regressions had an unexpected sign and one coefficient of the two variable equations had an unexpected sign. The stock variables were expected to be positively related to the basis but the coefficient on SU1 was negative (though nonsignificant at the 10 percent level). The coefficient on SC1 in the two variable regression with SC1 and MAYNSB was also negative.

The Durbin-Watson statistic indicated that one either failed to reject the null hypothesis of no autocorrelation or that the test was inconclusive at the 5 percent level of significance for all of the equations for the basis equations with the shorter sample period.

Three coefficients were significant at the 10 percent level and all three were of the correct sign. The R^2s of the equations with SC2 and PPROD were both high. The R^2 was higher and the MSE was lower in the equation with PPROD than the equation with SC2.

The basis equations were also estimated for the longer sample period 1975-1987. Two coefficients in single variable models and one coefficient in a two variable model had unexpected signs. The coefficient on SU1 remained nonsignificant and negative from the short sample period while the coefficient on SU2 became negative (though nonsignificant) in the longer sample period. There were no coefficients in the equations for the longer sample period that were significant at the 10 percent level. For several equations, the null hypothesis of no first-order autocorrelation in the residuals was rejected at the 5 percent level of significance.

The best model for the November basis was selected on the results of the short sample period since no best model could be selected for the longer period. The best model selected then specified the November basis as a function of the projected production, PPROD. Due to the autocorrelation in the residuals, LGNSB would also be added as an explanatory variable.

<u>The momentary variance of price equation</u>

The variance of a random variable cannot be negative. Therefore, the momentary variances were transformed by the natural logarithm into a series that was not truncated at zero. The dependent variable in the models of this section was the natural log of the momentary variance of

November cash price.

The OLS estimation results for the momentary variance of November cash price for the short sample period 1975-1980 are discussed first. There were three equations that had significant coefficients at the 10 percent level: the stock variables SU1 and SU2 and the stock variable SC2. The equation with SU2 had the largest R^2 and the lowest MSE of any of the equations by far.

The coefficients on the stock variables SU1 and SC1 did not have the anticipated signs. The coefficient on PPROUT was also not as expected. The hypothesis was that production or stocks near or above the capacity of the marketing system would tend to increase the variability of the cash price (see the Forecasting Considerations Chapter). The best model then from this sample period length was the model with SU2. This model had the largest R^2 and the smallest MSE of the models.

The OLS results of the variance of the price equation for the longer sample period 1975-1987 revealed a mixture of positive and negative coefficients on the stock and production variables. The equation with SU2 had a coefficient that changed value dramatically from the short sample period to the longer sample period. The coefficient on SU2 was more than 20 times smaller in magnitude in the longer sample period and was nonsignificant. For the longer sample period, there was only one equation that had a coefficient significant at the 10 percent level. That equation specified the variance of price as a function of the stock variable SC2. This equation had the highest R^2 and the lowest

MSE. The coefficient on SC2 changed relatively modestly between the short and the longer sample period and was significant at the 5 percent level in both sample periods. Therefore, this equation was selected as the best model for the momentary variance of November cash price.

<u>The momentary variance of the basis equation</u>

The momentary variance of the basis was transformed for the same reason that the momentary variance of the cash price was transformed: to create a series that was not truncated at zero.

The signs on the four stock variables were mixed in the short sample period. The two stock variables that represented only soybean stocks (SU1 and SC1) both had negative coefficients while the two stock variables that represented both soybean and corn stocks (SU2 and SC2) had positive coefficients. Three of the four stock variables had significant coefficients at the 10 percent level. The fact that the soybean and corn stock variables (SU2 and SC2) entered with positive signs was reasonable when one considered that corn and soybeans compete with one another for storage space and transportation space. Perhaps including both corn and soybeans in the stock variable measure identified the relationship between stock level and variability of the basis better than simply a soybean stock measure.

The coefficient on the projected production variable (PPROD) was also positive and significant at the 5 percent level. This would indicate that as production increased, the demands on the storage and transportation system would result in a more variable basis.

In the two variable model with MAYEXP and SC2 as explanatory variables, both coefficients were significant at the 5 percent level but the sign of the coefficient on the May export variable was unexpected. The coefficient on MAYEXP was positive (though nonsignificant) when it was the only explanatory variable. One would expect that with a higher level of exports, there would be more demands on the transportation system which would likely mean higher volatility in basis. The single variable equation with the highest R^2 and the lowest MSE had the stock variable SU2 as the explanatory variable. The next best equations were the one with SC2 and the one with PPROD.

In the longer sample period 1975-1987, the coefficients on SU1 and SC1 changed sign. The coefficient on SU1 became nonsignificant while the coefficient on SC1 became significant at the 10 percent level. The coefficients on SU2 and SC2 remained positive from the small sample period. The coefficient on SC2 was significant at the 5 percent level in both sample sizes. In the two variable equation with MAYEXP and SC2, the coefficient on MAYEXP changed sign and was now nonsignificant at the 10 percent level. The F-statistic for the equations was still significant at the 10 percent level however. The equation with SC2 was judged to be the best model of the momentary variance of the basis due to the relative stability in the magnitude of the coefficient as well as the low MSE and reasonably high R^2.

Joint Estimation of the Four Equation System

It is worth noting that the R^2s reported in this study may not be directly comparable with R^2s reported elsewhere. The R^2s will not be directly comparable if the other study had used the monthly mean endogenous variable (such as price) for all 12 months per year in their regression equations. In that case the R^2 would represent the percent of the variability of the monthly means about the overall average of the monthly means that is accounted for in the sample period. If there was any seasonality in the monthly means within a year, the R^2 would be greater than the R^2 reported in this dissertation. This dissertation uses only the November average for each year (for the spring forecast) in the regressions. Therefore, the presence of within year seasonality of the monthly mean does not inflate the R^2 in this study.

Note also that some of the models selected as the best model for each of four variables were not statistically significant models. The F-test of some of the OLS regressions indicated that none of the coefficients in the particular equation are significantly different from zero. One could argue that the best model in that case would be simply the mean of the past values of the endogenous variables. This study will include even the poor equations in the system of equations however so that the residuals from even a poor equation can influence the estimation of the coefficients in the other equations of the system. As suggested by Kmenta and Gilbert (1968), this study will chance erring on the side of including too many equations in the system.

This study also estimated a deflated cash price equation and a deflated basis equation in order to account for the effect of inflation over the period. Both the May consumer price index (CPI) and the May producer price index (PPI) were tried as deflators in the equations but there was no improvement in the significance of the coefficients or in the number of correct signs. Therefore, only nominal cash price and basis are used in the forecasting equations in this study.

The best OLS equations were estimated as a system of four equations but there was significant autocorrelation in the basis equation for four of the eight sample period lengths. Although the spring sample period does not include the spring 1974 data, it does include the September-December 1974 data. The lagged basis can then be used as an explanatory variable without losing a degree of freedom from the basis equation or from the other equations. Therefore the lagged basis (LGNSB) was included as a regressor in the basis equation to account for the autocorrelation. If there is no autocorrelation in an equation that has a lagged endogenous variable on the right hand side, the estimators are unbiased and consistent. The Durbin test was used to test for the presence of autocorrelation in an equation in the presence of a lagged dependent variable on the right hand side. The following results of the four equation system included the lagged endogenous variable as a regressor in the basis equation.

Tables 8.3, 8.4, 8.5, and 8.6 present the joint estimation results for the 1974-79 period and for the seven annual updates from the 1975-80 coefficients of the four models. The estimated coefficients and the respective probability of observing a t-value greater than or equal to the calculated t by chance are presented for each model. The probability of a t-value greater than or equal to the calculated t should be less than 0.10 (i.e., $\alpha = 0.10$) for that coefficient to be

Table 8.3. The Cash Price (SE) Equation Results from the Joint Estimation of the Four Equation System for the Seven Updates Needed During the 1980 to 1987 Period

Sample Period	Intercept	Coefficients and Variables[a]	DW	System R^2
1975-80	3.0407	0.05792 * MAYEXP (0.02)	1.330	0.81
1975-81	3.2445	0.05180 * MAYEXP (0.01)	2.204	0.76
1975-82	3.7684	0.03817 * MAYEXP (0.04)	1.462	0.43
1975-83	4.4993	0.03011 * MAYEXP (0.19)	2.226	0.46
1975-84	4.5176	0.02958 * MAYEXP (0.16)	2.588	0.60
1975-85	4.2322	0.03375 * MAYEXP (0.07)	2.579	0.60
1975-86	4.1090	0.03383 * MAYEXP (0.07)	2.313	0.29
1975-87	4.0907	0.03394 * MAYEXP (0.04)	2.409	0.32

[a]Probability of a t-value greater than the calculated t in parentheses.

Table 8.4. The November Basis (NSB) Equation Results from the Joint Estimation of the Four Equation System for the Seven Updates Needed During the 1980 to 1987 Period

Sample Period	Intercept	Coefficients and Variables[a]		DW
1975-80	-0.09920	0.0003246 * PPROD (0.04)	-0.2322 * LGNSB (0.48)	1.788
1975-81	-0.09709	0.0003206 * PPROD (0.01)	-0.2390 * LGNSB (0.26)	2.101
1975-82	0.03678	0.0001766 * PPROD (0.22)	-0.00783 * LGNSB (0.98)	1.131
1975-83	0.1337	-0.00001380 * PPROD (0.92)	0.6169 * LGNSB (0.05)	1.125
1975-84	0.02638	0.00003914 * PPROD (0.69)	0.6215 * LGNSB (0.01)	1.057
1975-85	-0.02480	0.00005762 * PPROD (0.54)	0.6577 * LGNSB (0.004)	1.055
1975-86	0.005529	0.00007603 * PPROD (0.57)	0.4718 * LGNSB (0.07)	0.975
1975-87	-0.002654	0.00007807 * PPROD (0.54)	0.4801 * LGNSB (0.05)	1.031

[a]Probability of a t-value greater than the calculated t in parentheses.

Table 8.5. The Log-of-the-Variance of Cash Price (TVSE) Equation Results from the Joint Estimation of the Four Equation System for the Seven Updates Needed During the 1980 to 1987 Period

Sample Period	Intercept	Coefficients and Variables[a]	DW
1975-80	-8.0145	2.5736 * SC2 (0.02)	1.925
1975-81	-7.8955	2.3233 * SC2 (0.22)	0.966
1975-82	-6.7493	1.5565 * SC2 (0.26)	1.113
1975-83	-6.6979	1.5919 * SC2 (0.19)	1.465
1975-84	-6.9097	1.7004 * SC2 (0.04)	1.615
1975-85	-6.7965	1.6400 * SC2 (0.03)	1.665
1975-86	-6.8857	1.5761 * SC2 (0.09)	1.480
1975-87	-6.8291	1.5314 * SC2 (0.07)	1.804

[a]Probability of a t-value greater than the calculated t in parentheses.

Table 8.6. The Log-of-the-Variance of November Basis (TVNSB) Equation Results from the Joint Estimation of the Four Equation System for the Seven Updates Needed During the 1980 to 1987 Period

Sample Period	Intercept	Coefficients and Variables[a]	DW
1975-80	-8.5446	1.6216 * SC2 (0.02)	3.093
1975-81	-8.7527	1.8317 * SC2 (0.07)	1.773
1975-82	-7.4963	1.0235 * SC2 (0.17)	2.260
1975-83	-6.8279	0.5854 * SC2 (0.40)	1.424
1975-84	-7.6158	1.0160 * SC2 (0.06)	1.589
1975-85	-8.0324	1.2273 * SC2 (0.03)	1.593
1975-86	-7.9952	1.1677 * SC2 (0.04)	1.298
1975-87	-8.0613	1.2140 * SC2 (0.02)	1.528

[a]Probability of a t-value greater than the calculated t in parentheses.

considered statistically significant in this study. Other statistics provided with each regression are the Durbin-Watson DW statistic and the system R^2.

Table 8.3 presents the results for the cash price (SE) model. The coefficient on MAYEXP changed over time and was nonsignificant at the 10 percent level in the 1975-1983 and the 1975-1984 sample periods. The system R^2 varied over time also. The DW statistic indicated that one failed to reject the null hypothesis of zero autocorrelation in the residual for all updates of the model.

Table 8.4 presents the joint estimation results for the November basis. The coefficient on PPROD was significant at the 10 percent level in the short sample periods but was nonsignificant with the sample period updates. For the 1975-1983 sample period, the coefficient on PPROD was negative but the coefficient was also nonsignificant. The coefficient on the lagged endogenous variable (LGNSB) was nonsignificant in the short sample periods but was significant at the 10 percent level in all of the longer sample periods. The coefficient on LGNSB changed sign but the coefficient was nonsignificant when it was negative. The DW statistic indicates that for all sample period lengths there was no significant autocorrelation in the residuals. An examination of the time series of the basis over the sample period revealed a sharp drop in the level of the basis in 1982 and that the basis did not rebound to near its pre-1982 level until 1986 and 1987. This may explain the autocorrelated errors in other specifications of the basis equation.

Table 8.5 presents the joint estimation results for the (transformed) momentary variance of cash price. The coefficient on SC2 was nonsignificant for three of the four shortest sample period lengths. In the longer sample periods the coefficient on SC2 was significant at the 10 percent level. There was no significant autocorrelation in the residuals for this equation in any of the sample periods.

Table 8.6 presents the joint estimation results for the (transformed) momentary variance of the November basis. The coefficient on SC2 was significant at the 10 percent level for all but two of the sample periods in Table 8.6. Again, there was no significant autocorrelation in the residuals.

Overall, the models for the cash price level and variance and the basis variance were good in terms of coefficient significance in the shorter and the longer sample periods while they were poor in terms of coefficient significance in the medium length sample periods. The significance of the coefficient on PPROD in the November basis model deteriorated as the sample period length increased.

Joint Estimation of the Two Equation System

The Durbin-Watson DW statistic from the OLS estimates of the basis equation indicated that four sample period lengths had significant first-order autocorrelation at the 5 percent level. Again the May basis (MAYNSB) was included as an additional explanatory variable with the expectation that it would purge the residuals of the autocorrelation. The significant autocorrelation remained however. Therefore it was decided to turn to the lagged basis as an additional explanatory variable in the basis equation, just as for the four equation system.

Tables 8.7 and 8.8 present the joint estimation results of the two equation system for each of the eight sample periods between 1975 and 1987. The results for the cash price equation indicate that the coefficient on MAYEXP was statistically significant at the 10 percent level in four of the eight equations in Table 8.7. The slope coefficient had the correct sign in all of the sample period lengths. The system R^2 fell slowly from the 1975-1981 sample period. The DW statistic indicated that there was no significant first-order autocorrelation in the residuals. The MSE of the cash price equation is presented since this information will be used in the later chapters to calculate the variance of the forecasted mean price.

Table 8.8 presents the joint estimation results for the basis equation in the two equation system. The coefficient on PPROD was significant at the 10 percent level in two of the sample period lengths while the coefficient on LGNSB was significant in four. The sign on PPROD was correct except for the 1975-84 and the 1975-85 sample period lengths. Both times however, the coefficient on PPROD was nonsignificant. The coefficient on LGNSB was negative in the short sample period lengths but turned positive and significant in the longer sample periods. The DW statistic indicated that there was no significant first-order autocorrelation at the 5 percent level.

The equations presented in Tables 8.3 through 8.6 are used in later chapters to forecast the cash price and basis and the momentary variance of cash price and basis. These forecasts represent the information that

Table 8.7. The Cash Price (SE) Equation Results from the Joint Estimation of the Two Equation System for the Seven Updates Needed During the 1980 to 1987 Period

Sample Period	Intercept	Coefficients and Variables[a]	DW	MSE	System R^2
1975-80	3.0172	0.05834 * MAYEXP (0.03)	1.335	0.9323	0.78
1975-81	2.9378	0.05717 * MAYEXP (0.01)	2.142	0.9290	0.81
1975-82	3.5725	0.04137 * MAYEXP (0.03)	1.407	1.1570	0.50
1975-83	4.6842	0.02708 * MAYEXP (0.25)	2.206	1.2600	0.27
1975-84	4.6549	0.02731 * MAYEXP (0.21)	2.577	1.1801	0.34
1975-85	4.4179	0.03055 * MAYEXP (0.11)	2.560	1.1284	0.41
1975-86	4.3623	0.02946 * MAYEXP (0.14)	2.267	1.1532	0.33
1975-87	4.2890	0.03043 * MAYEXP (0.09)	2.358	1.1024	0.34

[a]Probability of a t-value greater than the calculated t in parentheses.

Table 8.8. The November Basis (NSB) Equation Results from the Joint Estimation of the Two Equation System for the Seven Updates Needed During the 1980 to 1987 Period

Sample Period	Intercept	Coefficients and Variables[a]		DW	MSE
1975-80	-0.1228	0.0003364 * PPROD (0.04)	-0.2232 * LGNSB (0.51)	1.873	0.08208
1975-81	-0.1114	0.0003400 * PPROD (0.01)	-0.2917 * LGNSB (0.20)	2.060	0.07784
1975-82	-0.01905	0.0002599 * PPROD (0.14)	-0.2533 * LGNSB (0.55)	1.209	0.1393
1975-83	0.0606	0.0000223 * PPROD (0.89)	0.6368 * LGNSB (0.14)	1.135	0.1402
1975-84	0.0597	-0.0000010 * PPROD (0.99)	0.7416 * LGNSB (0.05)	1.191	0.1342
1975-85	0.05040	-0.0000030 * PPROD (0.98)	0.7701 * LGNSB (0.02)	1.207	0.1265
1975-86	0.000721	0.0000563 * PPROD (0.68)	0.6101 * LGNSB (0.03)	1.124	0.1232
1975-87	-0.00378	0.0000574 * PPROD (0.66)	0.6125 * LGNSB (0.02)	1.212	0.1170

[a]Probability of a t-value greater than the calculated t in parentheses.

one would have if one used the momentary variance as the relevant measure of risk for the marketing decision.

The equations presented in Tables 8.7 and 8.8 are used in the later chapters to forecast the cash price and basis. The measure of riskiness in the prices recommended by Peck is derived from these two equations. These forecasts represent the forecasts that one would have available if one followed the currently provided information.

CHAPTER 9. ESTIMATED FALL SYSTEMS OF EQUATIONS

The fall forecast, which is made in November, is used to decide which marketing alternative yields the highest expected utility: (1) storing the crop hedged until July, (2) storing the crop unhedged until July, or (3) selling the crop now in the fall. The forecasts needed for the fall decision are of the July cash price, July basis on the July contract, the momentary variance of cash price, and the momentary variance of the basis. This chapter first presents the definitions of the endogenous and the exogenous variables used in the models for the fall. The results of the estimation of the models follows this.

Table 9.1 presents the endogenous variables for the fall forecasting exercise. This table is very similar to Table 8.1 but now the July contract is used and the observations of the endogenous variables are in July. Table 9.2 presents the definitions of the exogenous variables used in the fall forecasting exercise. These variables are similar to those defined in Table 8.2 but the data used to form these variables are specific to the information known in the fall.

Ordinary Least Squares Estimations

The results of the estimation of the fall forecasting equations will first include the ordinary least squares estimates of the various models. The best models for the four variables from OLS estimation are then estimated jointly by Zellner's SUR method. Just as for the spring forecasting exercise, the estimates of the coefficients are made initially over a short sample period and these estimates are updated

Table 9.1. Definitions of the Endogenous Variables for the Fall Forecasting Equations

Endogenous variables	Variable definition
SE	Cash price of soybeans in southeast Iowa next July. Calculated as the monthly average of daily averages.
JSB	July soybean basis in southeast Iowa next July. Calculated as the monthly average of the difference between the daily closing futures prices and the daily average cash prices.
TVSE	Natural logarithm of the momentary variance of soybean cash price SE next July. Calculated from daily average SE.
TVJSB	Natural logarithm of the momentary variance of July soybean basis JSB in July. Calculated from daily average SE and daily closing July futures price.

Table 9.2. Definitions of the Exogenous and Predetermined Variables for the Fall Forecasting Equations

Exogenous variables	Variable definition
OCTSE	October SE.
OCTJSB	October JSB.
TOVSE	October TVSE.
TOVJSB	October TVJSB.
OCTFUT	July futures price in October of the forecasting year. (OCTSE + OCTJSB).
SU3	September Soybean stocks (all positions in Mill. bu.) in Iowa divided by the crop-year utilization.
SU4	September Soybean stocks and October Corn stocks (all positions in Mill. bu.) in Iowa divided by the crop-year utilization.
SC3	September Soybean stocks (all positions in Mill. bu.) in Iowa divided by Iowa storage capacity.
SC4	September Soybean stocks and October Corn stocks (all positions in Mill. bu.) in Iowa divided by Iowa storage capacity.
PROD	Actual production.
PROUT	PROD divided by crop-year utilization.
OCTEXP	Soybean exports for the month of October.

with the data for each year that follows. The initial estimates of the coefficients are made over the short sample period 1974-1979. This provides six observations for the initial estimation, the same number of observations as with the spring initial estimates. The long sample period will extend from 1974-1986. Diagnostic statistics used to evaluate each model include the Durbin-Watson DW statistic, the mean squared error (MSE), and the R^2.

The July cash price equation

There are several coefficients for this sample period that had unexpected signs. Of the single-variable equations, the coefficients on SU4, SC4, PROD, and PROUT were unexpected. One would expect these signs to be negative since higher stocks in the new crop year, whether from large carryover stocks or from large production, would lead to lower prices through the crop year.

The coefficients on the two stock variables SU3 and SC3 were of the expected sign. These two stock variables were formed with only soybean stocks whereas SU4 and SC4 were formed with both soybean and corn stocks. The addition of corn stocks in SU4 and SC4 apparently obscured the relationship between stocks and soybean price. None of the coefficients on the stock variables were significant at the 10 percent level, however.

The only coefficient with the correct sign that was significant at the 10 percent level was the coefficient on the October export variable OCTEXP. This coefficient remained significant at the 5 percent level in the three models in which it appeared. A model that included both

OCTEXP and SU3 had an unexpected sign on the coefficient of SU3. Despite the nonsignificance of the coefficient on SU3, the calculated F-statistic for that equation was still significant at the 5 percent level.

Of the models with the correct signs on coefficients, the model with the lowest MSE and the highest R^2 was the model with OCTEXP as the independent variable. The model with OCTEXP and OCTFUT had a slightly higher MSE, the same unadjusted R^2, and the coefficient on OCTFUT was nonsignificant at the 10 percent level. The model with OCTEXP alone was selected as the best model while the model with OCTEXP and OCTFUT was selected as a possible second choice.

Three coefficients that had unexpected signs in the short sample period also had unexpected signs in the longer sample period: SC4, PROD, and PROUT. The coefficient on SU4 and OCTFUT changed sign between the short and the long sample period. Both variables were nonsignificant at the 10 percent level in both sample lengths however. The R^2s for the models with the longer sample period lengths were very low and there was not a great deal of difference in the MSEs of the various models. The only coefficients that were significant at the 10 percent level were found in the two variable models where OCTEXP with SU3 and OCTEXP with OCTFUT were the explanatory variables. OCTEXP was not significant at the 10 percent level when it was the only explanatory variable.

The model that was selected as the best over both the short and the longer sample periods was the model with OCTEXP and OCTFUT as explanatory variables. The coefficient on OCTFUT changed sign between the short and the longer sample period but the coefficient was nonsignificant at the 10 percent level in the longer period.

The July basis equation

The results from the OLS estimation of the July basis model for the short sample period revealed that two of the coefficients had unexpected signs: the coefficient on SU3 and the coefficient on SC3. These stock variables were formed with only soybean stocks whereas the stock variables SU4 and SC4 were formed with both soybean and corn stocks. It was intued that the basis would be related more closely to the total amount of grains stored and transported rather than to the amount of soybeans. The coefficients on OCTJSB and PROD were the only coefficients that were significant at the 10 percent level. The MSE was lower and the R^2 was higher for the model with OCTJSB than for the model with PROD. The model with OCTJSB was selected as the best model for the short sample period and the model with PROD as the next best.

Several coefficients had unexpected signs for the long sample period. All of the coefficients on the stock variables had the incorrect sign though none of these coefficients was significant at the 10 percent level. In the two variable model with OCTEXP and PROUT, the coefficient on OCTEXP had an unexpected sign though it was nonsignificant at the 10 percent level. Only one single variable model in this sample period length had a coefficient that was significant at the 5 or even the 10 percent level. The model with PROUT as the explanatory variable had the lowest MSE of any of the models. This was selected as the best model in the long sample period 1974-1986.

The selection of the best model over both sample period lengths was not easy. Whereas the coefficients on PROD and OCTJSB were significant in the short sample period, both were nonsignificant in the long period. The coefficient on PROUT in the long sample period was significant but in the short period this coefficient was nonsignificant. A somewhat arbitrary decision was made that the model with PROUT as the explanatory variable was the best model over the two sample period lengths.

<u>The momentary variance of cash price equation</u>

The momentary variance of the cash price was transformed, just as for the spring forecasting case, in order to construct a series that was not truncated at zero. Again, the natural logarithm was chosen as the transformation. The dependent variable in each of the models discussed in this section is the log of the momentary variance of cash price (TVSE).

The OLS results for the models of the momentary variance of cash price for the short sample period 1974-1979 revealed that none of the equations was significant at the 10 percent level. There was essentially no basis to decide which of the models presented was the best for the short sample period. The OLS results for the models of the momentary variance of cash price for the long sample period 1974-1986 did not shed much light on the issue concerning the anticipated signs either. There was only one coefficient in this sample period length that was significant at the 10 percent level. The coefficient on the (transformed) October momentary variance of cash price (TOVSE) was positive and significant at the 5 percent level. The MSE of this equation was far below that of the other equations. This equation was selected as the best equation for the long sample period and was used as the best equation over both sample period lengths.

The momentary variance of the basis

This momentary variance was also transformed into a series that was not truncated at zero. The natural logarithm of the momentary variance of the basis (TVJSB) was the dependent variable in all of the models in this section.

OLS results of the models for the variance of the basis for the short sample period 1974-1979 indicated that there were no coefficients that were significant at the 10 percent level. The signs on the coefficients of the stock variables were mixed. The coefficients on SU3 and SC3 were positive while the coefficients on SU4 and SC4 were negative. Though none of the stock variable coefficients were significant at the 10 percent level, it was interesting to note the arrangement of signs and compare it with the results of Chapter 8. For the spring forecast of the momentary variance of the (November) basis, the signs on the comparable stock variables were reversed. The sign on the production variable PROD depended on what other variable, if any, was included in the equation. The sign of the coefficient on PROUT was unexpected. Again there did not appear to be a clear best model for the momentary variance of the basis for the short period.

As with the results of the short sample period, none of the coefficients were significant at the 10 percent level for the longer sample period. The signs of the coefficients on the stock variables did not change between the two sample period lengths but all of the coefficients were still nonsignificant. The case was similar for the production variables. The coefficients on PROD and PROUT when each was the only variable in the model were negative and unexpected in both the long and the short sample periods. The model with SC3 as the explanatory variable was selected, somewhat arbitrarily, as the best model for the variance of the basis for both the long and the short sample periods. The best model for that variable may have been the mean of the past values of that variable.

Joint Estimation of the Four Equation System

Some of the models selected as the best model for each of four variables were not statistically significant models. The F-test of some of the OLS regressions indicated that none of the coefficients in the particular equation were significantly different from zero. One could argue that the best model in that case would be simply the mean of the past values of the endogenous variables. As suggested by Kmenta and Gilbert (1968), this study will chance erring on the side of including too many equations in the system.

As for the spring set of forecasting equations, a deflated cash price equation and a deflated basis equation were estimated. There was no improvement in the estimated equations relative to the equation results presented in this chapter so only nominal price and basis were used in the final forecasting equations.

Tables 9.3, 9.4, 9.5, and 9.6 present the results of estimating the four equations jointly for the eight sample periods from the 1974-1979 to the 1974-1986 sample periods. The estimated coefficients and the respective probabilities of observing a t-value greater than or equal to the calculated t by chance are presented for each model. The probability of a t-value greater than or equal to the calculated t should be less than 0.10 (i.e., $\alpha = 0.10$) for that coefficient to be considered statistically significant in this study. Other statistics provided with each regression are the Durbin-Watson DW statistic and the system R^2.

The coefficient on OCTEXP was significant at the 10 percent level for five of the eight regressions in Table 9.3 and each had the correct sign. The coefficient on OCTFUT had an unexpected sign for the shortest sample period only. The coefficient on OCTFUT was significant at the 10 percent level in only the longest sample period. In Table 9.4, the coefficient on PROUT had the correct sign in all sample periods and the coefficient was significant in all but one of the eight sample period lengths.

Table 9.5 presents the joint estimation results for the (transformed) variance of the cash price for the eight sample periods. Only three of the coefficients on TOVSE were significant at the 10 percent level. The sign on the coefficient was negative for the first two sample period lengths but in both cases the coefficients were nonsignificant. Table 9.6 presents the joint estimation results for the (transformed) variance of the July basis equation. None of the

Table 9.3. The Cash Price (SE) Equation Results from the Joint Estimation of the Four Equation System for the Seven Updates Needed During the 1980 to 1987 Period

Sample Period	Intercept	Coefficients and Variables[a]		DW	System R^2
1974-79	5.3114	0.02730 * OCTEXP (0.05)	-0.09844 * OCTFUT (0.55)	3.009	0.59
1974-80	3.0584	0.03788 * OCTEXP (0.02)	+0.1379 * OCTFUT (0.35)	2.651	0.60
1974-81	4.6078	0.01825 * OCTEXP (0.20)	+0.08551 * OCTFUT (0.68)	2.221	0.34
1974-82	4.3885	0.01828 * OCTEXP (0.16)	+0.1067 * OCTFUT (0.58)	2.022	0.27
1974-83	3.9693	0.01909 * OCTEXP (0.12)	+0.1604 * OCTFUT (0.34)	2.138	0.33
1974-84	4.1940	0.01754 * OCTEXP (0.07)	+0.1403 * OCTFUT (0.33)	2.153	0.34
1974-85	3.4508	0.02041 * OCTEXP (0.03)	+0.2076 * OCTFUT (0.14)	1.903	0.37
1974-86	3.1650	0.01695 * OCTEXP (0.07)	+0.2731 * OCTFUT (0.05)	1.558	0.38

[a]Probability of a t-value greater than the calculated t in parentheses.

Table 9.4. The July Basis (JSB) Equation Results from the Joint Estimation of the Four Equation System for the Seven Updates Needed During the 1980 to 1987 Period

Sample Period	Intercept	Coefficients and Variables[a]	DW
1974-79	-0.1713	0.4304 * PROUT (0.13)	1.243
1974-80	-0.1924	0.4398 * PROUT (0.05)	2.358
1974-81	-0.2170	0.4425 * PROUT (0.10)	1.800
1974-82	-0.2702	0.4813 * PROUT (0.06)	1.636
1974-83	-0.3389	0.5418 * PROUT (0.02)	1.652
1974-84	-0.3538	0.5492 * PROUT (0.01)	1.588
1974-85	-0.3162	0.5068 * PROUT (0.01)	1.470
1974-86	-0.3154	0.5045 * PROUT (0.01)	1.480

[a]Probability of a t-value greater than the calculated t in parentheses.

Table 9.5. The Log-of-the-Variance of Cash Price (TVSE) Equation Results from the Joint Estimation of the Four Equation System for the Seven Updates Needed During the 1980 to 1987 Period

Sample Period	Intercept	Coefficients and Variables[a]	DW
1974-79	-2.8356	-0.04064 * TOVSE (0.85)	1.970
1974-80	-2.9657	-0.04918 * TOVSE (0.81)	2.746
1974-81	-2.1067	0.3551 * TOVSE (0.09)	1.141
1974-82	-2.3916	0.2415 * TOVSE (0.26)	1.900
1974-83	-2.3780	0.2459 * TOVSE (0.21)	1.927
1974-84	-2.6514	0.2218 * TOVSE (0.34)	1.558
1974-85	-2.4108	0.3138 * TOVSE (0.09)	1.694
1974-86	-2.2729	0.3843 * TOVSE (0.04)	1.605

[a]Probability of a t-value greater than the calculated t in parentheses.

Table 9.6. The Log-of-the-Variance of July Basis (TVJSB) Equation Results from the Joint Estimation of the Four Equation System for the Seven Updates Needed During the 1980 to 1987 Period

Sample Period	Intercept	Coefficients and Variables[a]	DW
1974-79	-6.2346	15.0956 * SC3 (0.27)	2.443
1974-80	-6.3361	13.0158 * SC3 (0.42)	1.534
1974-81	-5.8728	4.4305 * SC3 (0.76)	1.137
1974-82	-5.7863	1.4254 * SC3 (0.93)	1.017
1974-83	-5.7635	1.09366 * SC3 (0.94)	1.170
1974-84	-6.2456	4.6458 * SC3 (0.71)	1.045
1974-85	-6.3291	5.7628 * SC3 (0.63)	1.218
1974-86	-6.7221	9.8890 * SC3 (0.31)	1.088

[a]Probability of a t-value greater than the calculated t in parentheses.

coefficients on SC3 were significant at the 10 percent level although all of the coefficients were of the expected sign. Though the equations were not statistically significant for the transformed variance of the basis, this equation was kept in the system since it was expected that the errors in estimating this endogenous variable were contemporaneously correlated with the errors in at least one other equation.

Joint Estimation of the Two Equation System

Tables 9.7 and 9.8 present the joint estimation results for the two equation model. The same set of explanatory variables used in the cash price and the basis equations from the four equation system are used in the two equation system. Cash price equation results are presented in Table 9.7. The coefficients on OCTEXP were all of the correct sign and five of the eight coefficients on OCTEXP were significant at the 10 percent level. None of the coefficients on OCTFUT were significant at the 10 percent level. The system R^2s for the two shortest sample period lengths were considerably higher than for the longer sample period lengths. Table 9.8 presents the joint estimation results for the July basis. All but one of the coefficients on PROUT was significant at the 10 percent level and all coefficients had the expected sign. The MSE for the cash price and the basis equations are presented in Table 9.7 and Table 9.8. The MSE will be used to calculate the variance of the forecasted mean price and basis for the simulation chapters.

The equations presented in Tables 9.3 through 9.6 are used in Chapter 11 to forecast the cash price and basis and the momentary

Table 9.7. The Cash Price (SE) Equation Results from the Joint Estimation of the Two Equation System for the Seven Updates Needed During the 1980 to 1987 Period

Sample Period	Intercept	Coefficients and Variables[a]		DW	MSE	System R^2
1974-79	4.8495	0.02959 * OCTEXP (0.05)	-0.05393 * OCTFUT (0.75)	2.991	0.3837	0.72
1974-80	2.7976	0.03606 * OCTEXP (0.03)	+0.1910 * OCTFUT (0.25)	2.758	0.5108	0.72
1974-81	5.4130	0.01643 * OCTEXP (0.25)	-0.007857 * OCTFUT (0.97)	2.311	0.7097	0.33
1974-82	5.2600	0.01447 * OCTEXP (0.27)	+0.02313 * OCTFUT (0.91)	1.959	0.6890	0.29
1974-83	4.9745	0.01488 * OCTEXP (0.23)	+0.06397 * OCTFUT (0.72)	2.143	0.6466	0.38
1974-84	4.5427	0.01801 * OCTEXP (0.08)	+0.08698 * OCTFUT (0.58)	2.248	0.6248	0.41
1974-85	3.7333	0.02120 * OCTEXP (0.04)	+0.1596 * OCTFUT (0.29)	1.944	0.6429	0.44
1974-86	3.2003	0.01884 * OCTEXP (0.07)	+0.2485 * OCTFUT (0.11)	1.551	0.6815	0.42

[a]Probability of a t-value greater than the calculated t in parentheses.

Table 9.8. The July Basis (JSB) Equation Results from the Joint Estimation of the Two Equation System for the Seven Updates Needed During the 1980 to 1987 Period

Sample Period	Intercept	Coefficients and Variables[a]	DW	MSE
1974-79	-0.2311	0.4851 * PROUT (0.16)	1.335	0.1214
1974-80	-0.3020	0.5434 * PROUT (0.06)	2.341	0.1112
1974-81	-0.2928	0.5138 * PROUT (0.08)	1.806	0.1220
1974-82	-0.2867	0.4968 * PROUT (0.08)	1.638	0.1194
1974-83	-0.3491	0.5517 * PROUT (0.03)	1.663	0.1126
1974-84	-0.3583	0.5535 * PROUT (0.02)	1.593	0.1091
1974-85	-0.3321	0.5221 * PROUT (0.02)	1.480	0.1063
1974-86	-0.3080	0.4975 * PROUT (0.01)	1.475	0.1017

[a]Probability of a t-value greater than the calculated t in parentheses.

variances of cash price and basis. These forecasts represent the information that one would have if one used the momentary variance as the relevant measure of risk for the marketing decision. The equations presented in Tables 9.7 and 9.8 are used in the Chapter 11 to forecast the cash price and basis. The measure of riskiness in the prices recommended by Peck is derived from these two equations. These forecasts represent the forecasts that one would have available if one followed the currently provided information.

CHAPTER 10. ESTIMATED SYSTEMS OF EXPECTED UTILITY EQUATIONS

This chapter presents the estimation of the equations in which the dependent variables are expected utilities. These equations are used to forecast expected utility directly, in contrast to the typical approach which forecasts expected utility by forecasting the components separately. The expected utility of hedging for a given risk aversion level will be jointly estimated with the expected utility of remaining unhedged. This system will be estimated for both the spring and the fall decisions. The expected utility of selling in the cash market in the fall does not need to be included in the system since the current cash price is known to the producer at the time of the decision.

With the direct expected utility method of forecasting, a different equation must be estimated for each for each level of risk aversion considered and for each level of quantity marketed. Therefore, the expected utilities at only two levels of risk aversion are used in this chapter. The two risk aversion levels chosen here were selected by considering the results of Chapter 12 and Chapter 13. Two risk aversion levels were selected based on whether there could be interesting differences in the forecasting methods at those levels.

This chapter is divided into two sections. The first section discusses the estimations of the expected utility equations for the spring decision. The second section discusses the estimation of the expected utility equations for the fall decision.

Expected Utility Equations for the Spring

Note that at the time one makes the actual decision in the spring, one observes the November futures price and thus this term is not included in the calculation of the expected-utility-of-hedging variable. Over the sample period of 1975-1987, the actual momentary variances of cash price and basis were combined with the actual cash prices and bases to calculate the expected utilities. Then each expected utility was regressed by ordinary least squares on the pool of exogenous variables used in Chapter 8 and Chapter 9. Once reasonable equations are identified using OLS, the two expected utilities are jointly estimated by Zellner's seemingly unrelated regression (SUR).

Two levels of risk aversion are examined with the direct expected utility approach so for the spring, there are two series of 'expected utility of hedging' and two series of 'expected utility of not hedging'. The two risk aversion levels are L1 (= -0.0001) and L3 (= -0.001). Define the expected utility of hedging at L1 as EUHL1 and at L3 as EUHL3. Likewise, define the expected utility of not hedging at L1 as EUNL1 and at L3 as EUNL3.

OLS estimation results for the EUHL1 and the EUHL3 equations were mixed and the signs on the coefficients of the exogenous variables were consistent with the signs observed for the November basis equation (reported in Chapter 8). Since the November basis and the variance of the November basis enter EUHL1 and EUHL3 with negative signs, one should observe signs on coefficients that are opposite to those observed in Table 8.4 and Table 8.6. Many of the estimated equations for EUHL1 over the longer sample period (1975-1987) had significant first order autocorrelation at the 5 percent level just as with the November basis equation of Chapter 8. The autocorrelation was also present in the EUHL3 equation. Therefore, the actual lagged expected utility variable was added in both equations to account for the autocorrelation. All of the equations for the expected utility of hedging presented for the spring include the lagged expected utility. Since the estimation results of EUHL1 and EUHL3 were so similar, they will be discussed together.

Expected utility of hedging in the spring

In the short sample period, three stock variables entered the EUHL1 and EUHL3 equations with the correct signs (SU2, SC1, and SC2). Of these three stock variables, only the coefficient on SC2 was significant at the 10 percent level. In each of these cases, the coefficient on the lagged expected utility was nonsignificant. The coefficient on PPROD was of the correct sign and was significant at the 10 percent level. The F-test for this model indicated that the model was significant at the 10 percent level. The coefficient on PPROUT did not have the correct sign. The coefficient on MAYEXP had the correct sign but both this coefficient and the coefficient on the lagged endogenous variable were nonsignificant.

Next, this section turns to the OLS estimation results for the longer sample period of 1975-1987 for the expected utility of hedging. Three of the four stock variables entered the two equations with negative coefficients, which was the expected sign since the basis entered the expected utility of hedging with a negative sign. Although none of these stock variables were significant at the 10 percent level, the lagged expected utility variable was significant at the 5 percent level in all three models. Each of the three models had similar MSE and R^2 and according to the F-test, all three models were significant at the 5 percent level. The production variables PPROD and PPROUT entered with the correct signs though nonsignificant and in each case, the coefficient on the lagged expected utility variable was significant at the 5 percent level. There were very similar MSE and R^2 for the models with PPROD and PPROUT and both models were significant at the 5 percent level according to the F-test. From the OLS results for EUHL1 and EUHL3, the model selected to be used in the joint estimation specifies PPROD and LGEUH (lagged expected utility of hedging) as regressors.

Expected utility of not hedging in the spring

The notation for this endogenous variable is EUNL1 and EUNL3 for the two levels of risk aversion L1 and L3, respectively. The November cash price entered the expected utility of not hedging positively while the momentary variance of cash price entered negatively. Therefore, the signs on the coefficients in the models in this section should be the same as the coefficients in Table 8.3 for the cash price and opposite for coefficients in Table 8.5 for the variance of cash price. The only variable then that had a coefficient with an ambiguous sign was MAYEXP. For the short sample period, the coefficients on the stock variable SU1 and on the production variable PPROUT had the correct sign though both were nonsignificant. The coefficient on MAYEXP was positive and was significant at the 10 percent level.

Next are the OLS results of the expected utility of not hedging for the longer sample period 1975-1987. The two stock variables SU1 and SU2 had coefficients that had the correct sign though neither coefficient was significant at the 10 percent level. The coefficients on SC1, SC2 and the coefficient on PPROD entered with the incorrect sign. The sign on the coefficient on PPROUT was correct but was nonsignificant at the 10 percent level. The coefficient on MAYEXP was positive and was significant at the 12 percent level for both EUNL1 and EUNL3. For EUNL1 and EUNL3, the best model over both sample period lengths specified MAYEXP as the regressor.

Joint estimation of the expected utilities for the spring

Tables 10.1 through 10.4 present the joint estimation results for the expected utility of hedging at risk aversion levels L1 and L3. EUHL1 and EUNL1 were jointly estimated and EUHL3 and EUNL3 were jointly estimated for each of the eight sample period lengths from 1980 to 1987. Tables 10.1 indicates that the significance of the coefficient on PPROD varied greatly over the eight updates to the EUHL1 equation. The coefficient on LGEUH was nonsignificant for the first three updates to the 1975-1980 coefficients but was significant for the remaining updates. This pattern of significance was similar to the November basis equation discussed in Table 8.4 in Chapter 8. The sign of the coefficient on PPROD was wrong for one sample period length but the coefficient was also insignificant. The R^2s were low for many of the years but recall that there were no seasonal dummy variables to help

Table 10.1. The Joint Estimation Results for the Expected Utility of Hedging in the Spring for Risk Aversion L1

Sample Period	Intercept	Coefficients and Variables[a]		DW	System R^2
1975-80	0.09886	-0.0003388 * PPROD	-0.2274 * LGEUH	1.868	0.78
		(0.04)	(0.50)		
1975-81	0.08726	-0.0003423 * PPROD	-0.2917 * LGEUH	2.060	0.81
		(0.01)	(0.20)		
1975-82	-0.004546	-0.0002630 * PPROD	-0.2575 * LGEUH	1.215	0.50
		(0.13)	(0.54)		
1975-83	-0.06756	-0.00002397 * PPROD	0.63086 * LGEUH	1.133	0.26
		(0.88)	(0.15)		
1975-84	-0.06410	-2.01142E-07 * PPROD	0.7379 * LGEUH	1.190	0.34
		(0.99)	(0.05)		
1975-85	-0.05396	0.000001938 * PPROD	0.7676 * LGEUH	1.206	0.41
		(0.99)	(0.02)		
1975-86	-0.007571	-0.00005712 * PPROD	0.60925 * LGEUH	1.124	0.33
		(0.68)	(0.03)		
1975-87	-0.003222	-0.00005824 * PPROD	0.6116 * LGEUH	1.209	0.34
		(0.66)	(0.02)		

[a]Probability of a t-value greater than the calculated t in parentheses.

Table 10.2. The Joint Estimation Results for the Expected Utility of Not Hedging in the Spring for Risk Aversion L1

Sample Period	Intercept	Coefficients and Variables[a]	DW
1975-80	3.0099	0.05823 * MAYEXP (0.03)	1.332
1975-81	2.9323	0.05706 * MAYEXP (0.01)	2.137
1975-82	3.5641	0.04132 * MAYEXP (0.03)	1.411
1975-83	4.6730	0.02702 * MAYEXP (0.25)	2.211
1975-84	4.6473	0.02721 * MAYEXP (0.21)	2.574
1975-85	4.4142	0.03040 * MAYEXP (0.11)	2.557
1975-86	4.3564	0.02936 * MAYEXP (0.14)	2.266
1975-87	4.2824	0.03034 * MAYEXP (0.09)	2.357

[a]Probability of a t-value greater than the calculated t in parentheses.

Table 10.3. The Joint Estimation Results for the Expected Utility of Hedging in the Spring for Risk Aversion L3

Sample Period	Intercept	Coefficients and Variables[a]		DW	System R^2
1975-80	0.1156	-0.0003633 * PPROD (0.03)	-0.2473 * LGEUH (0.46)	1.843	0.78
1975-81	0.1091	-0.0003639 * PPROD (0.01)	-0.28808 * LGEUH (0.22)	2.027	0.81
1975-82	0.0128	-0.0002808 * PPROD (0.12)	-0.25139 * LGEUH (0.55)	1.249	0.49
1975-83	-0.0365	-0.00005080 * PPROD (0.76)	0.6178 * LGEUH (0.15)	1.137	0.27
1975-84	-0.0259	-0.00002756 * PPROD (0.86)	0.7374 * LGEUH (0.05)	1.191	0.34
1975-85	-0.01299	-0.00002591 * PPROD (0.86)	0.7709 * LGEUH (0.02)	1.210	0.41
1975-86	0.02848	-0.00007938 * PPROD (0.58)	0.6284 * LGEUH (0.03)	1.144	0.34
1975-87	0.03143	-0.00008028 * PPROD (0.55)	0.6296 * LGEUH (0.02)	1.207	0.36

[a]Probability of a t-value greater than the calculated t in parentheses.

Table 10.4. The Joint Estimation Results for the Expected Utility of Not Hedging in the Spring for Risk Aversion L3

Sample Period	Intercept	Coefficients and Variables[a]	DW
1975-80	2.9116	0.05780 * MAYEXP	1.312
		(0.03)	
1975-81	2.8110	0.05732 * MAYEXP	2.074
		(0.01)	
1975-82	3.4811	0.04104 * MAYEXP	1.442
		(0.03)	
1975-83	4.5759	0.02650 * MAYEXP	2.261
		(0.23)	
1975-84	4.5865	0.02627 * MAYEXP	2.545
		(0.20)	
1975-85	4.3826	0.02902 * MAYEXP	2.532
		(0.10)	
1975-86	4.3056	0.02846 * MAYEXP	2.256
		(0.13)	
1975-87	4.2282	0.02951 * MAYEXP	2.342
		(0.08)	

[a]Probability of a t-value greater than the calculated t in parentheses.

explain the total variation. Table 10.2 indicates that the coefficient on MAYEXP was significant for the short sample period lengths and for the longest sample period. This was similar to the significance seen in the November cash price equation in Table 8.3 in Chapter 8.

The results in Table 10.3 are similar to the results presented in Table 10.1 but the coefficient on PPROD was nonsignificant in more years than in Table 10.1. The coefficients in Table 10.3 were all quite close to the coefficients in Table 10.1. This means that even though the results in Table 10.3 reflect a risk aversion level that is 10 times the risk aversion level reflected in Table 10.1, the difference in forecasting will not be great. Similarly for Table 10.4. The coefficients are all quite close to the coefficients in Table 10.2 even though there is a 10 fold difference in risk aversion represented in the two tables.

Expected Utility Equations for the Fall

This section reviews the OLS estimation and the joint estimation for the expected utilities for the two marketing alternatives for the fall. Again, EUHL1 and EUHL3 represent the expected utilities of hedging for the risk aversion levels L1 and L3, respectively. EUNL1 and EUNL3 represent the expected utilities of not hedging for the two risk aversions.

Expected utility of hedging in the fall

For the 1974-1979 sample period, the two stock variables SU4 and SC4 entered the EUHL1 and EUHL3 equations with the correct sign though neither was significant. Both of these stock variables reflect soybean stocks and corn stocks. The coefficients on PROD, PROUT, and OCTEXP had the correct signs and PROD was significant at the 5 percent level.

For the 1974-1986 sample period, none of the stock variables entered with the correct sign in the EUHL1 and EUHL3 equations. The signs of the coefficients on PROD, PROUT, and OCTEXP were correct but this time the coefficient on PROUT was significant. An OLS estimation where both OCTEXP and the October futures price (OCTFUT) were included as regressors revealed that both coefficients were significant in the longer sample period while only the coefficient on OCTEXP was significant in the short sample period. There was no significant first order autocorrelation in any of the equations for either sample period. The model with PROUT was selected as the best model to be used in the joint estimation for both EUHL1 and EUHL3.

Expected utility of not hedging in the fall

The notation EUNL1 and EUNL3 are used for the fall also. For the short sample period, the coefficients on SU4 and SC3 had the correct signs but were nonsignificant at the 10 percent level. The coefficient on OCTEXP was positive and significant at the 5 percent level. Coefficients on the other variables had the wrong signs. The OLS results for EUNL1 and EUNL3 for the longer sample period revealed that three of the four stock variables had coefficients that were of the correct sign though none were significant. The coefficient on the production variable PROUT had the correct sign though it was not significant. The coefficient on OCTEXP for both the EUNL1 and EUNL3 models was positive and nonsignificant. For the EUNL1 and EUNL3 equations, OCTEXP and OCTFUT were selected as regressors for the joint estimation in the fall.

Joint estimation of the expected utilities for the fall

Tables 10.5 through 10.8 present the estimation results for the joint estimation of EUHL1 and EUNL1 and the estimation results for the joint estimation of EUHL3 and EUNL3. Table 10.5 indicates that the coefficient on PROUT was significant for nearly every sample period. The coefficient remained negative throughout the updates though the R^2 varied considerably. Table 10.6 finds the significance of the coefficient on OCTEXP the highest for the short sample periods and the longer sample periods and lowest for the middle sample period lengths. This was similar to the pattern significance seen in the cash price equation in Table 9.3 of Chapter 9.

The results in Table 10.7 were very close to the results in Table 10.5 in terms of the significance of the coefficients. The coefficients in Table 10.7 were consistently less than the coefficients in Table 10.5 in absolute value though not by much. The results in Table 10.8 were very close to the results in Table 10.6 in terms of the pattern of significance in the coefficients and the size of the coefficients. There was not a great deal of difference between the size of the coefficients on OCTEXP between the two tables but there was a difference in coefficients on OCTFUT between the two tables.

Table 10.5. The Joint Estimation Results for the Expected Utility of Hedging in the Fall for Risk Aversion L1

Sample Period	Intercept	Coefficients and Variables[a]	DW	System R^2
1974-79	0.1939	-0.4736 * PROUT (0.16)	1.338	0.72
1974-80	0.2715	-0.5372 * PROUT (0.06)	2.382	0.72
1974-81	0.2627	-0.5078 * PROUT (0.09)	1.805	0.33
1974-82	0.2579	-0.4917 * PROUT (0.08)	1.628	0.29
1974-83	0.3234	-0.5491 * PROUT (0.03)	1.657	0.37
1974-84	0.3323	-0.5505 * PROUT (0.02)	1.583	0.40
1974-85	0.3048	-0.5177 * PROUT (0.02)	1.465	0.44
1974-86	0.2829	-0.4951 * PROUT (0.02)	1.459	0.41

[a]Probability of a t-value greater than the calculated t in parentheses.

Table 10.6. The Joint Estimation Results for the Expected Utility of Not Hedging in the Fall for Risk Aversion L1

Sample Period	Intercept	Coefficients and Variables[a]		DW
1974-79	4.8044	0.02946 * OCTEXP (0.05)	-0.05144 * OCTFUT (0.76)	2.993
1974-80	2.7152	0.03619 * OCTEXP (0.03)	0.1966 * OCTFUT (0.24)	2.793
1974-81	5.3228	0.01643 * OCTEXP (0.25)	0.0003598 * OCTFUT (0.99)	2.367
1974-82	5.1734	0.01454 * OCTEXP (0.26)	0.03053 * OCTFUT (0.88)	2.019
1974-83	4.8921	0.0149 * OCTEXP (0.23)	0.0711 * OCTFUT (0.69)	2.193
1974-84	4.4854	0.01787 * OCTEXP (0.09)	0.09283 * OCTFUT (0.56)	2.297
1974-85	3.6966	0.02098 * OCTEXP (0.04)	0.1636 * OCTFUT (0.27)	2.002
1974-86	3.1846	0.01870 * OCTEXP (0.07)	0.2490 * OCTFUT (0.10)	1.605

[a]Probability of a t-value greater than the calculated t in parentheses.

Table 10.7. The Joint Estimation Results for the Expected Utility of Hedging in the Fall for Risk Aversion L3

Sample Period	Intercept	Coefficients and Variables[a]	DW	System R^2
1974-79	0.03708	-0.3690 * PROUT (0.25)	1.458	0.62
1974-80	0.1470	-0.4549 * PROUT (0.09)	2.626	0.69
1974-81	0.1764	-0.4575 * PROUT (0.15)	1.799	0.29
1974-82	0.1834	-0.4496 * PROUT (0.15)	1.564	0.24
1974-83	0.2707	-0.5255 * PROUT (0.05)	1.629	0.32
1974-84	0.2806	-0.5256 * PROUT (0.05)	1.524	0.34
1974-85	0.2418	-0.4816 * PROUT (0.04)	1.385	0.37
1974-86	0.2401	-0.4775 * PROUT (0.04)	1.381	0.36

[a]Probability of a t-value greater than the calculated t in parentheses.

Table 10.8. The Joint Estimation Results for the Expected Utility of Not Hedging in the Fall for Risk Aversion L3

Sample Period	Intercept	Coefficients and Variables[a]		DW
1974-79	4.4366	0.0287 * OCTEXP (0.09)	-0.03906 * OCTFUT (0.86)	2.706
1974-80	2.2517	0.03719 * OCTEXP (0.04)	0.2088 * OCTFUT (0.28)	2.963
1974-81	4.6573	0.01653 * OCTEXP (0.26)	0.05379 * OCTFUT (0.81)	2.882
1974-82	4.5024	0.01496 * OCTEXP (0.26)	0.08377 * OCTFUT (0.68)	2.586
1974-83	4.2633	0.0150 * OCTEXP (0.23)	0.1215 * OCTFUT (0.50)	2.653
1974-84	4.0396	0.01665 * OCTEXP (0.11)	0.1343 * OCTFUT (0.40)	2.745
1974-85	3.4134	0.01926 * OCTEXP (0.05)	0.1899 * OCTFUT (0.19)	2.568
1974-86	3.0551	0.01755 * OCTEXP (0.07)	0.2502 * OCTFUT (0.08)	2.191

[a]Probability of a t-value greater than the calculated t in parentheses.

CHAPTER 11. SPRING AND FALL FORECASTS

Chapter 8 presented the estimation results for the spring forecasting equations and Chapter 9 presented the estimation results for the fall forecasting equations. Chapter 10 presented the estimation results for the direct expected utility equations for the spring and fall. This chapter will use the estimated equations to forecast the variables needed in the simulations. The actual simulations will follow beginning in Chapter 12.

For all of the forecasts, the models estimated with data up to and including year t will be used to forecast the endogenous variables in year t+1. Recall that this study uses data from late 1974 through 1987. Spring forecasts will be made over the period 1975 through 1987 but forecasts from 1975 through 1980 are within-sample forecasts. The forecasts from 1981 through 1987 are post-sample period forecasts since they are one-step-ahead forecasts from models that are updated annually. Fall forecasts will be made over the period 1974 through 1986 but forecasts from 1974-1979 are the within-sample period forecasts. For the fall, the post-sample period forecasts are 1980-1986.

Spring Forecasts by the Typical Approach

For the typical forecasting approach, the forecasts of price, basis, and the momentary variances of price and basis are made separately and then combined linearly to forecast the expected utility of a marketing alternative. Therefore, in the notation of this chapter, the forecast of EUHL1 (which lacks only the current futures price of the expected utility seen in equation 4.7) by the typical approach is simply

$$EUHL1 = - NSB + (-0.0001) (5000) VNSB$$

and the forecast of EUNL1 by the typical approach is simply

$$EUNL1 = SE + (-0.0001) (5000) VSE$$

where SE, NSB, VSE, and VNSB are all forecasts by the typical approach and it is assumed that 5,000 bushels of soybeans are to be marketed. EUHL1 is the expected utility of hedging for risk aversion level L1. Similarly, EUNL1 is the expected utility of not hedging for risk aversion level L1.

The spring forecast of the cash price uses the coefficients from Table 8.3 of Chapter 8. The only exogenous variable in that model was May exports (MAYEXP). Table 11.1 presents the spring forecasts from the four equation model for each year along with the actual cash price in November. The best forecast of the cash price from the two equation model comes from the equations in Table 8.7 from Chapter 8. The forecast of the residual is zero. Table 11.1 also presents the spring forecast of the cash price from the two equation model for each year. The variance of the forecasted mean price, VFMP, is also derived from the two equation model. The Statistical Methods Chapter described how this variance is calculated from a set of seemingly unrelated regression equations.

The basis forecasts are straight forward. The model selected in Chapter 8 (see Tables 8.4 and 8.8) specified the basis equation with the true lagged basis. The Durbin test indicated that there was no significant first order autocorrelation at the 5 percent level in that

Table 11.1. Actual and Spring Forecasts of Cash Price and the Variance of the Forecasted Mean Price for November for the Within-and Post-Sample Periods

Year	Actual Cash Price	Four-Equation Forecast of SE	Two-Equation Model Forecast of SE	Two-Equation Model VFMP[a]
		(in dollars per bushel)		
Within-Sample Forecasts				
1975	4.547	4.494	4.482	1.3543
1976	6.29	5.908	5.905	1.0816
1977	5.642	6.232	6.232	1.0721
1978	6.374	7.634	7.644	1.2587
1979	6.022	5.751	5.747	1.0933
1980	8.48	7.337	7.344	1.1882
Post-Sample Forecasts				
1981	6.054	7.074	7.079	1.1397
1982	5.451	7.939	8.120	1.2252
1983	8.157	6.001	5.993	1.3058
1984	6.07	6.210	6.223	1.4432
1985	5.021	5.497	5.559	1.6181
1986	4.74	6.164	6.167	1.2438
1987	5.226	5.380	5.469	1.4030

[a]Variance of the forecasted mean price.

equation. Therefore, the forecasts of the basis using this equation do not need to be adjusted. The forecasts from both the four and the two equation models for the within sample period and the post sample period are presented in Table 11.2. The actual basis (NSB) is also presented in this table. The two equation model also yields the variance of the forecasted mean basis that is used as a measure of the riskiness of the basis. The variance of the forecasted mean basis, VFMB, for each of the years in the sample period is presented in Table 11.2 also.

The forecasts of the log of momentary variance of the November cash price are made with coefficients from Table 8.5 in Chapter 8. The logarithm of the momentary variance must be transformed back into the correct variance measure (VSE). The forecasts of the momentary variance of November cash price for the within- and the post-sample period are presented in Table 11.3 along with the actual momentary variance of the November cash price for each year. The forecasts of the momentary variance of the November basis are also from the four equation model. The coefficients used in this forecast are presented in Table 8.6 of Chapter 8. The momentary variance was transformed by the logarithm for the estimation stage so the forecasts must be transformed to find the correct variance measure (VNSB). The forecasts for the within- and the post-sample periods are presented in Table 11.3 along with the actual momentary variance of November basis. It is interesting to note the difference in the magnitudes between the variance of the forecasted mean price (VFMP) from Table 11.1 and the momentary variance of cash price in Table 11.3. There is also a large difference between the variance of

Table 11.2. Actual and Spring Forecasts of Basis and the Variance of the Forecasted Mean Basis for November for the Within- and Post-Sample Periods

Year	Actual Basis	Four-Equation Forecast of NSB	Two-Equation Model: Forecast of NSB	Two-Equation Model: VFMB[a]
Within Sample Forecasts		(in dollars per bushel)		
1975	0.278	0.282	0.279	0.084157
1976	0.304	0.257	0.251	0.084057
1977	0.268	0.327	0.325	0.083204
1978	0.329	0.425	0.425	0.083930
1979	0.549	0.494	0.498	0.084333
1980	0.542	0.485	0.492	0.085375
Post-Sample Forecasts				
1981	0.386	0.439	0.444	0.085120
1982	0.151	0.441	0.445	0.078841
1983	0.146	0.402	0.481	0.156231
1984	0.110	0.198	0.196	0.149081
1985	0.096	0.163	0.677	0.140468
1986	0.257	0.149	0.118	0.131550
1987	0.235	0.261	0.257	0.124588

[a]Variance of the forecasted basis.

Table 11.3. Actual and Spring Forecasts of Momentary Variances of the November Cash Price and the November Basis for the Within- and Post-Sample Periods

Year	Actual VSE	Forecasted VSE	Actual VNSB	Forecasted VNSB
Within-Sample Forecasts				
1975	0.00758	0.00859	0.001731	0.001514
1976	0.01422	0.01818	0.001960	0.002429
1977	0.04047	0.01966	0.002695	0.002553
1978	0.02563	0.02332	0.002094	0.002842
1979	0.04249	0.04041	0.005567	0.004019
1980	0.03198	0.05252	0.004770	0.004741
Post-Sample Forecasts				
1981	0.00267	0.02067	0.006890	0.002635
1982	0.01379	0.04885	0.002872	0.007386
1983	0.07949	0.02875	0.001951	0.004553
1984	0.00443	0.00605	0.000960	0.001943
1985	0.01030	0.00876	0.000815	0.001803
1986	0.00145	0.01470	0.001091	0.002233
1987	0.01841	0.02308	0.003880	0.003393

the forecasted mean basis (VFMB) reported in Table 11.2 and the momentary variance of the basis reported in Table 11.3.

Fall Forecasts by the Typical Approach

In the notation of this chapter, the fall forecast of EUHL1 by the typical approach is simply

$$EUHL1 = - JSB + (-0.0001)\ (5000)\ VJSB$$

and the forecast of EUNL1 by the typical approach is simply

$$EUNL1 = SE + (-0.0001)\ (5000)\ VSE$$

where SE, JSB, VSE, and VJSB are all forecasts by the typical approach and it is assumed that 5,000 bushels of soybeans are to be marketed. EUHL1 is the expected utility of hedging for risk aversion level L1. Similarly, EUNL1 is the expected utility of not hedging for risk aversion level L1.

The forecasts made in the fall are all straight forward since there is no significant autocorrelation. The forecasts of the July cash price are presented first in this section, followed by the presentation of the July basis, and the momentary variances of July cash price and July basis.

The coefficients from the four equation model that are used in the forecast of the July cash price are from Table 9.3 in Chapter 9. The actual July cash price and the forecasted cash price are presented in Table 11.4 for both the within- and post-sample periods. The coefficients of the July cash price equation from the two equation model

Table 11.4. Actual and Fall Forecasts of Cash Price and the Variance of the Forecasted Mean Price for July for the Within- and Post-Sample Periods

Year	Actual Cash Price	Four-Equation Forecast of SE	Two-Equation Model Forecast of SE	Two-Equation Model VFMP[a]
Within-Sample Forecasts		(in dollars per bushel)		
1974	5.271	5.310	5.320	0.5201
1975	6.708	6.474	6.404	0.4573
1976	6.239	6.307	6.275	0.4188
1977	6.441	6.878	6.844	0.4371
1978	7.440	7.007	7.060	0.4435
1979	6.882	7.005	7.079	0.4665
Post-Sample Forecasts				
1980	7.166	6.043	6.133	0.525
1981	6.067	7.894	7.841	0.680
1982	6.215	6.825	6.918	0.8887
1983	6.829	6.548	6.439	0.8196
1984	5.496	5.805	6.004	0.8661
1985	5.067	5.934	6.017	0.7655
1986	5.244	6.331	6.442	0.7683

[a]Variance of the forecasted mean price.

were presented in Table 9.7 of Chapter 9. The forecasts of cash price from the two equation model for the within- and the post-sample periods are presented in Table 11.4 also. The variance of the forecasted mean cash price (VFMP) for July is also derived from the cash price equation of the two equation model. The Statistical Methods Chapter describes the calculation of this variance from a system of seemingly unrelated regression equations. The variance of the forecasted mean of July cash price is presented under the heading VFMP in Table 11.4 for the within- and the post-sample period.

The forecasts of the July basis from the four equation model are made with coefficients from Table 9.4 of Chapter 9. There was no significant autocorrelation in the residuals so the forecasting equation is straight forward. The forecasts of the July basis from the four equation model for the within- and the post-sample period are presented in Table 11.5 along with the actual July bases for those years. The forecasts of the July basis are from the two equation model of Table 9.8 in Chapter 9. These forecasts are also presented in Table 11.5. The variance of the forecasted mean basis is derived from the basis equation of the two equation model. This variance is presented in Table 11.5 under the heading VFMB.

The forecast of the momentary variance of the July cash price uses coefficients from Table 9.5 of Chapter 9. The forecasting equation is straight forward since there was no significant autocorrelation in the residuals. The momentary variance was transformed for the estimation stage so the antilogarithm will need to be used to arrive at the correct

Table 11.5. Actual and Fall Forecasts of Basis and the Variance of the Forecasted Mean Basis for July for the Within- and Post-Sample Periods

Year	Actual Basis	Four-Equation Forecast of JSB	Two-Equation Model	
			Forecast of JSB	VFMB[a]
Within Sample Forecasts		(in dollars per bushel)		
1974	0.194	0.193	0.180	0.1286
1975	0.363	0.384	0.395	0.1270
1976	0.173	0.200	0.188	0.1280
1977	0.232	0.359	0.367	0.1254
1978	0.273	0.301	0.301	0.1239
1979	0.558	0.355	0.362	0.1252
Post-Sample Forecasts				
1980	0.122	0.199	0.186	0.128
1981	0.113	0.288	0.291	0.113
1982	0.148	0.255	0.256	0.124
1983	0.044	0.105	0.101	0.126
1984	0.140	0.220	0.220	0.114
1985	0.234	0.316	0.317	0.112
1986	0.185	0.207	0.207	0.107

[a]Variance of the forecasted mean basis.

variance measure (VSE). The forecasts of the momentary variance of the July cash price are presented in Table 11.6 along with the actual momentary variance of the July cash price for the within- and the post-sample periods.

The coefficients used to forecast the momentary variance of the July basis were presented in Table 9.6 of Chapter 9. Again the antilogarithm needs to be used to transform the forecasts into the correct measure of variance since the logarithm of the momentary variance was used in the estimation stage. The forecasts of the momentary variance of the July basis for the within- and the post-sample periods are presented in Table 11.6 along with the actual momentary variance of the July basis. There is a large difference in magnitude between the variance of the forecasted mean price VFMP reported in Table 11.4 and the momentary variance of price reported in Table 11.6. Likewise, there is a large difference between the variance of the forecasted mean basis reported in Table 11.5 and the momentary variance of basis reported in Table 11.6.

Spring and Fall Forecasts by the Direct Utility Approach

This section reports the spring forecasts from the direct expected utility equations presented in Chapter 10. Two levels of risk aversion were considered, L1 and L3. Recall that the actual expected utility of hedging is the current futures price observed by the producer in the spring plus either EUHL1 or EUHL3, depending on the risk aversion. The actual expected utility of remaining unhedged through the summer equals

Table 11.6. Actual and Fall Forecasts of Momentary Variances of the July Cash Price and the July Basis for the Within-and Post-Sample Periods

Year	Actual VSE	Forecasted VSE	Actual VJSB	Forecasted VJSB
Within-Sample Forecasts				
1974	0.044496	0.061493	0.004875	0.005999
1975	0.073143	0.064843	0.003538	0.008972
1976	0.102722	0.066851	0.021794	0.014330
1977	0.04042	0.068729	0.004277	0.004224
1978	0.039179	0.067833	0.018931	0.005879
1979	0.149165	0.063550	0.003302	0.005248
Post-Sample Forecasts				
1980	0.030003	0.063822	0.001173	0.008138
1981	0.005056	0.066118	0.000707	0.006440
1982	0.044102	0.024020	0.000898	0.004496
1983	0.038452	0.038544	0.003313	0.003551
1984	0.004664	0.040842	0.000479	0.003319
1985	0.00745	0.018024	0.003528	0.003000
1986	0.004575	0.019371	0.003362	0.004137

EUNL1 or EUNL3, depending on the risk aversion. The expected utility of selling in the cash market in the fall is simply equal to the selling price observed by the producer at that time.

Table 11.7 presents the spring-forecasted EUHL1 and EUHL3 along with the actual calculated values of EUHL1 and EUHL3. The forecasting equations used are from Table 10.1 and Table 10.3. Table 11.8 presents the spring-forecasted EUNL1 and EUNL3 along with the actual calculated values of EUNL1 and EUNL3 for the within- and the post-sample periods. These forecasting equations are from Table 10.2 and Table 10.4.

Table 11.9 presents the fall-forecasted EUHL1 and EUHL3 for the within- and the post-sample periods. The equations for these forecasts are from Table 10.5 and Table 10.7 from Chapter 10. Table 11.10 presents the fall-forecasted EUNL1 and EUNL3 for the within- and the post-sample periods. The forecasts are made from the equations in Table 10.6 and Table 10.8. Tables 11.9 and 11.10 also present the actual calculated EUNL1 and EUNL3.

Table 11.7. Actual and Spring Forecasts of Expected Utility of Hedging for Two Levels of Risk Aversion for the Within- and Post-Sample Periods

Year	Actual EUHL1	Forecasted EUHL1	Actual EUHL3	Forecasted EUHL3
Within-Sample Forecasts				
1975	-0.298	-0.300	-0.306	-0.302
1976	-0.325	-0.273	-0.334	-0.280
1977	-0.290	-0.346	-0.302	-0.358
1978	-0.350	-0.447	-0.36	-0.466
1979	-0.571	-0.521	-0.596	-0.545
1980	-0.564	-0.514	-0.586	-0.533
Post-Sample Forecasts				
1981	-0.409	-0.466	-0.440	-0.483
1982	-0.172	-0.467	-0.185	-0.480
1983	-0.167	-0.505	-0.176	-0.523
1984	-0.130	-0.218	-0.135	-0.241
1985	-0.116	-0.161	-0.120	-0.173
1986	-0.277	-0.139	-0.282	-0.155
1987	-0.257	-0.277	-0.274	-0.289

Table 11.8. Actual and Spring Forecasts of Expected Utility of Not Hedging for Two Levels of Risk Aversion for the Within- and Post-Sample Periods

Year	Actual EUNL1	Forecasted EUNL1	Actual EUNL3	Forecasted EUNL3
Within-Sample Forecasts				
1975	4.543	4.471	4.509	4.362
1976	6.28	5.892	6.219	5.773
1977	5.622	6.218	5.440	6.096
1978	6.361	7.628	6.246	7.495
1979	6.001	5.735	5.810	5.617
1980	8.464	7.329	8.320	7.199
Post-Sample Forecasts				
1981	6.053	7.064	6.041	6.936
1982	5.445	8.104	5.383	8.006
1983	8.117	5.981	7.760	5.882
1984	6.067	6.208	6.047	6.081
1985	5.016	5.548	4.970	5.456
1986	4.739	6.154	4.733	6.044
1987	5.216	5.459	5.134	5.374

Table 11.9. Actual and Fall Forecasts of Expected Utility of Hedging for Two Levels of Risk Aversion for the Within- and Post-Sample Periods

Year	Actual EUHL1	Forecasted EUHL1	Actual EUHL3	Forecasted EUHL3
Within-Sample Forecasts				
1974	-0.217	-0.207	-0.238	-0.275
1975	-0.384	-0.417	-0.400	-0.439
1976	-0.204	-0.215	-0.302	-0.282
1977	-0.254	-0.390	-0.273	-0.418
1978	-0.302	-0.326	-0.387	-0.368
1979	-0.580	-0.385	-0.595	-0.414
Post-Sample Forecasts				
1980	-0.142	-0.214	-0.147	-0.280
1981	-0.134	-0.315	-0.137	-0.349
1982	-0.169	-0.279	-0.173	-0.312
1983	-0.065	-0.125	-0.080	-0.167
1984	-0.160	-0.243	-0.163	-0.271
1985	-0.255	-0.339	-0.271	-0.360
1986	-0.207	-0.230	-0.222	-0.255

Table 11.10. Actual and Fall Forecasts of Expected Utility of Not Hedging for Two Levels of Risk Aversion for the Within- and Post-Sample Periods

Year	Actual EUNL1	Forecasted EUNL1	Actual EUNL3	Forecasted EUNL3
Within-Sample Forecasts				
1974	5.249	5.293	5.049	5.011
1975	6.671	6.365	6.342	6.018
1976	6.187	6.238	5.725	5.906
1977	6.421	6.802	6.239	6.445
1978	7.421	7.020	7.244	6.673
1979	6.807	7.040	6.136	6.697
Post-Sample Forecasts				
1980	7.151	6.103	7.016	5.804
1981	6.064	7.813	6.042	7.540
1982	6.193	6.876	5.994	6.529
1983	6.810	6.421	6.637	6.239
1984	5.494	5.969	5.473	5.676
1985	5.063	5.984	5.030	5.698
1986	5.242	6.405	5.221	6.101

CHAPTER 12. RESULTS OF SPRING SIMULATIONS

The Method of Analysis Chapter outlined the marketing decisions to be simulated and also the method by which the simulations will be evaluated. From the simulations, this study examines the closeness of marketing decisions made with two variance measures. If the same decisions are made regardless of the definition of variance used, then the cost of using the irrelevant measure of variance in terms of lost income is zero for this soybean marketing decision.

Two of the compensation rules discussed in the Inconsistency Chapter are used in the simulations in this chapter. One compensation rule specifies that an individual compensates for the lack of the momentary variance by using the variance of the forecasted mean (Peck's variance measure). The second compensation rule specifies that an individual compensates for the lack of the momentary variance by following the expected profit maximizing rule (i.e., any variance in returns is ignored by the individual).

The simulations in this chapter compare the spring decisions that are made as well as the outcomes from those decisions when the right decision rule uses the momentary variance and the wrong rule is one of the two compensation rules. Two levels of production are considered in this chapter in order to see the affect of quantity on the comparisons.

In this study, the simulations do not assume that the individual receives the monthly mean price in the current or decision month. Instead, all of the actual daily mean prices of the cash commodity and the actual daily closing futures prices of the decision month are used. In this way one can calculate the probability that a certain decision is made. For all simulations, the cost of hedging is assumed to be $0.02 per bushel.

Comparisons are made between the right decision rule and another decision rule in order to examine the closeness of these two decision rules. Recall from the Method of Analysis Chapter that one measure of closeness of two decisions is the probability that the two rules yield the same decisions which was defined as the probability Pr1 in that earlier chapter.

The second measure of closeness used in this study is the probability of making a wrong decision whose outcome (the return in November) is either greater than the outcome from the right decision or is only e less than the right outcome. This probability is defined as Pr2. This probability is associated with a given tolerance for reduced income. This tolerance for a lower income was defined as e in the Method of Analysis Chapter. There may be a producer who would consider the lower of two outcomes to be close enough to the higher if the difference was only $0.10 per bushel. For this producer, e would be $0.10 per bushel. An individual with no tolerance for an outcome lower than the right outcome would have an e equal to $0.00. The probability Pr2 reported in the results will be for e equal to $0.00 per bushel but comments will be made for cases in which Pr2 is sensitive to the value of e.

This chapter is divided into two sections. The first section presents the simulation results when the wrong decision rule uses the variance of the forecasted mean price as the measure of riskiness. The results of this simulation are discussed for both production levels, 5,000 and 25,000 bushels. The second section of this chapter presents the simulation results when the wrong decision rule is the expected income maximization rule. In this simulation then, the variances of prices are set equal to zero. Again, the results of this simulation are discussed for both the 5,000 and the 25,000 bushel levels.

Results of Spring Simulations Using Peck's Variance

The soybean marketing decisions in the spring were simulated for the right decision rule, the rule using the momentary variance, and the wrong decision rule, the rule using Peck's variance.

Table 12.1 presents the results of this simulation when the quantity marketed is 5,000 bushels. The results for each of the risk aversion levels are presented where L1 is the level of least risk aversion and L5 is the level of highest risk aversion. For each risk aversion level, the table presents the probability that the wrong decision rule will yield a hedge decision when the right rule yields a hedge. Likewise the probability that both rules yield a no hedge decision is presented. The sum of these two probabilities is Pr1. The probability that the two decision rules will yield different decisions is simply one minus Pr1.

The probability Pr2 presented in Table 12.1 is for e equal to $0.00 which implies no tolerance for an income lower than the right income

Table 12.1. Probability of the Two Rules Yielding the Same Decision and the Probability of Making a Decision Whose Outcome is Close Enough to the Right Outcome for the Spring Decision Using Peck's Variance When Q = 5,000

	Years						
Probability	1981	1982	1983	1984	1985	1986	1987
Risk Aversion L1							
Prob.							
Both Hedge	0.41	0	0.05	1	0.50	0	0.64
Neither Hedges	0	1	0	0	0	1	0
Pr1	0.41	1	0.05	1	0.50	1	0.64
Pr2	0.59	0	0	0	0.50	0	0.25
Risk Aversion L2							
Prob.							
Both Hedge	0.50	0	0.14	1	0.50	0	0.68
Neither Hedges	0	0	0	0	0	0	0
Pr1	0.50	0	0.14	1	0.50	0	0.68
Pr2	0.50	1	0	0	0.50	0.66	0.21

Risk Aversion L3							
Prob.							
Both Hedge	0.68	0	0.27	1	0.65	0	0.82
Neither Hedges	0	0	0	0	0	0	0
Pr1	0.68	0	0.27	1	0.65	0	0.82
Pr2	0.32	1	0	0	0.35	0.66	0.11
Risk Aversion L4							
Prob.							
Both Hedge	1	0	1	1	1	0	1
Neither Hedges	0	0	0	0	0	0	0
Pr1	1	0	1	1	1	0	1
Pr2	0	1	0	0	0	0.66	0
Risk Aversion L5							
Prob.							
Both Hedge	1	0.86	1	1	1	0	1
Neither Hedges	0	0	0	0	0	0	0
Pr1	1	0.86	1	1	1	0	1
Pr2	0	0.14	0	0	0	0.66	0

yielded by the right rule. In some cases in Table 12.1, Pr2 = 1 - Pr1. This indicates that for all combination of prices within the decision month and prices within the future month, the outcome from the wrong decision was greater than or equal to the outcome from the right decision when the two decisions were different. For the other cases, Pr2 < 1 - Pr1 which indicates that for some prices faced in the decision month and the future month, the outcome from the wrong decision rule was indeed less than the outcome from the right rule.

There were several cases in Table 12.1 where the probability of making the correct decision with the wrong rule was equal to 1. There tended to be more agreement between the right and the wrong decision rules for the hedge alternative than for the no hedge alternative. This bias can be explained by the bias (relative to the right rule) that the wrong rule had for hedging. As one can note by comparing the magnitudes of the one variance definition in tables 11.1 and 11.2 with the variance definition in Table 11.3 (see the Spring and Fall Forecasts Chapter), the variances of the forecasted means were considerably greater than the forecasted values of the momentary variances. A higher variance of price at a given level of risk aversion will tend to yield more hedges.

The probability Pr1 differed greatly among some years for a given risk aversion level. In most years, the probability of making the correct decision depended on one's risk preference. In some years, the probability of correctly hedging was substantially higher for the very risk averse while in other years the probability of correctly not hedging was substantially greater for the nearly risk neutral. In only one year was the probability of making the correct decision independent of the risk aversion level.

The probability of making a wrong decision that yielded an income greater than or equal to the income of the right decision also depended on the year. In some years, all wrong decisions yielded an outcome greater than or equal to the right outcome but in other years, the cost of the suboptimal decision was greater than $0.20 per bushel. For all risk aversion levels and years in this simulation, when the wrong rule did not yield the right decision, the error was to hedge when the right rule indicated a no hedge decision.

In only a few cases in Table 12.1 did Pr2 change over the range of e from $0.00 to $0.20 per bushel and all of these cases came in two years: 1986 and 1987. In 1986 for the four highest risk aversion levels, Pr2 equalled 0.81 at e = $0.05, 0.92 at e = $0.10, and 0.99 at e = $0.20. This means that although the probability of making the correct decision was zero in 1986, one still had a 0.81 probability of achieving an acceptable return as long as one's tolerance for a lower income was no greater than about five cents per bushel. Pr2 was also sensitive to the e chosen in 1987, although not as sensitive as in 1986. In 1987 for e = $0.20, Pr2 = 0.36 for risk aversion L1, Pr2 = 0.31 for risk aversion L2, and Pr2 = 0.18 for risk aversion L3.

Although not presented in Table 12.1, there are 13 cases (of 35) where the probability of a specified decision from the right rule is equal to neither 1 nor 0. This means that the decision made depends in part on the particular price one experiences at the time when one transacts business. This provides credence to the notion that one should take into account both the distribution of prices in the future month and the distribution of prices in the decision month. The typical approach in previous studies has been to assume that the individual observes the mean price in the decision month and that this mean price is used to evaluate the marketing alternatives. According to the results in Table 12.1, if one used the mean price for the decision month in order to make decisions for some risk aversion levels one would have overlooked the fact that the actual price one observes on the day the decision is made will influence the decision. Likewise, using the monthly mean price of the future month as the return from a decision will ignore that some combinations of price in the decision month and price in the future month will affect the judgement of whether two outcomes are close enough to one another. This fact has also not been addressed in other hedging studies.

Table 12.2 presents the simulation results for the case where again the right rule uses the momentary variance and the wrong rule uses the variance of the forecasted mean price but this time 25,000 bushels are marketed.

The probability of making the correct decision using the wrong rule is 1 for nearly every year for the three highly risk averse producers. In all cases except two, Pr1 was equal or higher in Table 12.2 than when the quantity marketed equalled 5,000 bushels. In both exceptions, the wrong rule yielded a hedge at the 25,000 bushel level whereas the wrong rule yielded a no hedge at the 5,000 bushel level. The simulation

Table 12.2. Probability of the Two Rules Yielding the Same Decision and the Probability of Making a Decision Whose Outcome is Close Enough to the Right Outcome for the Spring Decision Using Peck's Variance When Q = 25,000

Probability	Years						
	1981	1982	1983	1984	1985	1986	1987
Risk Aversion L1							
Prob.							
Both Hedge	0.50	0	0.14	1	0.50	0	0.68
Neither Hedges	0	0	0	0	0	0	0
Pr1	0.50	0	0.14	1	0.50	0	0.68
Pr2	0.50	1	0	0	0.50	0.66	0.21
Risk Aversion L2							
Prob.							
Both Hedge	0.82	0	0.73	1	0.85	0	1
Neither Hedges	0	0	0	0	0	0	0
Pr1	0.82	0	0.73	1	0.85	0	1
Pr2	0.18	1	0	0	0.15	0.66	0

Risk Aversion L3							
Prob.							
Both Hedge	1	0	1	1	1	0	1
Neither Hedges	0	0	0	0	0	0	0
Pr1	1	0	1	1	1	0	1
Pr2	0	1	0	0	0	0.66	0
Risk Aversion L4							
Prob.							
Both Hedge	1	1	1	1	1	1	1
Neither Hedges	0	0	0	0	0	0	0
Pr1	1	1	1	1	1	1	1
Pr2	0	0	0	0	0	0	0
Risk Aversion L5							
Prob.							
Both Hedge	1	1	1	1	1	1	1
Neither Hedges	0	0	0	0	0	0	0
Pr1	1	1	1	1	1	1	1
Pr2	0	0	0	0	0	0	0

results indicated that the probability of the right rule yielding a hedge was not as sensitive to a change in quantity as the probability of the wrong rule yielding a hedge. This can be explained by the considerable size difference between the momentary variance of a price and the variance of a forecasted mean price.

Results of Spring Simulations Using Income Maximization

Table 12.3 presents the results of the simulation where again the right decision rule uses the momentary variance but now the wrong rule is the expected income maximization rule and therefore variance is equal to zero. These simulations will indicate whether one is safe ignoring the variance altogether in this soybean marketing context. The simulations in this table are again for the 5,000 bushel level.

With the expected income maximization rule, as one would expect, there tends to be a higher probability of making the right decision when one is nearly risk neutral than if one is highly risk averse. This is just opposite the results from Table 12.1. The probability of making the right decision by following the income maximization rule is higher in most cases than this probability in Table 12.1, especially at the low risk aversion levels. For the three highest risk aversion levels in Table 12.3, the probability Pr1 is lower than the analogous Pr1 from Table 12.1 in 12 of 21 cases. The average cost of the suboptimal decision was less when one ignored the variance to make a decision for the three lowest risk aversion levels. Just the opposite was true for the highest two risk levels.

Table 12.3. Probability of the Two Rules Yielding the Same Decision and the Probability of Making a Decision Whose Outcome is Close Enough to the Right Outcome for the Spring Decision Ignoring Variance when Q = 5,000

	Years						
Probability	1981	1982	1983	1984	1985	1986	1987
Risk Aversion L1							
Prob.							
Both Hedge	0.27	0	0	1	0.25	0	0.36
Neither Hedges	0.59	1	0.95	0	0.50	1	0.36
Pr1	0.86	1	0.95	1	0.75	1	0.72
Pr2	0	0	0.05	0	0	0	0.02
Risk Aversion L2							
Prob.							
Both Hedge	0.27	0	0	1	0.25	0	0.36
Neither Hedges	0.50	1	0.86	0	0.50	1	0.32
Pr1	0.77	1	0.86	1	0.75	1	0.68
Pr2	0	0	0.14	0	0	0	0.02

Risk Aversion L3							
Prob.							
Both Hedge	0.27	0	0	1	0.25	0	0.36
Neither Hedges	0.32	1	0.73	0	0.35	1	0.18
Pr1	0.59	1	0.73	1	0.60	1	0.54
Pr2	0	0	0.27	0	0	0	0.06
Risk Aversion L4							
Prob.							
Both Hedge	0.27	0	0	1	0.25	0	0.36
Neither Hedges	0	1	0	0	0	1	0
Pr1	0.27	1	0	1	0.25	1	0.36
Pr2	0	0	1	0	0	0	0.13
Risk Aversion L5							
Prob.							
Both Hedge	0.27	0	0	1	0.25	0	0.36
Neither Hedges	0	0.14	0	0	0	1	0
Pr1	0.27	0.14	0	1	0.25	1	0.36
Pr2	0	0	1	0	0	0	0.13

The probability Pr2 in Table 12.3 is insensitive to the value of e over the range e = \$0.00 to e = \$0.20 for all years but 1987. In 1987 for all five risk aversion levels Pr2 increases with a higher tolerance for a lower income. For risk aversion level L1, Pr2 equalled 0.07 at e = \$0.10 and equalled 0.13 at e = \$0.20. For risk aversion level L2, Pr2 equalled 0.08 at e = \$0.10 and equalled 0.16 at e = \$0.20. For risk aversion level L3, Pr2 equalled 0.14 at e = \$0.10 and Pr2 = 0.26 at e = \$0.20. For the two highest risk aversion levels, Pr2 = 0.27 at e = \$0.10 and Pr2 = 0.42 at e = \$0.20.

There were many times during the simulation period that the income maximization rule yielded a hedge for some prices and a no hedge for other prices within the same decision month. Again, if one worked with only the monthly mean prices in the decision month and in the future month, one would have missed the fact that the distribution of prices within the current month and within the future month can be important in determining the right decision.

The only error that one could have made (given the set of forecasts) for every year but one when following the income maximization rule was to remain unhedged when the right rule said to hedge. In only one year for one risk aversion level could one have been able to hedge when the right rule said to remain unhedged. Over the seven years, the average probability of remaining unhedged when the right rule said to hedge was 0.12 for risk aversion level L1, 0.13 for L2, 0.22 for L3, 0.45 for L4, and 0.57 for L5. From these probabilities, one can propose that when a producer does not have access to a variance forecast, the risk averse producer will hedge less often than he would when he follows the expected income maximization rule. These findings may indicate one reason why farmers tend to hedge less than economists expect given economists' perceptions of farmers' aversion.

Table 12.4 presents the simulation results when the right rule uses the momentary variance and the wrong rule ignores the variance altogether but the quantity marketed is 25,000 bushels. For many years and risk aversion levels, the major effect of the higher quantity marketed was to reduce the probability that using the income maximization rule will yield the correct decision. For the four highest risk aversion levels in Table 12.4 (L2, L3, L4, and L5) there were 20 cases where the probability Pr1 was lower than the analogous probability in Table 12.2 where Peck's variance was compared with the momentary variance. Of these 20 cases, three showed a lower probability while seven showed a higher probability of making a decision whose outcome was acceptable (for e = \$0.00). This indicates that although an individual with one of these four risk averse levels makes more suboptimal decisions when he ignores the variance than he does when he uses Peck's variance, the probability of receiving an unacceptable outcome from the former suboptimal decisions are not higher in general.

The sensitivity of Pr2 to the value of e in the range of \$0.00 to \$0.20 is found only in 1987 again. For the risk aversion level L1, Pr2 = 0.16 at e = \$0.20. For the other four risk aversion levels, Pr2 = 0.42 at e = \$0.20.

The only error that one could make by using the wrong decision rule

Table 12.4. Probability of the Two Rules Yielding the Same Decision and the Probability of Making a Decision Whose Outcome is Close Enough to the Right Outcome for the Spring Decision Ignoring Variance When Q = 25,000

	Years						
Probability	1981	1982	1983	1984	1985	1986	1987
Risk Aversion L1							
Prob.							
Both Hedge	0.27	0	0	1	0.25	0	0.36
Neither Hedges	0.50	1	0.86	0	0.50	1	0.32
Pr1	0.77	1	0.86	1	0.75	1	0.68
Pr2	0	0	0.14	0	0	0	0.02
Risk Aversion L2							
Prob.							
Both Hedge	0.27	0	0	1	0.25	0	0.36
Neither Hedges	0.18	1	0.27	0	0.15	1	0
Pr1	0.45	1	0.27	1	0.40	1	0.36
Pr2	0	0	0.72	0	0	0	0.13

Risk Aversion L3							
Prob.							
Both Hedge	0.27	0	0	1	0.25	0	0.36
Neither Hedges	0	1	0	0	0	1	0
Pr1	0.27	1	0	1	0.25	1	0.36
Pr2	0	0	1	0	0	0	0.13
Risk Aversion L4							
Prob.							
Both Hedge	0.27	0	0	1	0.25	0	0.36
Neither Hedges	0	0	0	0	0	0	0
Pr1	0.27	0	0	1	0.25	0	0.36
Pr2	0	0	1	0	0	0.34	0.13
Risk Aversion L5							
Prob.							
Both Hedge	0.27	0	0	1	0.25	0	0.36
Neither Hedges	0	0	0	0	0	0	0
Pr1	0.27	0	0	1	0.25	0	0.36
Pr2	0	0	1	0	0	0.34	0.13

(given the set of forecasts) for the simulation reported in Table 12.4 is to remain unhedged when the right rule said to hedge. The average probability over the seven years of making this error is higher for the 25,000 bushel quantity of Table 12.4 than for the 5,000 bushel quantity of Table 12.3. The least risk averse producer would have missed the hedge decision an average of 13 percent of the time while the most risk averse producer would have missed the hedge decision an average of 73 percent of the time in the spring.

The simulations presented in this chapter indicated that using Peck's variance of the forecasted mean or using the income maximization rule yielded decisions that are quite close to the decisions of the right rule. Table 12.5 presents the total probability Pr1 + Pr2 for various tolerance levels e when one uses Peck's variance and markets 5,000 bushels. There is nearly a monotonic rise in this probability as the risk aversion increases. Table 12.6 presents the total probability when 25,000 bushels are marketed instead. There is a slightly bigger range of probabilities within Table 12.6 than within Table 12.5.

Table 12.7 presents the total probability when one ignores the variance altogether for the 5,000 bushel level. Table 12.8 presents then the case where 25,000 bushels are marketed. For Tables 12.7 and 12.8, there is a monotonic decrease in the total probability as the risk aversion increases which is just opposite the case in Tables 12.5 and 12.6. The cost of using no variance relative of the cost of using Peck's variance increases with the degree of risk aversion.

Table 12.5. The Average (Pr1 + Pr2) Over the Seven Years for the Spring When Using Peck's Variance and Q = 5,000

	Tolerance Level[a]				
Risk Aversion	0	0.05	0.1	0.15	0.2
L1	0.85	0.85	0.86	0.86	0.86
L2	0.81	0.84	0.86	0.87	0.87
L3	0.84	0.86	0.88	0.89	0.89
L4	0.95	0.97	0.99	1.00	1.00
L5	0.95	0.97	0.99	1.00	1.00

[a]Tolerance for a lower income level, e.

Table 12.6. The Average (Pr1 + Pr2) Over the Seven Years for the Spring When Using Peck's Variance and Q = 25,000

	Tolerance Level[a]				
Risk Aversion	0	0.05	0.1	0.15	0.2
L1	0.81	0.84	0.86	0.87	0.87
L2	0.91	0.93	0.95	0.96	0.96
L3	0.95	0.97	1.00	1.00	1.00
L4	1	1	1	1	1
L5	1	1	1	1	1

[a]Tolerance for a lower income level, e.

Table 12.7. The Average (Pr1 + Pr2) Over the Seven Years for the Spring When Ignoring the Variance and Q = 5,000

	Tolerance Level[a]				
Risk Aversion	0	0.05	0.1	0.15	0.2
L1	0.91	0.91	0.92	0.92	0.92
L2	0.89	0.89	0.90	0.90	0.91
L3	0.83	0.83	0.84	0.85	0.86
L4	0.72	0.72	0.74	0.75	0.76
L5	0.59	0.60	0.61	0.62	0.63

[a]Tolerance for a lower income level, e.

Table 12.8. The Average (Pr1 + Pr2) Over the Seven Years for the Spring When Ignoring the Variance and Q = 25,000

	Tolerance Level[a]				
Risk Aversion	0	0.05	0.1	0.15	0.2
L1	0.89	0.89	0.90	0.90	0.91
L2	0.76	0.78	0.78	0.79	0.81
L3	0.72	0.73	0.74	0.75	0.76
L4	0.48	0.54	0.58	0.60	0.62
L5	0.48	0.54	0.58	0.60	0.62

[a]Tolerance for a lower income level, e.

CHAPTER 13. RESULTS OF FALL SIMULATIONS

The results of the fall marketing decision that was outlined in the Method of Analysis Chapter are presented in this chapter. The same two compensation rules used in the simulations in the last chapter are used here. In each of the simulations in this chapter, the right decision rule uses the momentary variance in the mean-variance utility function. The first section of this chapter presents the simulation results of the first wrong rule which uses Peck's variance of the forecasted mean in the mean-variance utility function. The second section of this chapter presents the simulation results of the second wrong rule which ignores the variance altogether.

As with the spring simulations, this study does not assume that the individual receives the mean price in the decision month nor in the future month. Therefore, by using all of the actual daily average cash and daily closing futures prices in the two months, it is possible to calculate the probability of making the correct decision (Pr1) and the probability of making a wrong decision whose outcome is close enough to the outcome of the right decision (Pr2). These probabilities are presented for the case when 5,000 bushels are marketed and 25,000 bushels are marketed.

Results of Fall Simulations Using Peck's Variance

Table 13.1 presents the results of the simulation when 5,000 bushels are marketed in the fall. Results are presented for the five risk aversion levels and the seven years over which forecasts were made.

Table 13.1. Probability of the Two Rules Yielding the Same Decision and the Probability of Making a Decision Whose Outcome is Close Enough to the Right Outcome for the Fall Decision Using Peck's Variance When Q = 5,000

	Years						
Probability	1980	1981	1982	1983	1984	1985	1986
Risk Aversion L1							
Prob.							
Both Hedge	1	0	0	0	0.26	0	0
Neither Hedges	0	1	1	0	0	1	1
Both Sell Now	0	0	0	0.79	0.21	0	0
Pr1	1	1	1	0.79	0.47	1	1
Pr2 @ e = 0.00	0	0	0	0.03	0	0	0
@ e = 0.20	0	0	0	0.21	0.52	0	0
Risk Aversion L2							
Prob.							
Both Hedge	0.83	0	0	0	0	0	0
Neither Hedges	0	0	0	0	0	0	0
Both Sell Now	0	0	0	0.89	0.26	0	0
Pr1	0.83	0	0	0.89	0.26	0	0
Pr2 @ e = 0.00	0	1	0	0.01	0	0.62	0
@ e = 0.20	0	1	0.10	0.11	0.64	0.94	0.04

Risk Aversion L3							
Prob.							
Both Hedge	0	0	0	0	0	0	0
Neither Hedges	0	0	0	0	0	0	0
Both Sell Now	0	0	0	0.89	0.42	0	0
Pr1	0	0	0	0.89	0.42	0	0
Pr2 @ e = 0.00	0	1	0	0.01	0	0.62	0
@ e = 0.20	0	1	0.10	0.11	0.48	0.94	0.04
Risk Aversion L4							
Prob.							
Both Hedge	0	0	0	0	0	0	0
Neither Hedges	0	0	0	0	0	0	0
Both Sell Now	0	0.11	0	1	0.84	0	0
Pr1	0	0.11	0	1	0.84	0	0
Pr2 @ e = 0.00	0	0	0	0	0	0.62	0
@ e = 0.20	0	0	0.10	0	0.08	0.94	0.04
Risk Aversion L5							
Prob.							
Both Hedge	0	0	0	0	0	0	0
Neither Hedges	0	0	0	0	0	0	0
Both Sell Now	0.50	0.61	0.89	1	1	0.61	0
Pr1	0.50	0.61	0.89	1	1	0.61	0
Pr2 @ e = 0.00	0	0	0	0	0	0.06	0
@ e = 0.20	0	0	0	0	0	0.33	0.04

Table 13.1 presents the probability of making the correct decision with the wrong rule (Pr1) as the sum of three probabilities: the probability of correctly hedging, the probability of correctly not hedging, and the probability of correctly selling in the cash market in the fall. The probability of making an incorrect decision is simply one minus Pr1.

The results of this table indicate that there was very little agreement on hedged storage or on unhedged storage through the winter. What agreement there was came in the lowest two risk aversion levels where there was considerable agreement on the unhedged storage alternative. Throughout the seven years, Peck's rule yielded a nonzero probability of hedged storage in only three cases and all three were for the two lowest levels of risk aversion. There were only four cases when Peck's rule yielded a nonzero probability of unhedged storage and all four of these cases were for the lowest level of risk aversion. Peck's rule tended to select the most conservative of the three marketing alternatives with the greatest frequency, that is to sell in the cash market in the fall. For the three highest levels of risk aversion, Peck's rule yielded the cash sales alternative 100 percent of the time for each of the seven years. The right decision rule was not biased to any one particular marketing alternative.

Peck's decision rule selected the correct decision with high probability for the lowest level of risk aversion. Interestingly, Peck's rule also did well for the highest risk averse producer. Peck's rule performed poorly for the middle levels of risk aversion. The right rule and Peck's rule both chose the most conservative marketing alternative (i.e., sales in the cash market in the fall) for the most risk averse case examined. For the middle levels of risk aversion, Peck's rule was biased in favor of the current cash sales alternative relative to the right rule.

The probability of making a wrong decision whose outcome is close enough to the outcome of the right decision, Pr2, is surprisingly low for all risk aversion levels. In only five cases in Table 13.1 was there even a reasonably high probability of making an acceptable outcome from a wrong decision when e = \$0.00. What is more, all of these cases were for the middle levels of risk aversion where the probability of making a correct decision is rather low. If a producer had a greater tolerance for an outcome that was below the right outcome, such as e = \$0.20, the probability Pr2 was considerably higher in some cases as can be seen from Table 13.1.

From the results of these simulations, the average probability over the seven years that the wrong rule led to sell in the fall when the right rule yielded hedged storage was 0.11 for L1, 0.15 for L2, 0.24 for L3, 0.29 for L4, and 0.13 for L5. These probabilities indicate that using the wrong variance measure may explain some of the lack of use of the futures markets by farmers.

Table 13.2 presents the simulation results for a producer who uses Peck's variance but who markets 25,000 bushels. Peck's rule again selected the cash sales alternative with high frequency, especially for the highly risk-averse producers. There was considerable agreement between the two decision rules for the highly risk averse but for many

Table 13.2. Probability of the Two Rules Yielding the Same Decision and the Probability of Making a Decision Whose Outcome is Close Enough to the Right Outcome for the Fall Decision Using Peck's Variance When Q = 25,000

	Years						
Probability	1980	1981	1982	1983	1984	1985	1986
Risk Aversion L1							
Prob.							
Both Hedge	0.83	0	0	0	0	0	0
Neither Hedges	0	0	0	0	0	0	0
Both Sell Now	0	0	0	0.89	0.26	0	0
Pr1	0.83	0	0	0.89	0.26	0	0
Pr2 @ e = 0.00	0	1	0	0.01	0	0.62	0
@ e = 0.20	0	1	0.10	0.11	0.64	0.94	0.04
Risk Aversion L2							
Prob.							
Both Hedge	0	0	0	0	0	0	0
Neither Hedges	0	0	0	0	0	0	0
Both Sell Now	0	0	0	1	0.58	0	0
Pr1	0	0	0	1	0.58	0	0
Pr2 @ e = 0.00	0	1	0	0	0	0.62	0
@ e = 0.20	0	1	0.10	0	0.33	0.94	0.01

Risk Aversion L3							
Prob.							
Both Hedge	0	0	0	0	0	0	0
Neither Hedges	0	0	0	0	0	0	0
Both Sell Now	0	0.11	0	1	0.84	0	0
Pr1	0	0.11	0	1	0.84	0	0
Pr2 @ e = 0.00	0	0	0	0	0	0.62	0
@ e = 0.20	0	0	0.10	0	0.08	0.94	0.04
Risk Aversion L4							
Prob.							
Both Hedge	0	0	0	0	0	0	0
Neither Hedges	0	0	0	0	0	0	0
Both Sell Now	1	1	1	1	1	1	1
Pr1	1	1	1	1	1	1	1
Pr2	0	0	0	0	0	0	0
Risk Aversion L5							
Prob.							
Both Hedge	0	0	0	0	0	0	0
Neither Hedges	0	0	0	0	0	0	0
Both Sell Now	1	1	1	1	1	1	1
Pr1	1	1	1	1	1	1	1
Pr2	0	0	0	0	0	0	0

cases in the low risk aversion levels, the probability Pr1 was very low. For the lowest risk aversion level in Table 13.2, all but one of the years had a lower Pr1 than the comparable Pr1 in Table 13.1.

In only a few cases in Table 13.2 was the probability Pr2 lower than the comparable probability in Table 13.2. The Pr2 are surprisingly low in Table 13.2 but some of the Pr2 are substantially higher for a producer willing to accept a higher e.

These simulations indicate that the average probability that the wrong rule says to sell in the cash market in the fall when the right decision rule yielded hedged storage was 0.15 for L1, 0.20 for L2, 0.29 for L3, and zero for L4 and L5.

Results of Fall Simulations Using Income Maximization

The simulations here presume that a producer does not have access to a variance forecast or that a producer does not use Peck's variance measure as a measure of riskiness and the producer in fact behaves as an expected profit maximizer. Table 13.3 indicates that the probability of making the correct decision using the income maximization rule is rather high for all risk aversion levels. The highest risk aversion level found the least agreement between the two decision rules. There were only a handful of cases in Table 13.3 where Pr1 was lower than the comparable Pr1 of Table 13.1 and these were by and large found in the highest risk aversion levels.

Since the probability of making the right decision was so high for so many years, the probability of making a wrong decision whose outcome

Table 13.3. Probability of the Two Rules Yielding the Same Decision and the Probability of Making a Decision Whose Outcome is Close Enough to the Right Outcome for the Fall Decision Ignoring Variance When Q = 5,000

	Years						
Probability	1980	1981	1982	1983	1984	1985	1986
Risk Aversion L1							
Prob.							
Both Hedge	1	0	0	0.21	0.79	0	0
Neither Hedges	0	1	1	0	0	1	1
Both Sell Now	0	0	0	0.74	0.16	0	0
Pr1	1	1	1	0.95	0.95	1	1
Pr2	0	0	0	0.03	0.05	0	0
Risk Aversion L2							
Prob.							
Both Hedge	1	0	0	0.10	0.74	0	0
Neither Hedges	0	1	1	0	0	1	1
Both Sell Now	0	0	0	0.74	0.16	0	0
Pr1	1	1	1	0.84	0.90	1	1
Pr2	0	0	0	0.12	0.10	0	0

Risk Aversion L3							
Prob.							
Both Hedge	1	0	0	0.10	0.58	0	0
Neither Hedges	0	1	1	0	0	1	1
Both Sell Now	0	0	0	0.74	0.16	0	0
Pr1	1	1	1	0.84	0.74	1	1
Pr2	0	0	0	0.12	0.26	0	0
Risk Aversion L4							
Prob.							
Both Hedge	1	0	0	0	0.16	0	0
Neither Hedges	0	0	1	0	0	1	1
Both Sell Now	0	0	0	0.74	0.16	0	0
Pr1	1	0	1	0.74	0.32	1	1
Pr2	0	0	0	0.21	0.68	0	0
Risk Aversion L5							
Prob.							
Both Hedge	0.50	0	0	0	0	0	0
Neither Hedges	0	0	0.11	0	0	0.39	1
Both Sell Now	0	0	0	0.74	0.16	0	0
Pr1	0.50	0	0.11	0.74	0.16	0.39	1
Pr2	0.50	0	0.89	0.21	0.84	0.04	0

is acceptable will be low. In many cases in Table 13.3 the Pr2 are very close to 1 - Pr1.

According to these simulation results, the average probability of the wrong rule selecting unhedged storage when the right rule yielded hedged storage was zero for all risk aversion levels except the two highest where this probability was less than 0.13.

Table 13.4 presents the same simulation but marketing 25,000 bushels. For the highly risk averse, Pr1 is considerably lower than the comparable Pr1 of Table 13.2. Whereas in Table 13.2, Pr1 was nearly always equal to one for the highly risk averse, in Table 13.4, Pr1 is rarely equal to one for those risk aversions and is often equal to zero. There was considerable agreement between the two decision rules for the low levels of risk aversion in Table 13.4.

The probability of making a wrong decision whose outcome is acceptable was quite high. In fact, there were only three cases in Table 13.4 where, when there was a nonzero probability of making an error, Pr2 was zero. This indicates that when one made a wrong decision while following the income maximization rule, that error was not costly in terms of lost return.

The average probability of the wrong rule selecting unhedged storage when the right rule yielded hedged storage was zero for all risk aversion levels except for L3 where the probability was 0.13.

Table 13.5 presents the total probability of making the correct decision using Peck's variance or at least a decision whose outcome is close enough to the right outcome which is simply Pr1 + Pr2. This total

Table 13.4. Probability of the Two Rules Yielding the Same Decision and the Probability of Making a Decision Whose Outcome is Close Enough to the Right Outcome for the Fall Decision Ignoring Variance When Q = 25,000

	Years						
Probability	1980	1981	1982	1983	1984	1985	1986
Risk Aversion L1							
Prob.							
Both Hedge	1	0	0	0.10	0.74	0	0
Neither Hedges	0	1	1	0	0	1	1
Both Sell Now	0	0	0	0.74	0.16	0	0
Pr1	1	1	1	0.84	0.90	1	1
Pr2	0	0	0	0.12	0.10	0	0
Risk Aversion L2							
Prob.							
Both Hedge	1	0	0	0	0.42	0	0
Neither Hedges	0	1	1	0	0	1	1
Both Sell Now	0	0	0	0.74	0.16	0	0
Pr1	1	1	1	0.74	0.58	1	1
Pr2	0	0	0	0.21	0.42	0	0

Risk Aversion L3							
Prob.							
Both Hedge	1	0	0	0	0.16	0	0
Neither Hedges	0	0	1	0	0	1	1
Both Sell Now	0	0	0	0.74	0.16	0	0
Pr1	1	0	1	0.74	0.32	1	1
Pr2	0	0	0	0.21	0.68	0	0
Risk Aversion L4							
Prob.							
Both Hedge	0	0	0	0	0	0	0
Neither Hedges	0	0	0	0	0	0	0
Both Sell Now	0	0	0	0.74	0.16	0	0
Pr1	0	0	0	0.74	0.16	0	0
Pr2	1	0	1	0.21	0.84	0.38	1
Risk Aversion L5							
Prob.							
Both Hedge	0	0	0	0	0	0	0
Neither Hedges	0	0	0	0	0	0	0
Both Sell Now	0	0	0	0.74	0.16	0	0
Pr1	0	0	0	0.74	0.16	0	0
Pr2	1	0	1	0.21	0.84	0.38	1

Table 13.5. The Average (Pr1 + Pr2) Over the Seven Years for the Fall When Using Peck's Variance and Q = 5,000

	Tolerance Level[a]				
Risk Aversion	0	0.05	0.1	0.15	0.2
L1	0.89	0.91	0.93	0.99	1.00
L2	0.52	0.54	0.56	0.64	0.69
L3	0.42	0.44	0.46	0.52	0.57
L4	0.37	0.38	0.39	0.41	0.44
L5	0.67	0.68	0.68	0.70	0.71

[a]Tolerance for a lower income level, e.

is presented for five levels of e (in dollars per bushel). For the nearly risk neutral, Peck's rule correctly yielded unhedged and hedged storage while for the very risk averse, Peck's rule correctly yielded the conservative alternative of selling in the fall.

Table 13.6 presents the sum Pr1 + Pr2 using Peck's variance but this time for the higher quantity marketed. Tables 13.5 and 13.6 have similar patterns in that the total probability is higher for the extremes in risk aversion than for the middle risk aversions. There is a greater difference among the probabilities within Table 13.6 than within Table 13.5.

Table 13.6. The Average (Pr1 + Pr2) Over the Seven Years for the Fall When Using Peck's Variance and Q = 25,000

	Tolerance Level[a]				
Risk Aversion	0	0.05	0.1	0.15	0.2
L1	0.52	0.54	0.56	0.64	0.69
L2	0.46	0.47	0.48	0.53	0.57
L3	0.37	0.38	0.39	0.41	0.44
L4	1	1	1	1	1
L5	1	1	1	1	1

[a]Tolerance for a lower income level, e.

Table 13.7 presents the total probability when one ignores the variance entirely at the 5,000 bushel level. This table indicates that for the nearly risk neutral, ignoring the variance yields the correct decision with great frequency. Even for the very risk averse the probability is still quite high.

Table 13.8 presents the total probability when one ignores the variance at the 25,000 bushel level. The probabilities in this table are only slightly less than those probabilities in Table 13.7.

The fall simulation results indicate that one can use either Peck's variance measure or ignore the variance altogether and still make many

Table 13.7. The Average (Pr1 + Pr2) Over the Seven Years for the Fall When Ignoring the Variance and Q = 5,000

	Tolerance Level[a]				
Risk Aversion	0	0.05	0.1	0.15	0.2
L1	1.00	1.00	1	1	1
L2	0.99	1.00	1	1	1
L3	0.99	1.00	1	1	1
L4	0.85	0.86	0.86	0.86	0.86
L5	0.77	0.78	0.79	0.81	0.82

[a]Tolerance for a lower income level, e.

Table 13.8. The Average (Pr1 + Pr2) Over the Seven Years for the Fall When Ignoring the Variance and Q = 25,000

	Tolerance Level[a]				
Risk Aversion	0	0.05	0.1	0.15	0.2
L1	0.99	1.00	1	1	1
L2	0.99	1.00	1	1	1
L3	0.85	0.86	0.86	0.86	0.86
L4	0.76	0.78	0.79	0.81	0.82
L5	0.76	0.78	0.79	0.81	0.82

[a]Tolerance for a lower income level, e.

of the right decisions. Furthermore, when the decision is wrong, the costs in terms of lower income are not great on average. The fall simulation results support the notion that the distribution of prices within the decision month and within the future month are important in identifying the decision made. Finally, the results lend support to the notion that use of the wrong measure of variance (whether Peck's variance or whether one ignores variance altogether) can result in less hedging than economists expect given economists' perception of the risk preference of the producer.

CHAPTER 14. RESULTS OF SIMULATIONS USING DIRECT FORECASTS OF EXPECTED UTILITY

In contrast to the results in Chapters 12 and 13, this chapter presents results of simulations where both decision rules use the momentary variance in the expected utility equation. The difference between the two decision rules in this chapter is the method of forecasting expected utility. Previous studies and Chapters 12 and 13 of this study have forecasted expected utility by first forecasting the prices and variances that enter the expected utility equation. For this chapter, the second decision rule forecasts directly the expected utility of the marketing alternatives. This will provide an interesting contrast to the results of Chapters 12 and 13. The first section in this chapter presents the results of the spring simulation for the post sample period when the second decision rule forecasts expected utility directly. The second section of this chapter presents the fall simulations for the same second rule.

Spring Simulation Results

Table 14.1 presents the simulation results that compare the two forecasting approaches. This table presents Pr1 and Pr2 calculated for two risk aversion levels. The two risk aversion levels presented in this table were selected based on the spring and fall simulation results that were presented in Chapters 12 and 13. In those chapters, the right rule, the rule using the momentary variance as the measure of risk, hedged almost entirely for the very risk averse producers but indicated

Table 14.1. Probability of the Two Approaches Yielding the Same Decision and the Probability of Making a Decision From the Direct Approach Whose Outcome is Close Enough to the Outcome of the Typical approach for the Spring Decision When Q = 5,000

	Years						
Probability	1981	1982	1983	1984	1985	1986	1987
Risk Aversion L1							
Prob.							
Both Hedge	0.32	0	0	1	0.25	0	0.36
Neither Hedges	0.59	1	0.95	0	0.50	1	0.36
Pr1	0.91	1	0.95	1	0.75	1	0.72
Pr2	0	0	0.05	0	0	0	0.02
Risk Aversion L3							
Prob.							
Both Hedge	0.68	0	0.04	1	0.65	0	0.64
Neither Hedges	0.27	1	0.73	0	0.30	1	0.18
Pr1	0.95	1	0.77	1	0.95	1	0.82
Pr2	0.05	0	0.23	0	0.05	0	0.04

that both marketing alternatives were useful for the more risk neutral producers. The two risk aversion levels selected have a difference in magnitude of 10 times.

The results of Table 14.1 indicate that the two forecasting methods yield the same decision with about the same frequency for the two risk aversion levels. In all cases, there was at least 0.72 probability of the two rules yielding the same decision. The probabilities are generally quite high especially when compared with Pr1 in Table 12.1 of Chapter 12. It is interesting to note for the lowest risk aversion level in Table 14.1 that Pr1 was greater in only one of the seven years compared with this risk aversion level in Table 12.3. For the risk aversion level L3, Pr1 in Table 14.1 was greater than or equal to Pr1 in Tables 12.1 and 12.3.

Forecasting expected utility by forecasting the prices and variances separately will yield the same decision as forecasting expected utility directly with high probability. This is due in part to the closeness of the two methods of forecasting and in part to the nature of the payoff function. The results in Table 12.3 in Chapter 12 indicate that one can use a rather crude forecast of expected utility (forecast of expected income alone) and still have a high probability of making the correct decision.

In half the cases in Table 14.1 where there was less than a 100 percent chance of making the same decision, Pr2 was very close to 1 - Pr1. This indicates that the cost of making a different decision, in terms of reduced income, was very low. The simulation results indicated also that, using the direct expected utility method of forecasting, the average probability of remaining unhedged when the typical forecasting method selected a hedge was 0.11 and 0.14 for the two risk aversion levels L1 and L3, respectively. Using direct expected utility forecasts, the average probability of hedging when the typical forecasting method led to a no hedge decision was essentially zero.

Table 14.2 presents the average total probability Pr1 + Pr2 over the seven years. The averages are very high even for an e = $0.00. For both risk aversion levels, it does not appear to matter which of the two forecasting approaches one uses in forecasting expected utility of the two marketing alternatives.

Table 14.2. The Average (Pr1 + Pr2) for the Spring Over the Seven Years for the Two Forecasting Approaches When Q = 5,000

	Tolerance Level[a]				
Risk Aversion	0	0.05	0.1	0.15	0.2
L1	0.91	0.92	0.92	0.92	0.93
L3	0.98	0.98	0.98	0.99	0.99

[a]Tolerance for a lower income level, e.

Fall Simulation Results

Table 14.3 presents the results of the simulations where one decision rule uses the typical forecast of expected utility and the other decision rule uses the direct forecast of expected utility. Again only two risk aversion levels were selected for the simulations reported here.

There was only two years in Table 14.3 where there was not complete agreement in the decisions made for the two forecasting methods. Pr1 was very high even in 1983 and 1984 for both risk aversion levels. The Pr1 in Table 14.3 are equal to or substantially higher than the Pr1 in Table 13.1 of Chapter 13. The Pr1 in Table 14.3 are nearly all equal to the Pr1 in Table 13.3 of Chapter 13. This indicates that in the fall, whether forecasts of expected utility are made by the typical approach, made by the direct expected utility approach, or even made by setting expected utility equal to the expected income, the decisions are all very similar for the fall decision. Peck's forecast of the expected utility using the variance of the forecasted mean price yields different decisions frequently relative to the three other forecasts.

Using the direct forecasting method, the probability of making a different decision whose outcome is within e of the outcome from using the typical forecasting approach is quite low for small values of e. At an e of $0.20 however, the Pr2 equals 1 - Pr1 in two of the three cases in Table 14.3.

Nevertheless, the average total probability of making the same decision as when using the typical forecasting approach is very high for

Table 14.3. Probability of the Two Approaches Yielding the Same Decision and the Probability of Making a Decision From the Direct Approach Whose Outcome is Close Enough to the Outcome of the Typical approach for the Fall Decision When Q = 5,000

	Years						
Probability	1980	1981	1982	1983	1984	1985	1986
Risk Aversion L1							
Prob.							
Both Hedge	1	0	0	0.21	0.74	0	0
Neither Hedges	0	1	1	0	0	1	1
Both Sell Now	0	0	0	0.79	0.21	0	0
Pr1	1	1	1	1	0.95	1	1
Pr2 @ e = 0.00	0	0	0	0	0	0	0
@ e = 0.20	0	0	0	0	0.05	0	0
Risk Aversion L3							
Prob.							
Both Hedge	1	0	0	0	0.42	0	0
Neither Hedges	0	1	1	0	0	1	1
Both Sell Now	0	0	0	0.89	0.42	0	0
Pr1	1	1	1	0.89	0.82	1	1
Pr2 @ e = 0.00	0	0	0	0.01	0	0	0
@ e = 0.20	0	0	0	0.11	0.16	0	0

both risk aversion levels, as seen in Table 14.4. There is essentially no difference in the decisions made by the two forecasting approaches for either risk aversion level even if one's tolerance for a reduced income is very low.

Table 14.4. The Average (Pr1 + Pr2) for the Fall Over the Seven Years for the Two Forecasting Approaches When Q = 5,000

	Tolerance Level[a]				
Risk Aversion	0	0.05	0.1	0.15	0.2
L1	0.99	0.99	0.99	0.99	1
L3	0.96	0.97	0.98	0.99	1

[a]Tolerance for a lower income level, e.

CHAPTER 15. SUMMARY AND CONCLUSIONS

This study examined the affect on marketing decisions of ignoring the variability of price or in measuring the variability incorrectly for risk averse producers. Previous research has acknowledged the importance of considering the riskiness of alternatives but has typically provided only forecasts of price levels for the producers. Some studies have included risk in their work but it is a contention here that the variance used in these studies is not the relevant variance for the decisions described. Peck maintained that the variance of past monthly mean prices was not the relevant variance and instead asserted that the variance of the forecasted mean price was the relevant variance to consider for within-year marketing decisions. In this dissertation, however, it is maintained that neither of the two previous definitions of variance are appropriate for within year marketing decisions when, as is usually the case, the producer can not guarantee transacting business at the mean price in the month. This dissertation proposed that the relevant variance to consider for marketing decisions is the momentary variance.

The momentary variance is calculated from the distribution of momentary prices within the month in question. At each moment of time there is a price observed in a market. When a producer transacts business within the month, he draws a price from the distribution of momentary prices. Typically, the producer can not guarantee receiving the monthly mean price when he sells or when he buys. Therefore the distribution of the momentary prices is the relevant distribution when examining the riskiness of an alternative.

The concept of a momentary variance is applicable to more than just a situation where a producer plans to buy or sell within a particular month. There is also a momentary variance of the distribution of momentary prices within a quarter or even within a week. The relevant distribution depends on the nature of the particular decision but in each case the relevant variance is the variance of the momentary prices within that period of time.

Previous studies have not only assumed that when hedging an individual always transacts business at the monthly mean price in the future month when the producer offsets his futures position and sells the cash commodity but that the producer always transacts business at the mean price in the initial decision month also. This dissertation maintained that except at the moment of the decision, the producer does not know exactly what prices he faces. It was felt that the distribution of prices within the decision month was an important factor in determining the actual decision made and in determining the outcome from that decision. What is more, the distribution of prices within the decision month along with the distribution of prices within the future month are important in examining the relative outcomes from different decision rules.

This study examined two soybean marketing decisions, one in the spring and one in the fall. In both cases, it was assumed that the producer knew a specific month in which he would transact in the market.

The producer was faced with two marketing alternatives in the spring (June): hedge or remain unhedged. In the fall (November), the producer had three marketing alternatives: store the crop hedged until July, store the crop unhedged until July, or sell the crop now in the fall. These marketing decisions were simulated for five risk aversion levels that were calculated from utility equations estimated in previous studies. Simulations were conducted using actual daily prices for the period 1980-1987.

The simulations were used to examine whether decisions would have differed greatly had one used the wrong measure of variance or had one ignored the variance altogether relative to the case where the individual used the momentary variance to make the decision. There were two aspects to the closeness of two decision rules that were considered in this study. One measure of closeness was simply the probability that one would make the same decision using the an irrelevant variance as one would have made by using the relevant variance. The second measure of closeness was an expost measure and addressed the issue of how close are the outcomes from the right and the wrong decision rules. For this measure of closeness, this study calculated the probability that one would have made a different decision from that indicated by the right decision rule but that, at worst, the income from the wrong decision was only e less than the income from the right decision. The small dollar amounts e examined in this study ranged from zero cents per bushel to 20 cents per bushel.

The results of the spring simulations indicated that there was a relatively high probability of making the same decision using Peck's variance of the forecasted mean price as using the momentary variance. The average probability of making the correct decision using Peck's variance was 65 percent at the most risk neutral level considered and was 83 percent at the most risk averse level. This probability at the medium risk aversion level was 49 percent.

For the fall simulations, the probability that using Peck's variance measure would lead to the correct decision was 89 percent for the most risk neutral level and was 65 percent for most risk averse level considered. At the medium levels of risk aversion considered, this probability was 19 percent. For both the spring decision and the fall decision, the probability of making the correct decision using Peck's variance was greatest if one was either quite risk averse or quite risk neutral.

The results of the simulations also indicated that when one made a wrong decision using Peck's variance the cost of that error in terms of lost income was not great.

An overall indication of the closeness of using Peck's variance relative to using the momentary variance is the probability of making the correct decision or making a decision whose outcome is considered close enough to the outcome of the right decision. The average of this total probability over the simulation period for the spring decisions was 85 percent and 95 percent for the most risk neutral and the most risk averse individual considered, respectively (for e = $0.00). For the fall decisions, the average of the total probability was 89 percent and 67 percent for the most risk neutral and most risk averse levels considered, respectively (for e = \$0.00).

The results of the spring simulations that compared the case where a risk averse individual ignored the variance entirely with the case where he used the momentary variance indicated that the probability of making the correct decision was very high (average of 90 percent) for the most risk neutral level considered. The average probability was 43 percent for the highest risk aversion level considered. This probability was higher for the most risk neutral individual and lower for the most risk averse individual for the fall simulations relative to the spring simulations.

Overall, the probability on average of making the right decision or making a decision that is considered good enough by the individual is quite high for both the spring and the fall decisions examined. These probabilities vary considerably however between years. So, a risk averse producer who uses the wrong measure of variance or who ignores variance entirely make much of the same decisions they would have had they used the momentary variance.

For both the spring and the fall simulations, the particular decision made by any of the decision rules examined depended on which price the decision maker observed on the day he made his decision. This indicates that studies that assume that a producer always receives the monthly mean price are missing the fact that the distribution of prices within the decision month are important to the decision maker. This is true whether the producer is an expected utility maximizer or whether he is an expected income maximizer.

In addition to examining the sensitivity of the decisions made to the measure of variance, this study also examined the sensitivity of the decisions made to the forecast method. This study examined whether using the typical approach to forecasting expected utility would yield the same results as forecasting expected utility directly. The typical approach is to forecast prices and bases separately and then combine these forecasts to forecast expected utility. The best forecast of a sum of variables is not necessarily the sum of individual forecasts. Therefore, this study, for two risk aversion levels, compared the decisions made using the typical approach and using the direct forecast of expected utility. These results indicated that there was very little difference in the decisions made for both the spring and the fall. The average total probability of making the same decision or a decision whose outcome was greater than or equal to the outcome of the typical approach was greater than 90 percent for both levels of risk aversion and for both the spring and the fall decision.

The results of this study indicate that there has not been a great cost to using the wrong measure of variance in the type of soybean marketing decisions examined in this study.

Very little work has been done in economics since Peck's 1975 article concerning the relevant variance for decisions under risk. Economists have accepted the notion that the variance of the forecasted mean price is the relevant variance without additional discussion. Although this study maintains that the momentary variance is the relevant variance to be used in marketing decisions, additional work in the economics profession is in order to better understand decision making under uncertainty and to hopefully provide information to decision makers that will be of the most use to them.

This study has laid out some important considerations for future work in this area. Questions were raised concerning how individuals respond to information that does not fully meet their needs and how individuals would respond to new information that indicated that they were either better off or worse off than they had thought previously. Would an individual be willing to pay for information that told him that he was not as well off as he had thought?

This study also examined how one can measure the closeness of two decision rules as far as the individual is concerned. This study has raised the point that some information on the nature of decision making is lost when the distributions of prices within the decision month and within the future month are ignored and only monthly mean prices are used.

Finally for future work in this area, this study has provided an alternative method by which one can calculate the momentary variance that requires only the high and low prices and does not require resorting to an enormous amount of daily or hourly data.

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APPENDIX A: GRAPHICAL PRESENTATION OF THE POSSIBLE DECISIONS AND ERRORS FOR THE FALL

The figures in this appendix present a graphical representation the information contained in Table 4.1 of the Methods of Analysis Chapter. The regions in these figures were used to calculate the probability that two decision rules yield the same decision.

Figure A.1 is the same as Figure 4.2 and presents the situation where the forecasts of the July cash price, the July basis, the momentary variance of July cash price and the momentary variance of July basis are such that $G_{1HN} > G_{2HN}$, $G_{1NS} > G_{2NS}$, and $G_{2HS} > G_{1HS}$. The possible errors made in Case A are 1) Hedge/Sales, 2) Unhedge/Sales, and 3) Unhedge/Hedge where the notation is read 'right decision/wrong decision' and the three errors are for regions IIa, IVa, and Va, repectively. For all cases, region I is where both decision rules sell in the cash market, region III is where both rules hedge, and region VI is where both rules remain unhedged.

Figure A.2 is Case B where $G_{2HN} > G_{1HN}$, $G_{1NS} > G_{2NS}$, and $G_{2HS} > G_{1HS}$. The possible errors in Case B are 1) Hedge/Sales, 2) Unhedge/Sales, and 3) Hedge/Unhedge.

Figure A.3 is Case C where $G_{2HN} > G_{1HN}$, $G_{2NS} > G_{1NS}$, and $G_{2HS} > G_{1HS}$. The possible errors in Case C are 1) Hedge/Sales, 2) Sales/Unhedge and 3) Hedge/Unhedge.

Figure A.4 is Case D where $G_{2HN} > G_{1HN}$, $G_{2NS} > G_{1NS}$, and $G_{1HS} > G_{2HS}$. The possible errors in Case D are 1) Sales/Hedge 2) Sales/Unhedge

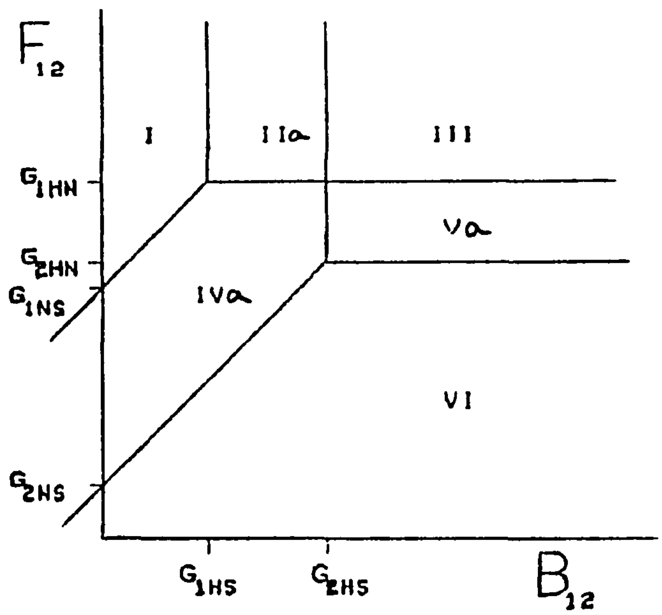

Figure A.1. Combination of Futures Price and Basis Where the Decisions from Two Decision Rules Coincide for Case A

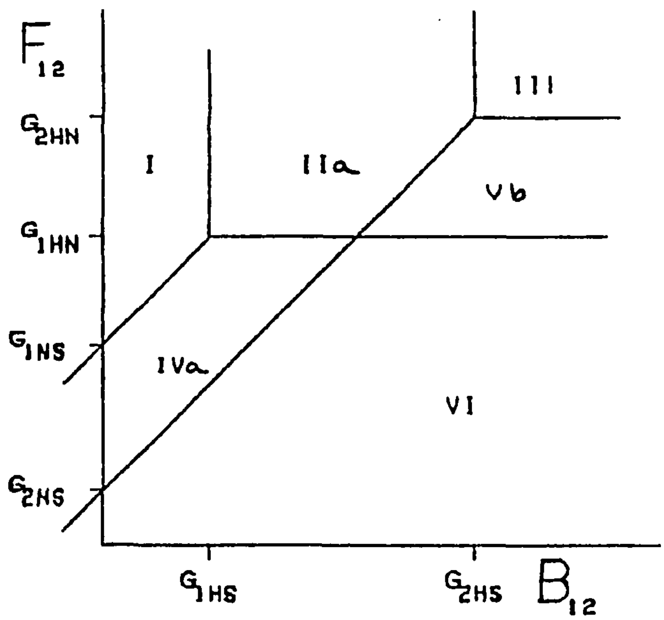

Figure A.2. Combination of Futures Price and Basis Where the Decisions from Two Decision Rules Coincide for Case B

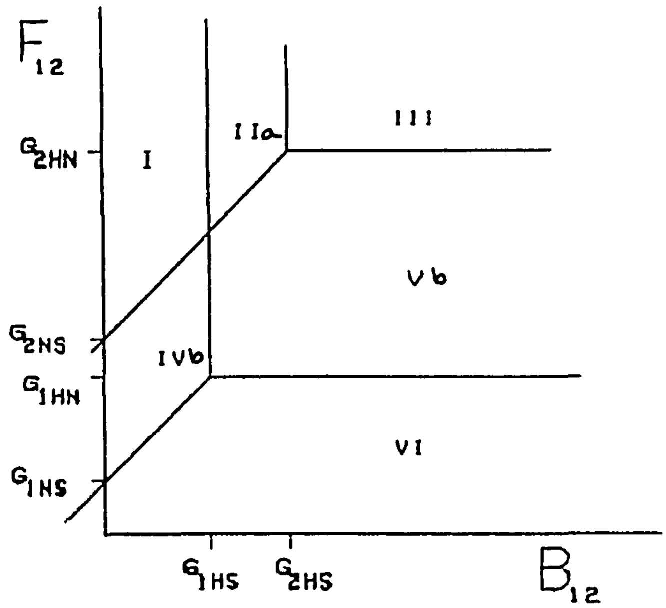

Figure A.3. Combination of Futures Price and Basis Where the Decisions from Two Decision Rules Coincide for Case C

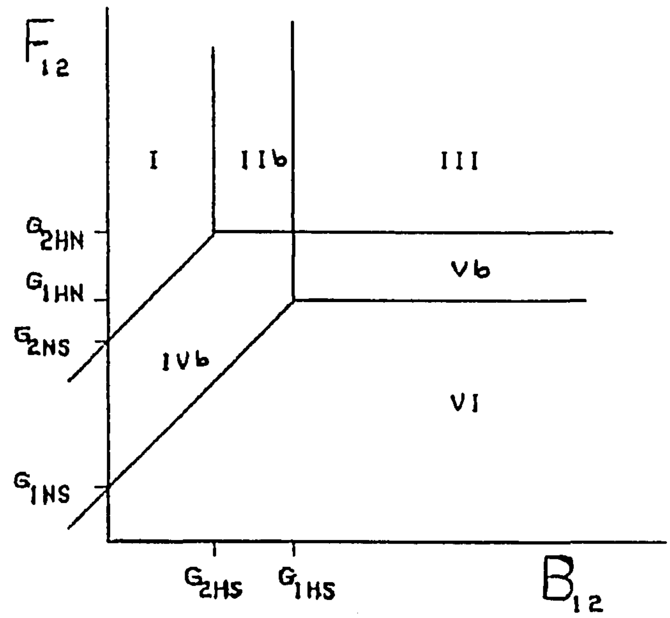

Figure A.4. Combination of Futures Price and Basis Where the Decisions from Two Decision Rules Coincide for Case D and 3) Hedge/Unhedge.

Figure A.5 is Case E where $G_{1HN} > G_{2HN}$, $G_{2NS} > G_{1NS}$, and $G_{1HS} > G_{2HS}$. The possible errors in Case E are 1) Sales/Hedge, 2) Sales/Unhedge, and 3) Unhedge/Hedge.

Figure A.6 is Case F where $G_{1HN} > G_{2HN}$, $G_{1NS} > G_{2NS}$, and $G_{1HS} > G_{2HS}$. The possible errors in Case F are 1) Sales/Hedge, 2) Unhedge/Sales, and 3) Unhedge/Hedge.

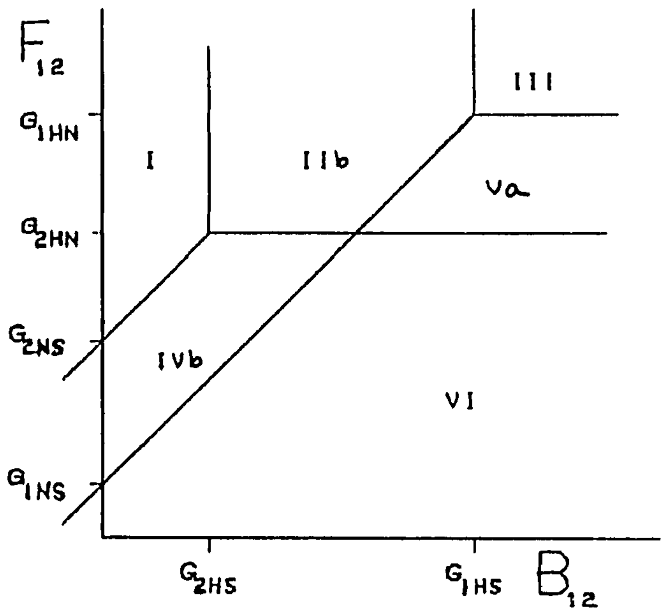

Figure A.5. Combination of Futures Price and Basis Where the Decisions from Two Decision Rules Coincide for Case E

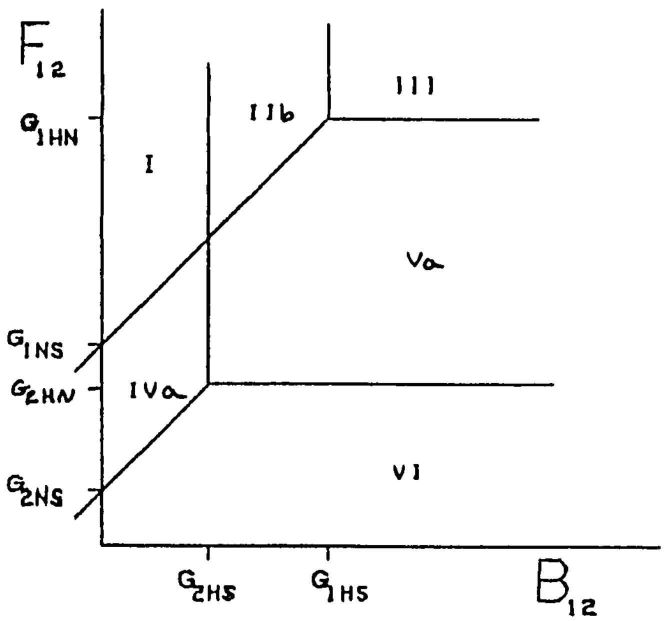

Figure A.6. Combination of Futures Price and Basis Where the Decisions from Two Decision Rules Coincide for Case F .

APPENDIX B: GRAPHICAL COMPARISONS OF THE TWO METHODS OF CALCULATING MOMENTARY VARIANCE

The Statistical Methods Chapter discussed two methods by which one could estimate the true momentary variance within a given month. One method simply used the daily average cash prices to calculate the momentary variance. This method is straightforward but, as discussed in that chapter, it underestimates the true momentary variance. The second method for estimating the true momentary variance used the month's high and low price and the equation for a $100(1-\alpha)$ percent prediction interval. This method requires one to select a level of α and yet there is no set procedure by to make this selection. Therefore, the figures in this appendix present the average momentary variance for each calendar month calculated over the period 1975-1987 calculated by the two methods.

Figure B.1 presents the average momentary variance of soybean cash price calculated with daily means as the solid line in the center. The dashed line above this solid line represents the calculation of the momentary variance using the month's high and low price with $\alpha = 0.10$. The lower dashed line also uses the month's high and low price but with $\alpha = 0.05$.

Note that the calculation of the momentary variance of cash price depends on what prices are considered relevant by the producer for his particular decision. For example, the prices in the last one-third of November would not be used to calculate the momentary variance of the

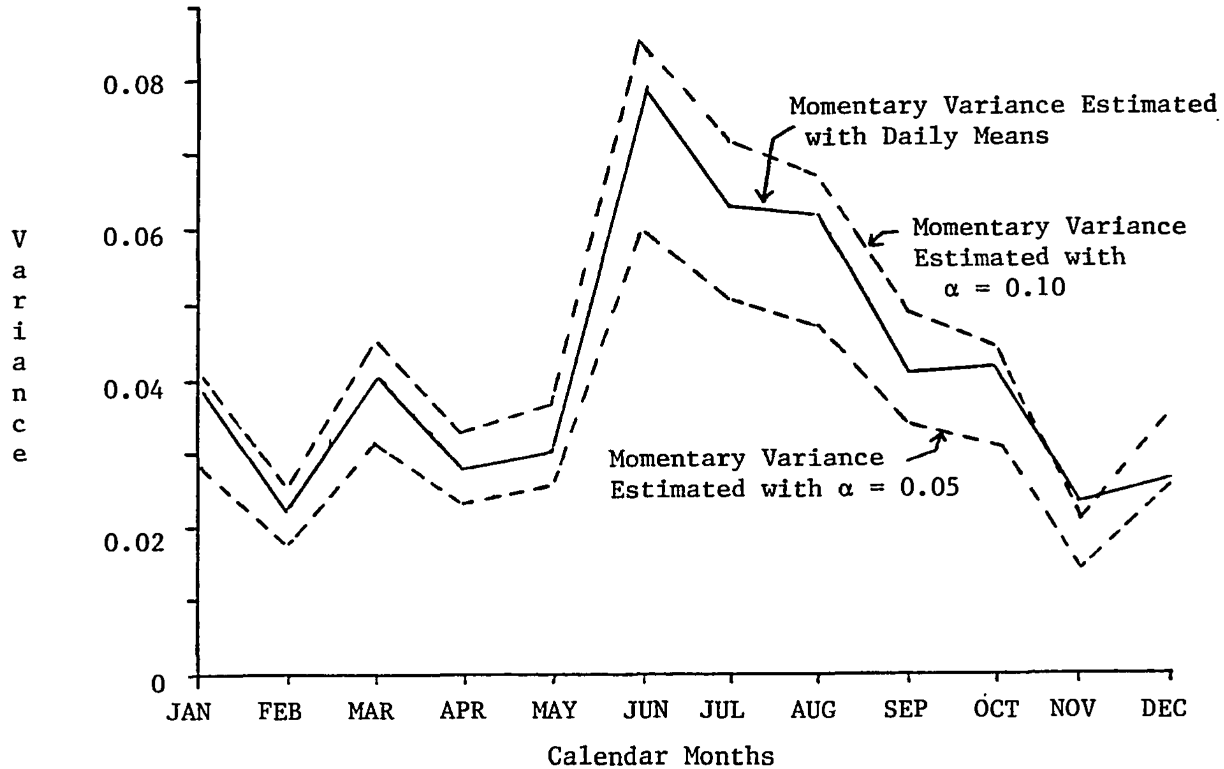

Figure B.1. The Average Momentary Variance of Soybean Cash Price for Each Calendar Month Calculated With Daily Means and With the Monthly High and Low Price

November cash price when one is considering hedging using the November contract since the November contract is not traded after about the 20th of November. In Figure B.1, all days prices are used in all months except for November where only the prices in the first two-thirds of the month are used.

Figure B.2 presents the average momentary variance of the November basis calculated by both methods. The solid line represents the variance calculated using daily means. The upper and lower dashed lines are calculated using the month's high and low basis with $\alpha = 0.10$ for the upper and $\alpha = 0.05$ for the lower.

Figure B.3 presents the same information for the July basis. The solid line represents the calculation using daily means. The upper and lower dashed lines are calculated with $\alpha = 0.10$ and $\alpha = 0.05$, respectively, and the month's high and low basis.

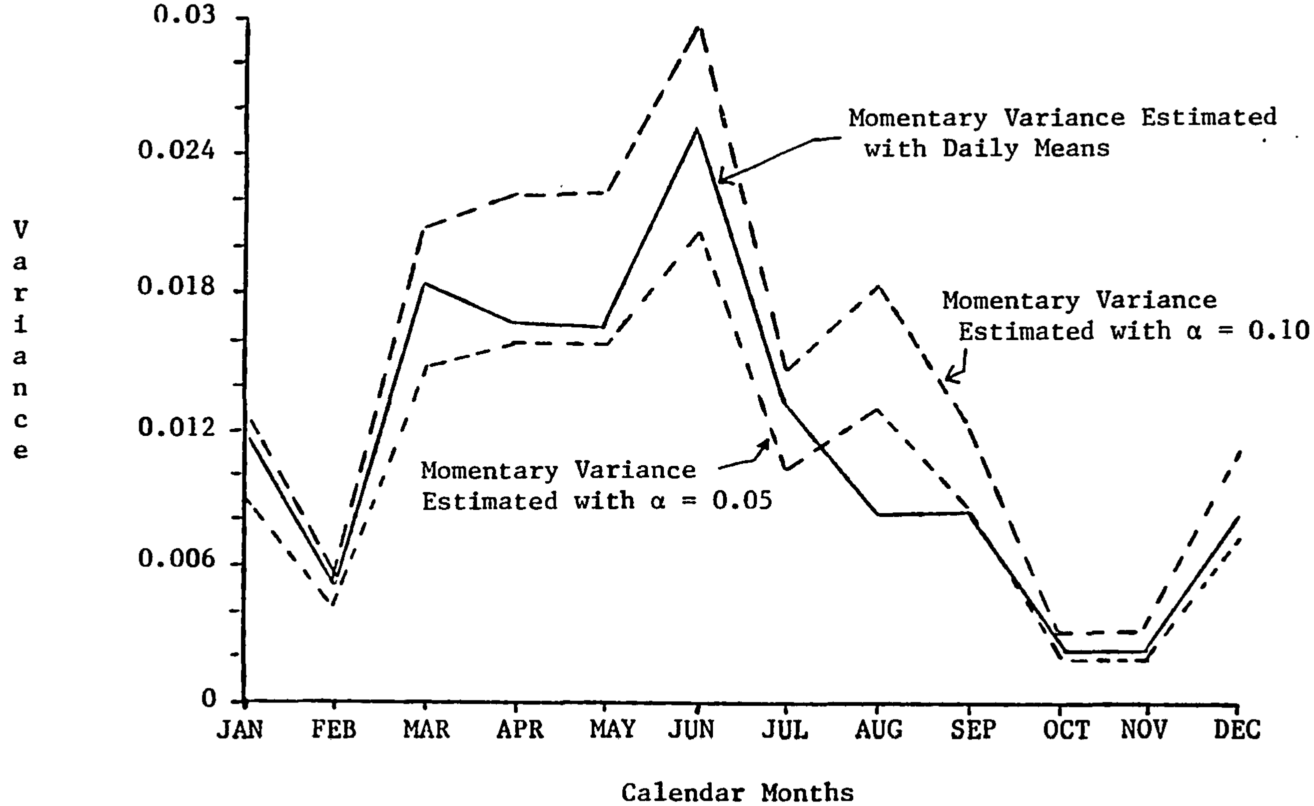

Figure B.2. The Average Momentary Variance of November Basis for Each Calendar Month Calculated With Daily Means and With the Monthly High and Low Basis

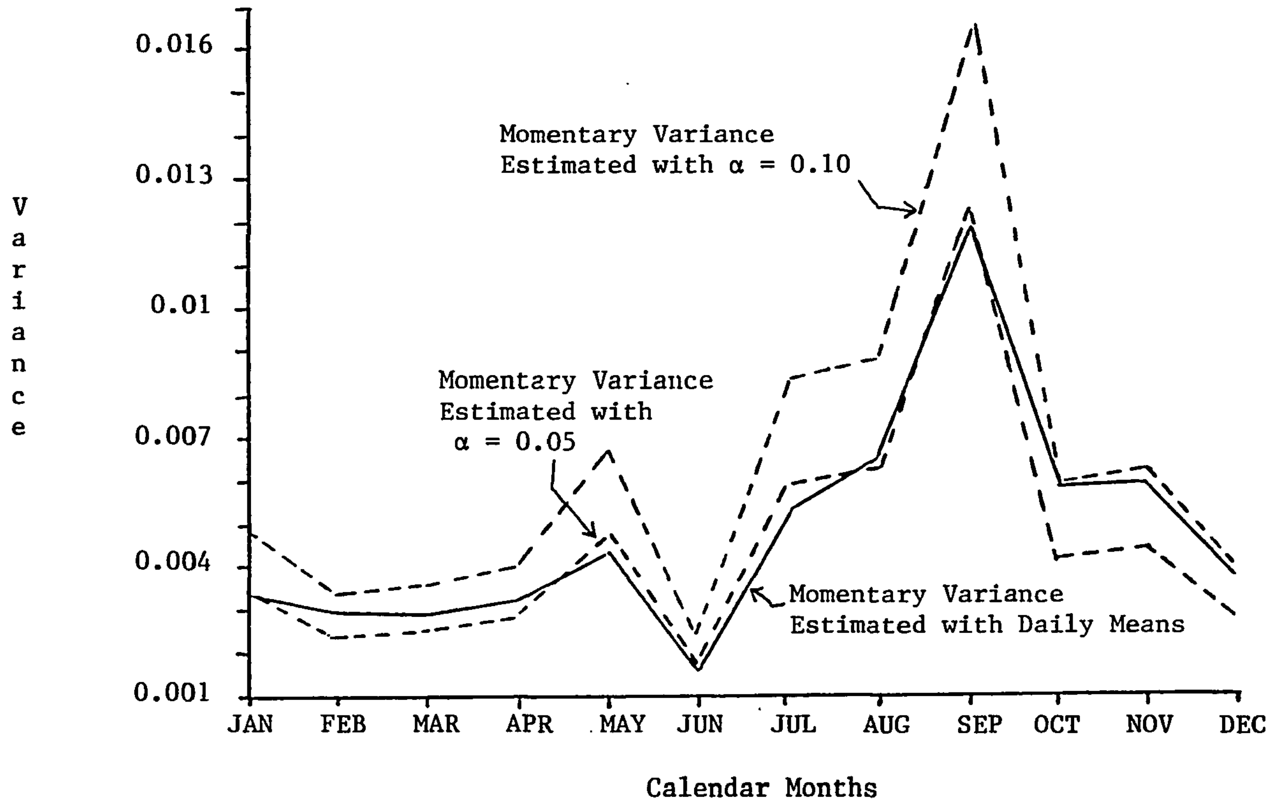

Figure B.3. The Average Momentary Variance of July Basis for Each Calendar Month Calculated With Daily Means and With the Monthly High and Low Basis