THE DESIGN AND EVALUATION OF PRICE RISK MANAGEMENT STRATEGIES IN THE U.S. HOG INDUSTRY

DISSERTATION

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ABSTRACT

During recent years, more U.S. hog producers and meat packers are involved in marketing contracts to enhance net revenue and to limit downside price risk. This research explores new ways to efficiently price a subset of these contracts, window contracts, and to evaluate the effectiveness of these contracts to help producers and packers enter contracts that more effectively satisfy their preferences.

A Monte Carlo simulation model in which thousands of paths for hog, corn and soybean meal prices are simulated is developed. These commodity prices are assumed following a random walk with drift. Futures prices are used to calibrate the means of the expected joint distribution of these three spot prices. To calibrate volatility of prices, the forecasting power of several frequently used volatility forecasting methods are examined; implied volatility is used to forecast volatility for near term and historical volatility is used for longer term horizons. Historical correlation is introduced to capture the co-movement of the three price series. Alternative basis forecasting approaches are also compared. The futures spread model performs best for short-term while a five-year historical average is best for long-term forecasting.

The window contracts are decomposed into a portfolio of long Asian-Basket put and short Asian-Basket call options. A projected breakeven price is used to determine the floor price, and then the Monte Carlo simulation method is applied to price both a
moving and a fixed window contract. These methods provide unbiased pricing of fixed and moving window contracts of one-year duration. A moving window contract may be preferred by contract issuers who value volatility reduction and due to cumulative performance issues.

This same Monte Carlo method is also used to forecast net revenue for hog producers. Based on this forecasting model and the assumption of a mean-variance utility function, the prospective evaluation, which utilizes the Monte Carlo simulation methods described above, is compared with retrospective evaluation, which uses only past performance of the risk management strategy, for a net revenue and a utility maximizing producer. Prospective evaluation is marginally better than retrospective evaluation in terms of net revenue enhancement and risk reduction.
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CHAPTER 1

INTRODUCTION

The United States is the world's second largest producer, consumer, exporter, and importer of hogs and pork products. Hog production is a complex process. During this process, hog producers face much risk: the cost of feeds, the efficiency of hog growth, the price of feeder and live hogs, weather shocks, and so on. These sources create substantial financial risk for an individual producer. Among them, the price risks of live hogs and feeds are the biggest concern for hog producers. To achieve profit and risk objectives, hog producers must understand the nature of the underlying price risk and the ability of various marketing strategies to alter this risk. During recent years the structure of the U.S. hog production industry has experienced profound changes. One obvious tendency is that the industry is getting more vertically integrated and concentrated. This further increases the use of risk management tools because more hog producers and meat packers are involved in production and marketing contracts. However, little research has examined the fair and efficient price of a key class of emerging risk management tools such as fixed and moving window contracts. There also exists little research on methods to evaluate the desirability of marketing options from the point of view of hog producers. The predominant method of evaluating alternative strategies is still limited to examining
only the historical performance of alternative risk management tools rather than fully utilizing current market information to look forward. To find a new way to attack these problems, I build a model to forecast hog and feed prices by Monte Carlo simulation method, explore the underlying mechanism of these risk management tools and prospectively evaluate their performance using all the available market information.

To forecast hog and feed prices, I must figure out their joint distribution to use Monte Carlo simulation. Namely, I have to forecast the mean, volatility and co-movement of these price series, then simulate paths for each of the prices. To do this, I embrace the efficient market hypothesis and use futures prices, adjusted by forecasted basis, to provide a forecast for the means of these prices. To forecast volatility of these prices, the relative forecasting power of historical volatility, implied volatility and GARCH-based volatility is examined. Consistent with recent research, the performance of these three methods is both commodity- and horizon-specific, which means there is no single best predictor. However, implied volatility often performs well in near-term and historical volatility performs well in the long term horizons. Thus, implied and historical volatility are used to forecast variance for corresponding horizons. Historical correlation is introduced to capture the co-movement of the price series.

Once I build the Monte Carlo simulation model, I can use it as a tool to study the design and pricing of some of the most popular marketing contracts such as window contracts and so forth in the hog industry. Almost all marketing contracts involve clauses to reduce market or price risk for hog producers. In fact, they do help hog producers survive during severe downturn of hog cycles. The lack of research attention given to the issue of the underlying mechanism of these marketing contracts means not much is
known about their fair design and pricing. These marketing contracts, from the view of modern finance theory, can be viewed as a portfolio of option contracts. Thus option pricing theory can be applied to determine a fair price. A few researchers, for example, Unterschultz et al. (1998) follow this way and study the design of fixed window contracts. However, marketing contracts in real life are much more complicated in that they involve moving average price of multiple assets. Multiple assets in hog industry normally refer to the output, hogs and two major feeds, corn and soybean meal. Thus these marketing contracts involve exotic options such as Asian, basket and spread options. In this research, I utilize exotic option pricing methods to design these more complicated but more real marketing contracts. The results show the marketing contracts designed based on the Monte Carlo simulation model are fair and efficient because the contracts’ performance is unbiased in a risk-neutral world.

The evaluation and comparison of alternative risk management tools are another critical issue for hog producers. At a certain point of time, a hog producer has to choose among various risk management strategies, including futures contracts, option contracts and any type of marketing contracts signed between hog producers and meat packers or to use no risk management options. The choice of risk management strategies will substantially influence the hog producer’s risk and return. The dominant evaluation method currently in use is retrospective evaluation. This method examines the historical performance of alternative strategies and the efficacy of decisions made based on it. This method, though easy to implement, ignores the important market information reflected by the futures and options markets. Also, it is based on the assumption that history will repeat itself. To solve these problems, first I propose a net revenue forecasting model
based on the Monte Carlo simulation method that fully utilize the futures and options market information. This net revenue forecasting model performs very well as judged by its out-of-sample forecasts. Then the distributions of net revenue under alternative risk management strategies are forecasted. Decisions are then made by comparing the net revenue and mean-variance utility produced by each strategy. The research results show that decisions made by prospective evaluation provide marginally greater utility and net revenue than those made using retrospective evaluation.

In summary, this thesis contributes to the existing literature by application of exotic option pricing methods to the hog sector for the purpose of marketing contract design and by assessing the potential loss associated with relying upon retrospective evaluation instead of prospective evaluation of hog marketing strategies.

The rest of this dissertation is structured as follows. Chapter 2 introduces some necessary background knowledge on U.S. hog industry, including general industry knowledge, the concept of net revenue and details of alternative risk management tools. In chapter 3, I propose the Monte Carlo simulation model to simulate output and input price series. The issues of the mean, volatility, co-movement of prices and basis forecasting are critical sub-parts of this chapter. In chapter 4, I apply the simulation method introduced in chapter 3 to design marketing contracts using exotic option pricing methods. In chapter 5, I build the net revenue forecasting model based on the simulation method in chapter 3 and examine its performance. Then the net revenue forecasting model is used as a decision tool to compare alternative risk management strategies including the marketing contracts designed in chapter 4. The decisions emanating from
prospective and retrospective evaluation methods are compared. Chapter 6 will draw conclusions and outline avenues to improve and extend the research.
CHAPTER 2

BACKGROUND


The United States is the world's second largest producer, consumer, exporter, and importer of pork and pork products. Pork accounts for about a fourth of domestic meat consumption. Currently, the U.S. hog herd stands at nearly 60 million animals, with about 68 percent of them in the Corn Belt area, where they have access to that region's abundant supplies of feed grains and soybean meal (U.S. Department of Agriculture, 2002). Another 20 percent of hogs are produced in the Southeast (U.S. Department of Agriculture, 2002).

Hog production is a complex and time-consuming process. A complete hog production process, from farrowing to marketing, requires six months for completion. Various inputs have to be added during this process. These inputs can be divided into variable and fixed inputs. Variable inputs include feed, feeder pigs, marketing services, electricity, fuel, labor, financing services, etc. Fixed inputs are equipment, buildings, management and so on. Nationally, 83 percent of the market hogs are marketed by the
operation that farrowed them (Hog Industry Handbook, 1998). There is a slight tendency for the larger and medium sized operations to sell more feeder pigs compared to smaller operations. Transactions of market hogs typically take place in two ways: at public markets such as terminals and auctions and via direct relationships or contracts with packers or other market agents. Today most market hogs are transacted in the second manner. Furthermore, while many hogs marketed are sold on a live weight basis, carcass merit sales programs have become increasingly popular in recent years. For example, in 1997, 73 percent of the market hogs were sold on a carcass basis. Premiums and discounts associated with backfat depth or percent lean (i.e., grid pricing) and carcass yield (i.e., grade and yield) were the two most common pricing methods (Hog Industry Handbook, 1998). Normally, it is assumed a live hog has a carcass yield of 74 percent or that 74 percent of the hog’s live carcass weight can be sold as meat cuts or products. Currently, the most common live weights that receive top prices are 240 pounds to 260 pounds. Though there is a slight upward trend (the national average is 262 pounds in 2000), 250 pounds is still a valid approximation to the average marketing weight. Feeder pigs typically weigh 40-60 pounds with an average of 50 pounds, though there has been a movement toward the use of very light feeder pigs (less than 20 pounds) that have been subjected to segregated early weaning (Hog Industry Handbook, 1998). To grow a 50-pound feeder pig into a 250-pound market hog, 1999 data from Ohio State University Extension Livestock Budgets suggest that 560 pounds of feed are needed, which is to say, the feed conversion rate is 2.8 pounds of feed to one pound of gain. Corn, soybean meal and some miscellaneous feeds such as vitamins are the main component of the feeds.
Corn accounts for 8.5 bushels (476 pounds) of the feed mix while soybean meal accounts for the other 84 pounds.

During recent years the structure of the hog production industry has experienced profound changes including the rapid emergence of larger operations that have gained substantial efficiencies by exploiting economies of size. However, even the largest hog producers experienced negative returns in 1998 and 1999, which was a period of historically low hog prices. Periods of negative returns, including the severe negative returns during 1998 and 1999, have driven many small hog producers out of the industry; often larger and more technologically complex units replace them during periods of expanding profits. For example, in 1997, 145 firms marketing 50,000 hogs or more a year marketed 33.1 million heads (approximately 37 percent of US marketed hogs). This is a big jump compared to 1988 when only 7 percent of US market hogs were produced by firms in this size class. In 1988 vertical integration involved a relatively small number of growers and hogs (Grimes and Meyers, 2001). By 1997, however, 40 percent of the hogs farrowed and 44 percent of the hogs finished were by producers involved in various production contracts. This number is up from 29 percent in 1994. Most of the growth was on farms with over 50,000 heads. Half or more of the contract production came from the 18 largest producers (Lawrence et al., 1999). Figure 2.1 and Table 2.1 show the sharp decrease of the number of hog producers and increased importance of large producers. These structural changes have been associated with lower production costs via economies of size. However, larger producers are typically less diversified and, hence, face greater profit risk.
Another obvious tendency is that more producers and packers are involved in long- or short-term marketing contracts, in which producers’ revenues are partially or fully insulated from systematic price risk in the finished hog market.¹ Many producers engage in such contracts to enhance average hog price and to limit downside price risk (Lawrence and Grimes, 2001). In the 1980s, there were few contracts of any kind in U.S. hog industry. In 1993, only 11 percent of hogs were transacted under a marketing or production contract. In mid-1990s, the importance of long-term marketing links between producers and packers quickly grew (Hayenga et al. 1996). In February through May of 1998 two surveys were conducted to collect information from more than 8,300 hog producers. The results show in 1997, the transaction of about 57 percent of market hogs involved some type of contracts. In 2001, it is estimated that about 83 percent of hogs were marketed by marketing contracts (Grimes and Meyer, 2001). The most common marketing contract is a formula price contract tied to the cash market. The price paid may be a three-day or weekly average price of a specified market, but most of the price risk is still borne by the producer. Within this overall trend towards contracting, the prevalence of marketing contracts that transfer finished hog price risk from the producer to the contractor has also increased.² In 1997 8.4 percent of all hogs were transacted under such contracts while in 2001 that figure increased to 22.8 percent (Grimes and Meyer, 2001). Since input and output price risks are among the most important risk factors in the realization of profit, it is not surprising that hog producers have increased participation in risk-shifting marketing contracts. Such contracts can effectively reduce downside risk without requiring the producer to engage in continuous market price and
basis recognizance as is often required for implementing forward, futures and options contracts.

2.2. Producers’ Net Revenue.

We can represent the hog producer’s profit for the periods from time 0 to T as:

\[ \bar{\pi}_T = \sum_{t=0}^{T} (\bar{p}_{t,H} \bar{Q}_{t,H} - \bar{p}_{t,C} \bar{Q}_{t,C} - \bar{p}_{t,S} \bar{Q}_{t,S} - \bar{p}_{t,F} \bar{Q}_{t,F} - \bar{p}_{t,Y} \bar{Q}_{t,Y} - FC) \]

Where ~ indicates a random variable and \( \bar{\pi}_T \) is the profit from hog finishing activities over the time period 0 to T. \( \bar{p}_{t,H} \) is the price received for finished live hogs at time \( t \); \( \bar{p}_{t,C}, \bar{p}_{t,S}, \text{ and } \bar{p}_{t,F} \) are the prices paid for corn, soybean meal and feeder pigs at time \( t \), respectively; \( \bar{p}_{t,Y} \) is a price vector for other variable inputs at time \( t \); FC is the fixed costs applied during these \( T \) periods; \( \bar{Q}_{t,H} \) is the number of hogs sold at time \( t \); \( \bar{Q}_{t,C}, \bar{Q}_{t,S}, \text{ and } \bar{Q}_{t,F} \) are the quantity of corn, soybean meal and feeder pigs purchased at time \( t \), respectively; \( \bar{Q}_{t,Y} \) is a quantity vector of other variable inputs purchased at time \( t \).

Optimal levels of the quantity variables will depend upon absolute and relative prices and upon the production technology this particular producer uses. However, the purpose of this study is not to help hog producers figure out the optimal production plans or the best marketing time. Rather, it is to help them manage various price risks they face for a given technology and production plan. Hence, to simplify the exposition, the fixed costs are removed and all quantity variables are assumed to be exogenous. Namely, the quantities of inputs and outputs are assumed to be perfectly known in advance, that these
quantities are internally consistent with common hog production technology, and that the
timing of purchases and sales are predetermined by the producer. Among all the
variables, feed costs and live hog prices dominate the profitability of hog production.
Feed costs accounted for about 40 percent of total costs each year from 1992 to 1999 in
U.S. (USDA Hog Market Report, 2000), while live hog prices had an obvious impact on
firm profitability. Compared to feed costs and hog price, feeder pig purchasing costs play
a small role in the profit realization process. USDA Hog Market Report (2000) shows
feeder pig costs accounted for less than 10 percent of total costs each year from 1992 to
1999. Furthermore, feeder pig price data are not associated with any futures contract and
are commonly priced as a function of projected profits. Hence, to ground the model in
variables for which there exist publicly traded futures prices, we drop the feeder pig
component out of the model.

The restricted model focuses on two key feed ingredients (corn and soybean meal)
and live hog prices. Define net revenue for a hog producer as:

\[
\tilde{R}_T = \sum_{t=0}^{T} (\tilde{P}_{t,H} Q_{t,H} - \tilde{P}_{t,C} Q_{t,C} - \tilde{P}_{t,S} Q_{t,S}),
\]

where \( \tilde{R}_T \) is the revenue from hog finishing activities over the time period 0 to \( T \) net of
corn and soybean meal costs; \( \tilde{P}_{t,H} \) is the price received for finished live hogs at time \( t \);
\( \tilde{P}_{t,C} \) and \( \tilde{P}_{t,S} \) are the prices paid for corn and soybean meal at time \( t \), respectively; \( Q_{t,H} \)
is the number of hogs sold at time \( t \); \( Q_{t,C} \) and \( Q_{t,S} \) are the quantity of corn and soybean
meal purchased at time \( t \), respectively; and a superscript ~ indicates a random variable.

Hog production technology and, hence, production parameters can vary
considerably across hog producers. However, to move forward, the model is
parameterized using benchmark production parameters taken from the 1999 Ohio State University Extension Livestock Budgets. These benchmarks assume that a hog is marketed at 250 pounds \((Q_H)\) and that it consumes 8.5 bushels of corn \((Q_C)\) and 84 pounds of soybean meal \((Q_S)\) during its growth from a 50-pound feeder pig. These assumptions yield the following per hog net revenue function:

\[
R_t = 250 * \tilde{P}_{H,t} - 8.5 * \tilde{P}_{C,t} - 84 / 2000 * \tilde{P}_{S,t}
\]

where \(R_t\) is the net revenue for a particular time period in dollars, other variables are defined the same as in equation (2.2), with the price of live hog in $/pound, that of corn in $/bushel and that of soybean meal in $/ton (1 ton = 2,000 pounds).

2.3. Alternative Risk Management Strategies.

Since input and output price risks are the most important risk factors in the realization of profit, all hog producers are motivated to understand and perhaps protect against downside risk. Methods currently available to hog producers to limit downside risk include the use of forward, futures, options and/or the rapidly expanding set of marketing contracts. A brief review of commonly-used risk management tools in the hog industry is given below.

2.3.1. Forward Contract.

A forward contract is a contract between a buyer (normally a meat packer or a marketing agent) and a seller (normally a hog producer), where the producer agrees to sell, at a future date, a specified number of hogs to a buyer for a predetermined price. One who buys this contract is said to take a long position on the contract and one who sells such a contract is said to take a short position on the contract. From the perspective
of a producer, he/she needs to take a short position on the forward contract. Let $K$ denote the predetermined price. The payoff for a forward short position is shown in Figure 2.2. Forward contracts for market hogs have been available for most major meat packers for a number of years and are a popular form of marketing contract. In 1999, about eight percent of market hogs were marketed by forward contract. While the forward contract allows the producer to lock in a particular selling price and avoid downside risk, it may also cause him/her to miss out on greater profits if the hog price rises.

2.3.2. Futures Contract.

Similar to forward contracts, futures contracts are also an agreement between two parties to buy or sell an asset at a certain time in the future for a certain price. Unlike a forward contract, it is a standard contract traded on an exchange and the use of it does not require the possession of hogs or the involvement of a packer. Futures market hedging occurs when a producer takes equal and opposite positions in the futures and cash markets. A producer wishing to establish a price on hogs to be sold later will sell the appropriate number of hog futures contracts, which expire after the delivery date to obtain a forward price. Then, when the hogs are ready for delivery in the cash market, the producer buys back the futures contract to offset the previous futures sale. He/she then delivers the hogs to the local market. Thus, profits (losses) made in one market are largely offset by losses (profits) made in the other market. This relationship is shown in figures 2.3 and 2.4. The payoff pattern for selling a futures contract is identical to that of selling a forward contract (Figure 2.2). The cash position the producer takes is shown in Figure 2.3. Figure 2.4 shows the combined position the producer takes. $K-K^*$ is called
basis; it is the difference between futures and cash price. The size of this difference is not
known to the producer beforehand and, hence, it is the only price-related risk the
producer has to bear under a futures hedge. More discussion about basis risk can be
found in Chapter 3.

Producers can also buy corn and/or soybean meal futures to hedge the feed costs.
Figure 2.5 shows the payoff for taking a long position on a feed asset.

The live hog futures contract, demarcated in pounds of live hog weight and with
one contract representing 40,000 pounds, was traded on the Chicago Mercantile
Exchange (CME) from 1966 to 1997. Since 1997 the lean hog futures contract has been
traded and represents 40,000 pounds of lean hog carcass weight. A hog typically yields a
processed carcass weight that is 74 percent of its live weight; hence the CME lean hog
futures contract represents about 54,054 pounds of live hogs or about 216 head of live
hogs weighing 250 pounds each. The underlying asset upon which the contract is based
is a lean hog carcass with 51 to 52 percent lean content. The amount of lean carcass
content is now standard for many hogs while hogs transacted in previous decades had a
lower lean content. The lean hog futures contract matures in February, April, June, July,
August, October and December; starting in 2002 a May contract was also added. The
trading in each contract begins approximately one year prior to the contract’s maturity
date and the last trading day is the second Friday of these contract months. Far-from-
maturity lean hog futures are thinly traded. For example, on August, 15, 2001, the open
interests for October, 2001, December, 2001, February, 2002 and April, 2002 futures
contracts are about 30,000, 10,000, 4,000 and 1,000 respectively. For futures contracts
expiring after April, 2002, the open interests are trivial.
Corn and soybean meal futures have been traded on the Chicago Board of Trade (CBOT) from 1877 and 1951, respectively. The trading unit for a corn futures contract is 5,000 bushels and that for a soybean meal futures contract is 100 tons. Corn futures contracts expire in the months of March, May, July, September and December; starting from November, 2000, January and November contracts have been added. Soybean meal futures contracts expire in the months of January, March, May, July, August, September, October and December. Both corn and soybean meal contracts expire at the business day prior to the 15th calendar day of the contract month.

When used in hedging, futures contracts, like forward contracts, eliminate both downside risk and upside potential; unlike forward contracts, the producer must bear basis risk. Also, futures contracts cannot be tailored to individual needs because of the standard trading unit. A margin account has to be maintained because a futures account is mark-to-market daily, thus, the account value is adjusted each day based on the current futures price and a producer may receive margin calls if the margin in the account cannot offset the loss caused by adverse movement of futures price. Another disadvantage of futures hedging is transaction costs and brokerage fees. Because of these disadvantages, relatively few hog producers use futures contracts directly.

2.3.3. Options.

An option contract gives its owner the right to buy or sell the asset outlined in the contract. The buyer of an option is referred to as an option holder and the seller of an option is referred to as an option writer. There are two types of options: put and call options. The call option gives the holder the right, but not the obligation, to buy the underlying asset from the option writer at a specified price, also called strike price or
exercise price, on or before the option expiration date. The put option gives the holder
the right, but not the obligation, to sell the underlying asset to the option writer at the
strike price. If an option can be exercised only on the expiration date, it is called a
European type option. If it can be exercised on or before the expiration date, it is called
an American type option. The price paid for an option is called an option premium.
Because U.S. commodity options are written on futures contracts and can be exercised on
or before expiration date, this kind of option is called an American futures option.

To hedge by using options, select the option whose underlying futures will expire
closest to, but not before, the time the physical commodity will be delivered. Typical risk
management strategies used by a hog producer include buying a put option on a hog
futures contract if the motive is to guard against downward price risk and buying a call
option on corn and/or soybean meal futures against adverse increases of input prices.
The payoff from the long position on a put option and a call option are shown in Figure
2.6 and 2.7, respectively.

Option trading for corn and hogs began in February 1985, while that for soybean
meal began in 1987. All the hog, corn and soybean meal options are written on each
corresponding futures. The last trading day for the lean hog option is the same as that for
the lean hog futures. Those for corn and soybean meal options are the end of the month
just before the futures expiration month.

The advantage of an option is that it can limit the downside risk but not the upside
potential and there is no margin account required to purchase options. However, the
hedger has to pay the transaction costs and option premium.
2.3.4. Minimum (Floor) Price Contract.

A minimum price contract, or a floor price contract, is similar to a put option. The producer agrees to deliver a specified number of hogs to a packer at a future date and the packer guarantees the producer a minimum price or floor price for the hogs. Usually, the producer receives the higher of the floor price or market price at delivery minus a discount. The discount works like the option premium to compensate the packer for the costs of providing the guaranteed floor price. The floor price is usually determined by a formula based on feed costs or based on current hog futures price. In 1999, about six percent of market hogs were marketed under such a contract (Lawrence, 2000). Some minimum price contracts involve a ledger account. The minimum price and the ledger account simply smooth the cash flow over time. However, the ledger has the potential to cause a great fluctuation in cash flow when it is cleared at the end of the contract. When the hog market price is below the floor price, the difference is accounted in the ledger as a debit to the producer and as a credit to the packer (Buhr, 1999). Compared to futures and options, marketing contracts incur fewer transaction costs and need less expertise. Marketing contracts can also be tailored to both parties’ individual needs.

2.3.5. Window Contract.

Window contracts are one popular contractual form found in the hog sector. A window contract specifies a price window with a floor and a ceiling for the duration of the contract. If the reference market price for hogs used in the contract falls within the window, the producer receives the reference price; hence only price risk within the window is assumed by the producer during the contract. If the reference price moves above (below) the window, the packer pays the ceiling (floor) price. In certain window
contracts, if the reference price is above (below) the window, the producer receives the ceiling (floor) price plus (minus) one-half the difference between the reference price and ceiling (floor) price. Similar to a minimum price contract, the floor and ceiling price are often determined by a formula based on the hog futures price or feed costs. Window contracts are one of the most popular marketing contracts; 6.6 percent of all hogs are transacted under such contracts (Grimes and Meyer, 2001) and more than 18 percent of all hogs marketed by firms with annual marketing of 10,000 to 500,000 thousand hogs are transacted under such contracts (Lawrence and Grimes, 2001). Lower costs and expertise and more flexibility are the advantages of window contracts. A window contract can be viewed as an option portfolio. The design, pricing and equitability of such contracts will be the subject of Chapter 4.

2.3.6. Hog Revenue Insurance.

Hog revenue insurance is a relatively new risk management strategy in the hog industry. Two pilot programs were available in 2001 in Iowa. There are two six-month insurance periods each year and insurance is bought at the beginning of each period. When the net revenue based on equation (2.2) is below the target, the difference will be paid by the insurer to the producer. Otherwise, the producer accepts the net revenue gained in the market. The target revenue could be a formula of feed costs or futures price. The insurance contract can be viewed as a put option on net revenue. It can be tailored to an individual marketing plan and it should be cheaper than buying options on hog, corn and soybean meal separately because the net revenue insurance may take advantage a natural hedge that sometimes emerges from the typical co-movement of output and input prices (i.e., corn prices are historically positively correlated to hog
prices). Hog revenue insurance is an emerging risk management tool and its popularity is unknown and needs further monitoring. Some preliminary research based on historical data shows it could compete with but not outperform other alternatives (Lawrence, 2001).

To choose the right marketing strategy that helps achieve profit and risk objectives, hog producers have to understand the ability of various strategies to alter price risk. The present study develops a prospective net revenue forecasting model based on Monte Carlo simulation that allows agribusinesses to design and price marketing contracts and for hog producers to evaluate various risk management strategies.

Figure 2.1: Number of Farms Raising Hogs and Hogs per Farm, U.S., 1980-2000.
Figure 2.2: The Payoff for a Short Position on a Forward or a Futures Contract.

Figure 2.3: The Payoff for Long Cash Position.
Figure 2.4: The Payoff for a Short Futures Hedging.

Figure 2.5: The Payoff for a Long Position on a Forward or a Futures Contract.
Figure 2.6: The Payoff for Long Position on a Put Option.

Figure 2.7: The Payoff for Long Position on a Call Option.
<table>
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<tr>
<th>Size of Operation (1,000 Head)</th>
<th>1988 (Percent)</th>
<th>1991 (Percent)</th>
<th>1994 (Percent)</th>
<th>1997 (Percent)</th>
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<td>23</td>
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<tr>
<td>&gt;50</td>
<td>7</td>
<td>9</td>
<td>17</td>
<td>37</td>
</tr>
</tbody>
</table>


**Table 2.1: Hogs Produced by Size of Operation, U.S., 1988-1997.**
A MONTE CARLO SIMULATION MODEL

3.1. Monte Carlo Simulation.

Either to forecast net revenue for hog producers or to study risk management marketing contracts involving both output and input prices, I need to know the joint distribution of the prices for the three commodities - hog, corn and soybean meal. A widely accepted model describing one commodity price movement is Geometric Brownian Motion:

\[
\frac{dP}{P} = \mu dt + \sigma dz
\]

where \( P \) is the commodity price; \( \mu \) and \( \sigma \) are the growth rate and volatility of the price respectively; \( dz \) is a Wiener process that has a drift rate of zero and a variance rate of one, namely a standard normal distribution. The discreet version of Geometric Brownian Motion implies a random walk with drift model in the natural logarithm level:

\[
\ln(P_{t,i}) = \ln(P_{t-1,i}) + \mu_i + \epsilon_{t,i},
\]

where \( \ln \) denotes the natural logarithm; \( P_{t,i} \) is the price of the commodity \( i \) at time \( t \); \( \mu_i \) is the drift for commodity \( i \); and \( \epsilon_{t,i} \) is an innovation term at time \( t \) for commodity \( i \) that
follows a normal distribution. The drift term denotes the intrinsic force driving the price movement. It could include the influence of interest rate, storage cost, convenience yield and so on. The innovation term is the random shock outside the intrinsic factor. Thus, the joint distribution for the natural logarithm level prices can be modeled as:

\[
\ln(P_t) = \ln(P_{t-1}) + \mu + \varepsilon_t,
\]

where \(P_t\) is a price vector at time \(t\); \(\mu\) is a vector for drifts; \(\varepsilon_t\) is an innovation vector at time \(t\), i.e.,

\[
P_t = \begin{bmatrix} P_{t,1} \\ P_{t,2} \\ P_{t,3} \end{bmatrix}, \quad \mu = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{bmatrix}, \quad \varepsilon_t = \begin{bmatrix} \varepsilon_{t,1} \\ \varepsilon_{t,2} \\ \varepsilon_{t,3} \end{bmatrix} \sim \mathcal{N}(0, \Sigma) \quad \text{and} \quad \Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{13} \\ \sigma_{12} & \sigma_2^2 & \sigma_{23} \\ \sigma_{13} & \sigma_{23} & \sigma_3^2 \end{bmatrix},
\]

where the subscript 1, 2, and 3 denote hogs, corn and soybean meal respectively, and \(\Sigma\) is the symmetric covariance matrix. The variance terms in the matrix are weekly variance, which are derived by dividing the square of corresponding implied volatilities by 52. The covariance terms can be derived from the following equation:

\[
\hat{\sigma}_{t,i,j} = \rho_{t,i,j} \sigma_i \sigma_j
\]

where \(\hat{\sigma}_{t,i,j}\) is the forecasted weekly covariance for commodity \(i\) and \(j\) starting from time \(t\); \(\rho_{t,i,j}\) is the correlation of the return series for commodity \(i\) and \(j\) for the two years prior to the start of the forecasting period; \(\sigma_i\) and \(\sigma_j\) are the forecasted volatility for commodity \(i\) and \(j\) respectively.

Because I have assumed the three commodity prices follow a random walk process with drift, I can conduct Monte Carlo simulation in a straightforward manner. Monte Carlo simulation is a very popular method in forecasting and in option pricing. By using this method, I need to repeatedly generate random numbers following the
multivariate normal distribution. But before that, I have to figure out those parameters, namely, all the variance and covariance terms in the covariance matrix and the best point estimations for each price. I will use the futures prices of these three commodities as the point forecasts of the cash prices in a future time period. For the variance or volatility terms, I will choose among the three popular volatility forecasting methods: implied volatility, GARCH-based volatility and historical volatility.

3.2. Data.

To compare the forecasting power of alternative volatility forecasting methods for hog, corn and soybean meal price series, I need to calculate the cash return series for these commodities. To calculate the implied volatility for these three return series, I also need the futures prices, options data and the risk-free interest rate. The continuously compounded rate of return is used to a great extent when futures and options are being priced. So I define the rate of return as:

\[
R_{t,i} = \ln(P_{t,i}) - \ln(P_{t-1,i}),
\]

where \( R_{t,i} \) is the weekly rate of return of the price series at time \( t \) for commodity \( i \); \( \ln \) is the natural logarithm; and \( P_{t,i} \) is the Wednesday price of commodity \( i \) at week \( t \). Since many hog producers market hogs once each week or once every several weeks, it is reasonable to use weekly price rather than daily price in this forecasting model. When the Wednesday price is not available, the Thursday price is used as an alternative.

The cash and futures prices and options data for these three commodities are from 1991 to 2000. There are 520 observations in the sample. The hog cash price ($/pound) is the price of Eastern Corn Belt plant delivered US 1-2 51-52 percent live hogs. The corn
cash price ($/bushel) is the price of Toledo No.2 yellow corn. The soybean meal price ($/ton) is the price of truck-delivered Illinois 48 percent soybean meal. I take the average of the reported low and high price of each commodity each Wednesday as the Wednesday price used in the model for all of the three commodities. The risk-free interest rate used in the analysis is the 6-month t-bill rate from the Federal Reserve. I also utilize the Wednesday settlement futures and options prices for hog contracts from Chicago Mercantile Exchange and those for corn and soybean meal contracts from Chicago Board of Trade. This dataset will be used throughout this entire dissertation and all the results of data analysis are based on it. The cash and nearby futures prices for all the three commodities are shown in Figure 3.1 – 3.3. The volatility of cash prices for all the three commodities are shown in Figure 3.4 – 3.6.

3.3. Point Forecasts.

To make a point forecast for the three commodity prices at a future date, I adopt the efficient market hypothesis (EMH) proposed by Fama (1970 and 1991). An efficient market is one that has incorporated all known information in determining price. Thus, the observed futures price of a commodity should be an unbiased forecast of the commodity spot price at the futures expiration date, provided that a valid reason for a risk premium does not exist, i.e.

$$F_{0,i} = E(P_{T,i}),$$

where $F_{0,i}$ is the currently observed futures price for a futures contract expired at time $T$ for commodity $i$ and $P_{T,i}$ is the spot price at time $T$ for commodity $i$. The assumption that the futures market is efficient is a controversial one. There are large literatures on this
issue, with diverse procedural approaches taken, and with diverse conclusions drawn. Across all commodities, the evidence favors futures market efficiency. For example, Zulauf and Irwin (1998) indicate that the futures market can be used as a source of unbiased information for crops. However, there is a greater tendency to find inefficient livestock futures markets (Garcia, Hudson and Waller, 1988; Kolb 1992 and 1996). Especially, Zulauf (1999) found the hog futures market is downward biased to some extent though Wright (2001) found no significant statistical evidence of such a bias in the live or lean hog futures contract over the 1975 to 2001 time period. A 2000 survey shows hog producers are evenly divided in their agreement with the statement that the futures market price of hogs to be delivered in six months is an unbiased estimate of the cash price (Patrick et al., 2000). Thus, it may be important that simple futures-based price forecasting procedures allow for possible underlying biases. However, at this stage, the EMH is adopted for the three commodities used in this model. Thus, currently, I use the observed futures price as the point estimates for the spot prices and the drift terms in the price process can be determined by linear interpolation of the observed futures prices with different maturities and the forecasting of spot price movement is formulated based on this hypothesis.

3.4. Volatility Forecasting.

The covariance matrix of the joint distribution of the three price series is another key for forecasting the distribution of net revenue for hog producers at a future date. Three widely used volatility forecasts for the variance terms in the covariance matrix are: historical volatility, implied volatility and GARCH-based volatility. Their relative
forecasting power has been compared in the fields of stock indices (Canina and Figlewski, 1993; Lamoureux and Lastrapes, 1993) and currency indices (Amin and Ng, 1997). Also there has been increasing interest in applying hybrid forecasting methods, which combine different forecasting methods together by weighted average or a simple regression model (Diebold and Lopez, 1998). One application of hybrid approaches to forecasting volatility of individual agricultural commodities has been conducted by Manfredo, Leuthold and Irwin (1999). However, applications to forecasting the joint distribution of agricultural commodities are limited (e.g. Baillie and Myers, 1991). Given that variance and covariance among these series are critical for forecasting net revenue, I explore several approaches to forecasting the variance structure of the three cash time series. Historical correlation and the best forecasted volatilities are used for forecasting covariance terms. Manfredo, Leuthold and Irwin (1999) examined the relative forecasting power of several forecasting methods including implied volatility, historical volatility and GARCH volatility for fed cattle, feeder cattle and corn. Using similar evaluation methods, I test the relative forecasting power of historical, implied and GARCH-based volatility for the price returns of hog, corn and soybean meal. The results show that implied volatility usually outperforms the other two forecasting methods for the near term forecasting and historical volatility does for longer term forecasting. It is common practice in the volatility forecasting literature to constrain the mean return of a series to be zero when developing volatility forecasts. I will do this for all the three forecasting methods and the realized volatility.

Historical volatility can be derived from the observed historical return series. It is defined as:
(3.7) \[ \hat{\sigma}_{t+1, i} = \sqrt{\frac{1}{T} \sum_{m=0}^{T-1} R_{t-m, i}^2} , \]

where \( \hat{\sigma}_{t+1, i} \) is the next period’s (weekly) volatility forecast for commodity \( i \); \( T \) is the number of past observations of the return series used in the calculation; and \( R_{t}^{2, i} \) is the square of realized return defined as in equation (3.5) at time \( t \) for commodity \( i \). To forecast the volatility for a horizon longer than one period, I multiply the forecast for time \( t+1 \) by the square root of the horizon, \( h \), i.e.

(3.8) \[ \hat{\sigma}_{t+h, i} = \hat{\sigma}_{t+1, i} \sqrt{h} . \]

Implied volatility is the annualized volatility derived from the futures price and options premium. Because it is the forecasted volatility based on all the currently available market information, it is widely believed to be superior to other alternatives. The use of implied volatility for commodity return series was first suggested by Black and Sholes (1973) and Black (1976). Drawn from these seminal works, the option pricing model for a futures contract is:

(3.9) \[ C = e^{-rT} [F_0 N(d1) - XN(d2)], \]
\[ P = e^{-rT} [XN(-d2) - F_0 N(-d1)], \]
\[ d1 = \frac{\ln(F_0/X) + IV^2 T / 2}{IV \sqrt{T}}, \]
\[ d2 = d1 - IV \sqrt{T} , \]

where \( C \) and \( P \) are the option premium for a call and a put option respectively; \( r \) is the risk-free interest rate; \( T \) is the time to expiration of the option; \( F_0 \) is the futures price; \( X \) is the strike price of the option; \( N(\cdot) \) is the cumulative probability distribution function for a standard normal distribution; \( IV \) is the implied volatility in annualized form. Numerical
methods are needed to solve equation (3.9) to get the implied volatility. Because I use weekly price of the three commodities, the volatility forecast for an $h$-week horizon is defined as:

\[ \hat{\sigma}_{t,h,i} = IV_{t,i,\frac{\sqrt{h}}{\sqrt{52}}}, \tag{3.10} \]

where $IV_{t,i}$ is the implied volatility at time $t$ for commodity $i$. All the options are written on the futures contracts. So the implied volatility is an exact measure of the volatility of futures price. However, as in Manfredo et al.’s paper, I use it as a proxy for the volatility of the cash price series.\(^6\)

GARCH-based volatility is another popular way to forecast the volatility of returns. Bollerslev (1986) first suggested GARCH (Generalized Autoregressive Conditional Heteroskedasticity model). Since then, there have been a large number of studies on financial data based on GARCH model (eg. Bollerslev et al. 1992). The GARCH (1, 1) model with a normal distribution has been the most frequently used model in financial data analysis; such a model is often favored over GARCH models with different orders, different distributional assumptions and other extensions. However, because of the seasonality observed in commodity return volatilities, I need to add in terms that can capture seasonality. Monthly dummy variables and a Fourier expansion proposed by Roberts (2000) are two available choices. The problem of using monthly dummy variables is that it causes a big jump of the volatility forecasting from the end of one month to the beginning of the following month. A Fourier expansion can cure this problem by smoothing the seasonality of volatility. So the GARCH (1, 1) model with Fourier expansion is defined as:
$$\sigma_{t,i}^2 = \alpha_0 + \alpha_i R_{t-1,i}^2 + \beta_i \sigma_{t-1,i}^2 + \sum_{m=1}^{M} [\phi_m \sin(2\pi m \tau) + \varphi_m \cos(2\pi m \tau)],$$

where $\sigma_{t,i}^2$ is the conditional variance at time $t$ for commodity $i$; $R_{t-1,i}$ is the return of commodity $i$; $\sigma_{t-1,i}^2$ is the variance at time $t-1$ for commodity $i$; $\tau (0 \leq \tau \leq 1)$ is the time of year of the observation. For example, $\tau$ is 2/52 for the observation of the second week of a year. $\sum_{m=1}^{M} [\phi_m \sin(2\pi m \tau) + \varphi_m \cos(2\pi m \tau)]$ is the Fourier expansion term. $\alpha_0, \alpha_i, \beta_i, \phi_m, \varphi_m$ are parameters estimated by maximum likelihood method. By fitting equation (3.11) to the dataset, $M$ is determined by likelihood ratio test. The results show $M=1$ best captures the seasonality of volatility for all the three commodities. So the model is simplified as:

$$\sigma_{t,i}^2 = \alpha_0 + \alpha_i R_{t-1,i}^2 + \beta_i \sigma_{t-1,i}^2 + \phi_1 \sin(2\pi \tau) + \varphi_1 \cos(2\pi \tau).$$

This is actually a GARCH (1,1) model with two independent variables in the variance equation. As what I did in estimating the historical volatility, the data used are from the beginning of our dataset, the first week of 1991, up to the start of the forecasting period. Following the method of Kroner, Kneafsey and Claessens (1994), I can get the volatility forecast for $h$ horizon by the square root of the sum of the $h$ conditional variances. Equation (3.13) shows the specific calculation process:

$$\sigma_{t+h,i}^2 = \alpha_0 + \alpha_i R_{t,i}^2 + \beta_i \sigma_{t,i}^2 + \phi_1 \sin(2\pi \tau) + \varphi_1 \cos(2\pi \tau) \quad \text{if } h=1,$$
$$\sigma_{t+h,i}^2 = \alpha_0 + (\alpha_i + \beta_i) \sigma_{t+h-1,i}^2 + \phi_1 \sin(2\pi \tau) + \varphi_1 \cos(2\pi \tau) \quad \text{if } h>1$$
$$\hat{\sigma}_{t,h,i} = \sqrt{\sum_{j=1}^{h} \hat{\sigma}_{t+j,i}^2}$$

To evaluate the three volatility-forecasting methods, I define the realized (ex post) volatility as:
where \( \sigma_{t, h, i} \) is the realized volatility from time \( t \) to \( t+h \) for commodity \( i \); \( R_{t,i} \) is the return of commodity \( i \).

The beginning of the forecasting period is the first Wednesday of 1993. I put the 104 observations of 1991 and 1992 as the base to generate initial forecasts. I choose seven different horizons, which are \( h=1, 2, 4, 8, 12, 26 \) and 52 weeks. At each week during 1993 to 2000, I make volatility forecasts by using the three alternative methods for each of the forecasting horizon. When this method causes autocorrelation of the volatility forecasts because of the overlapping forecasting periods, I use Harvey, Leybourne and Newbold test (HLN test, 1997) to cure it. In Manfredo’s study, they selected two non-overlapping periods. One advantage of my selection rule is I make the sample size as large as possible.

All the volatility forecasts for each horizon are ranked according to the size of the mean squared prediction error (MSPE); the HLN test is used to decide whether the MSPE of two methods are significantly different. The test statistic is defined as:

\[
(3.15) \quad S_1^* = \left[ \frac{n + 1 - 2h + n^{-1}h(h-1)}{n} \right]^{1/2} S_1
\]

where \( S_1 = \left[V(\bar{e})\right]^{-1/2} \bar{e} \), \( S_1^* \) is the HLN test statistic; \( n \) is the number of observations; \( h \) is the number of overlapping periods; \( \bar{e} \) is the sample mean of the difference and \( V(\bar{e}) \) is the asymptotic variance of \( \bar{e} \), which takes into account of the autocorrelation. \( S_1^* \) follows a Student’s t-distribution with \((n-1)\) degrees of freedom.
When $S$ exceeds the critical value, one forecasting method is superior to another. Table 3.1 through 3.3 show the empirical results of comparison of historical volatility, implied volatility and GARCH-based volatility for hogs, corn and soybean meal. Forecasting methods are ranked according to the size of MSPE and the HLN test has been carried out for each pair of forecasting methods.

From these tables, I confirm what Manfredo et al. found: the relative forecasting power of historical volatility, implied volatility and GARCH based volatility vary across horizons and commodities. Implied volatility seems to be the best in most of the cases. For soybean meal, implied volatility dominates the other two when the forecasting horizon is 1, 2 and 4 weeks and significantly outperforms rank 3 method when $h = 8, 12$ and 26. However, historical volatility dominates for $h = 52$. Things are similar to corn, implied volatility outperforms up to 26 weeks then historical volatility dominates. For hog, implied volatility weakly outperforms up to 8 weeks then GARCH-based volatility performs well for 12 and 26 weeks with very close implied volatility forecasts ranking as No. 2. Again, for 52 weeks, historical volatility dominates the other two methods. The reason for poor performance of implied volatility in long-term forecasting might be that far-from-maturity futures and options markets, especially hog futures and options market are very thin; so implied volatility does not fully incorporate all the market information. Another point worth noting is that by comparing the MSPE for each of the three commodities, we found that the hog returns volatility is the most difficult one to forecast, while that of corn can be forecasted the most accurately. In summary, implied volatility seems to be the best among these three methods for near and mid term forecasts up to a 26-week horizon and historical volatility dominates thereafter. Based on this conclusion,
I use implied volatility for all the three commodities as the variance forecasting method up to 6 months and historical volatility after that.

3.5. **Basis Forecasting.**

One key assumption for the net revenue forecasting model is the unbiasedness of hog futures market. When futures prices are used to forecast future cash prices, the question of basis has to be addressed. Basis is defined as the difference between the nearby futures price and the cash price. Particularly, I define it in this dissertation as

\[ B = P - F \]

where \( B \) is basis; \( P \) is cash price and \( F \) is the nearby futures price. There are several main factors causing and affecting basis. The first factor is that of time. Cash price is determined by the current demand and supply condition while futures price is determined by the expected demand and supply condition at the maturity date. Theoretically, as time approaches the futures expiration date, basis should decrease accordingly. Second, the futures price reflects the national market condition while the local cash price reflects the local market condition. A big change in local market may drive local cash price but have little impact on the national price. This is called location factor. The third one is that of product quality. The futures price stands for a specific quality of hog. Basis can reflect the expected discount or premium due to delivery of hogs with different quality.

The variation of basis is called basis risk. Compared to price risk, basis risk is usually less influential. Sometimes unexpected basis does cause a serious problem, which can hurt producers’ incomes and invalidate hedging efforts. So, getting an accurate out-of-sample forecast of basis is another key contribution of this net revenue
forecasting model. Many basis forecasting methods have been studied and their relative forecasting powers have been compared for agricultural commodities. These methods include using: current basis, last year's basis, historical average basis, the futures spread method, predictions from an economic structural model, predictions from a seasonal ARIMA (Autoregressive Integrated Moving Average) model, predictions from a neural network model and so on. Hauser et al. (1990) use the Theil coefficient as a comparison criterion for Illinois soybean basis forecasting and found the futures spread method outperforms alternatives for the post-harvest period. During other periods, a historical average seems to be the best. Garcia and Sanders (1996) compare an economic structural model, an ARIMA model and a three-year historical average model based on root mean squared error and Henriksson-Merton test for sign prediction for Omaha and Illinois live hog basis and found the first two generally outperform the last one. They also point out the live hog basis has strong seasonality, which is consistent with my data. But the data they use are monthly basis figures and they have not examined the basis forecasting based on lean hog futures. Jiang and Hayenga (1997) examine the alternative forecasting methods for corn and soybeans in several different markets. Their conclusion is that, based on RMSE, a three-year historical average, seasonal ARIMA (SARIMA) and three-year historical average plus current market information model are among the best and can compete with each other for short term forecasting for corn basis. For long term forecasting for corn basis, however, no method outperformed the three-year historical average. For soybean basis, a three-year historical average plus current market information model and a SARIMA generally outperformed three-year historical average. Dhuyvetter and Kastens (1998) found for Kansas crops such as corn and soybeans, a five
to seven year historical average was preferred and the futures spread model incorporating
current market information improves forecasting power for near term forecasting but not
for long term horizons. Kastens et al. (1998) also indicate that, for Kansas crops and
livestock, forecasting cash price by adding up deferred futures price and historical
average basis has the greatest accuracy. Kastens and Dhuyvetter (1999) use this method
to study the hedged grain storage decision and found hedging tends to decrease risk but
does not affect profit. Based on the results of these recent researches and data
availability, a three to five year historical average, futures spread model and seasonal
ARIMA are considered as possible candidates for basis forecasting in the Monte Carlo
simulation model.

The basis forecasting by \( n \)-year historical average can be defined as:

\[
\hat{B}_{i,T,n} = \frac{1}{n} \sum_{t=T-i}^{T-n} B_{i,t},
\]

where \( B \) is basis, \( i \) is the week of year, \( t \) and \( T \) are year and \( n \) is the number of years in the
historical average (\( n = 3, 4, \) or 5).

The potential advantage of futures spread model is that it incorporates current
market information because it is believed that the futures spread, which is the difference
between two futures contract with different expiration dates, reflects different market
expectations for commodity price at different date in the future. The basis forecasting
model is

\[
\hat{B}_{i+h} = (1 + ((F2_i - F1_i)/F1_i))^{h/w} C_i - F_{i+h}
\]

where \( B_{i+h} \) is the basis to be forecasted at week \( i \) and the forecasting horizon is \( h \); \( C_i \) is the
cash price at week \( i \); \( F1_i \) is the nearby futures price to week \( i \) and \( F2_i \) is the first deferred
futures price to week \( i \); \( w \) is the number of weeks between the nearby and first deferred
futures contracts to week \( i \); \( F_{i+h} \) is the nearby futures price to week \( i+h \). For example, assume the starting point of the forecasting period is the first week of a year and the forecasting horizon is 26 weeks, then the February and April hog futures contracts are the nearby and first deferred hog futures contracts to the first week of this year, respectively, and the July futures contract is the nearby futures contact to the end of the forecasting period, namely, the 27\(^{th}\) week of this year.

The general form of the seasonal ARIMA model SARIMA(p,d,q)(P,D,Q) is:

\[
(3.19) \quad \Phi_P(L^S) \phi_p(L)(1-L)^d (1-L)^D B_t = \Theta_Q(L^S) \theta_q(L)
\]

where \( L \) is the lag factor; \( S \) is the seasonal period (for weekly data it is 52); \( p, d, q \) are the orders of autoregressive, differencing and moving average terms respectively; \( P, D, Q \) are the orders of seasonal counterparts of \( p, d, q \); \( \Phi, \phi, \Theta, \) and \( \theta \) are the coefficients for seasonal autoregressive, regular autoregressive, seasonal moving average and regular moving average terms.

Since the dataset is from 1991 to 2000 and the methods involve five-year historical average, the forecasted period is from 1996 to 2000. Because corn basis experienced extreme patterns during 1996, 1996 corn basis is excluded when its historical average is calculated. The forecasting horizons \( h \) are 1, 2, 4, 8, 12, 26 and 52 weeks, which are consistent with the horizons in volatility forecasting. The specification of the seasonal ARIMA model is determined by the Akaike Information Criterion (AIC) and the model is re-specified each year. As shown in Figure 3.7, 3.8 and 3.9, Hog basis shows very strong seasonality and a 52-week seasonal term is included. Corn basis shows weak seasonality and soybean meal basis has little seasonal pattern, so a seasonal term is not included. The basic criterion for comparison of forecasting power of these methods is
still Mean Squared Error (MSE). The results are shown in table 3.4. This approach is limited to pair wise comparisons. A complementary method proposed by Kastens et al. (1998) is to collapse the information contained in a stack of forecasting error into a regression model where forecasting error is the dependent variable. The regression model is:

\[
(3.20) \quad RSE = \beta_0 + \beta_1 \cdot 3YAVE + \beta_2 \cdot 4YAVE + \beta_3 \cdot FS + \beta_4 \cdot SARIMA \\
+ \beta_5 \cdot FS \cdot H + \beta_6 \cdot SARIMA \cdot H + \beta_7 \cdot FS \cdot H^2 + \beta_8 \cdot SARIMA \cdot H^2 \\
+ \beta_9 \cdot Jan + \beta_{10} \cdot Feb + \ldots + \beta_{19} \cdot Nov
\]

where \(RSE\) is the stack of root squared error (same as absolute error) across methods and forecasting horizons; \(3YAVE, 4YAVE, FS\) and \(SARIMA\) are dummy variables correspond to three to four year historical average, futures spread and Seasonal ARIMA model. Five-year historical average is excluded from this model as a benchmark. \(H\) is the forecasting horizon. The second line of equation (3.20) includes the linear interaction and quadratic terms. Three to four year average is excluded because their forecasts do not change by horizon. \(Jan, Feb, \ldots\) and \(Nov\) are monthly dummy variables with December used as the benchmark. The results for this regression are shown in Table 3.5.

Another test performed is the timing test. The Henriksson-Merton (HM) timing test evaluates the ability to predict the sign of actual basis by a particular method (Breen et al. 1989). The test is to run the regression
\[(3.21) \quad DF_{t-i} = \alpha_i + \beta_i DA_t + \varepsilon_t\]

where \(DF_{t-i} = 1\) if a positive basis is forecasted for time \(t\) at time \(t-i\)

\[= 0 \text{ otherwise}\]

\(DA_t = 1\) if the actual basis is positive at time \(t\)

\[= 0 \text{ otherwise}\]

where \(\beta_i = 0\) is tested. \(\beta_i > 0\) indicates superior timing ability while \(\beta_i < 0\) means perverse timing ability and \((1+\beta_i)/2\) is the expected probability of correctly predicting the sign of the basis. The results for \((1+\beta_i)/2\) are shown in Table 3.6.

From Table 3.4 and 3.6, the MSE and timing of three to five year historical averages are constant across horizons because of the nature of these methods. The SARIMA model outperforms alternatives for near term forecasting but deteriorates fast as the horizon increases. The performance of the futures spread model is between SARIMA and the historical average for near term forecasting and also deteriorates as the time horizon increases, but not as fast as SARIMA. SARIMA marginally outperforms the futures spread method for very near term forecasts. Specifically, the five-year historical average is the best one among the three historical average models according to MSE and timing. For hogs, SARIMA outperforms the five-year historical average for one and two week horizons while the futures spread marginally outperforms the five-year historical average for the one-week horizon. For corn, both SARIMA and futures spread degenerate after the eight-week horizon compared to the five-year historical average while the SARIMA outperforms futures spread for one and two week horizons. For soybean meal, both SARIMA and futures spread degenerate after the 12-week horizon compared to the five-year historical average and SARIMA outperforms futures spread for
a one-week horizon. The deterioration of the SARIMA and futures spread models across forecasting horizon is further confirmed by the significant parameters in Table 3.5. It seems that the SARIMA for corn and both the SARIMA and the futures spread models for soybean meal are significantly better than the benchmark, five-year historical average by observing the model dummy variables only. But the forecasting time horizon also needs to be considered due to the interaction terms. All the linear interaction terms for the three commodities are positive and significant, which is to say SARIMA and futures spread degenerate as the forecasting horizon increases. Because SARIMA just outperforms the futures spread model for very near term forecasting and because SARIMA is the one with the highest computational cost among the alternatives, this method is dropped. The futures spread model, which incorporates current market information, is used for near term forecasting and the five-year historical average is used for longer term forecasting. The switches in forecasting methods occur at one week for hogs, eight weeks for corn and 12 weeks for soybean meal. To account for the uncertainty of basis, historical data is examined and, under most cases, the basis for the same time period in different years follows a normal distribution. The standard deviation of the normal distribution varies with the time of the year examined, which is consistent with seasonality of basis. Thus, it is assumed that, at any time within a year, the basis follows a normal distribution with a mean forecasted by the appropriate method (futures spread or five-year historical average) and variance forecasted by historical variance specific to the time of the year. Also, historical data show there is no statistically significant correlation among the level of basis for the three commodities; hence the basis correlation factors are set to zero.
Now that all the parameters including point estimation for all the three prices, volatility of the three prices, covariance among the three prices, point estimation for the three basis terms, variances of the three basis terms and covariance among the three basis terms have been forecasted by appropriate methods, random numbers following the joint distribution are repeatedly generated 3,000 times. Thus, 3,000 paths for each of hogs, corn and soybean meal cash prices are simulated. Both the marketing contract design and pricing in Chapter 4 and net revenue forecasting in Chapter 5 will be based on these 3,000 groups of simulated cash prices.
Figure 3.1: Live Hog Cash Price and Nearby Futures Price, 1991-2000.
Figure 3.2: Corn Cash Price and Nearby Futures Price, 1991-2000.
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Figure 3.3: Soybean Meal Cash Price and Nearby Futures Price, 1991-2000.
Figure 3.4: Live Hog Cash Price Volatility, 1991-2000.
Figure 3.5: Corn Cash Price Volatility, 1991-2000.
Figure 3.6: Soybean Meal Cash Price Volatility, 1991-2000.
Figure 3.7: Eastern Corn Belt Live Hog Nearby Basis, 1991-2000.
Figure 3.8: Toledo No.2 Yellow Corn Nearby Basis, 1991-2000.
Figure 3.9: Illinois 48 Percent Soybean Meal Nearby Basis, 1991-2000.
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<th>Rank</th>
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1 All MSPE are multiplied by 1,000.
* Rank 1 method is significantly superior to Rank 2 method.
* Rank 1 method is significantly superior to Rank 3 method.
** Rank 2 method is significantly superior to Rank 3 method.

Table 3.1: MSPE of Hog Cash Price Volatility.
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1 All MSPE are multiplied by 1,000.
# Rank 1 method is significantly superior to Rank 2 method.
* Rank 1 method is significantly superior to Rank 3 method.
** Rank 2 method is significantly superior to Rank 3 method.

Table 3.2: MSPE of Corn Cash Price Volatility.¹
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* All MSPE are multiplied by 1,000.
*° Rank 1 method is significantly superior to Rank 2 method.
* Rank 1 method is significantly superior to Rank 3 method.
*° Rank 2 method is significantly superior to Rank 3 method.

Table 3.3: MSPE of Soybean Meal Cash Price Volatility.
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<th>Futures Spread</th>
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<td>144.10</td>
<td>125.63</td>
<td>108.66</td>
<td>230.86</td>
<td>147.41</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3.4: Mean Squared Error by Alternative Basis Forecasting Methods for Hogs, Corn and Soybean Meal.
<table>
<thead>
<tr>
<th></th>
<th>Hog</th>
<th>Corn</th>
<th>Soybean Meal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>2.030* (12.62)</td>
<td>6.408* (4.17)</td>
<td>6.495* (10.02)</td>
</tr>
</tbody>
</table>

Forecasting Model Dummy Variables; Default is 5-year Historical Average.

<table>
<thead>
<tr>
<th></th>
<th>Hog</th>
<th>Corn</th>
<th>Soybean Meal</th>
</tr>
</thead>
<tbody>
<tr>
<td>3YAVE</td>
<td>0.113 (0.61)</td>
<td>1.006 (0.57)</td>
<td>1.453* (1.96)</td>
</tr>
<tr>
<td>4YAVE</td>
<td>0.058 (0.32)</td>
<td>0.066 (0.04)</td>
<td>0.543 (0.73)</td>
</tr>
<tr>
<td>SARIMA</td>
<td>-0.139 (-0.89)</td>
<td>-4.798* (-3.19)</td>
<td>-3.936* (-6.27)</td>
</tr>
<tr>
<td>FS</td>
<td>-0.026 (-0.16)</td>
<td>-2.875 (-1.91)</td>
<td>-3.277* (-5.22)</td>
</tr>
</tbody>
</table>

Forecasting Model and Horizon Interactions.

<table>
<thead>
<tr>
<th></th>
<th>Hog</th>
<th>Corn</th>
<th>Soybean Meal</th>
</tr>
</thead>
<tbody>
<tr>
<td>SARIMA*H</td>
<td>0.024* (2.37)</td>
<td>0.800* (8.31)</td>
<td>0.321* (7.71)</td>
</tr>
<tr>
<td>FS*H</td>
<td>0.132* (12.79)</td>
<td>0.338* (3.51)</td>
<td>0.250* (6.00)</td>
</tr>
<tr>
<td>SARIMA*H^2</td>
<td>-0.0003 (-1.55)</td>
<td>-0.008* (-4.74)</td>
<td>-0.005* (-5.72)</td>
</tr>
<tr>
<td>FS*H^2</td>
<td>-0.002* (-11.30)</td>
<td>-0.004* (-2.05)</td>
<td>-0.003* (-3.87)</td>
</tr>
</tbody>
</table>

Monthly Dummy Variables; Default is December.

<table>
<thead>
<tr>
<th></th>
<th>Hog</th>
<th>Corn</th>
<th>Soybean Meal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan</td>
<td>0.451* (2.97)</td>
<td>2.834* (2.03)</td>
<td>-0.563 (-0.92)</td>
</tr>
<tr>
<td>Feb</td>
<td>-0.526* (-3.47)</td>
<td>1.568 (1.12)</td>
<td>-1.026 (-1.68)</td>
</tr>
<tr>
<td>Mar</td>
<td>-0.186 (-1.26)</td>
<td>-0.756 (-0.55)</td>
<td>-1.841* (-3.10)</td>
</tr>
<tr>
<td>Apr</td>
<td>0.018 (0.12)</td>
<td>-1.299 (-0.97)</td>
<td>-2.301* (-3.95)</td>
</tr>
<tr>
<td>May</td>
<td>0.119 (0.81)</td>
<td>0.030 (0.02)</td>
<td>-1.988* (-3.36)</td>
</tr>
<tr>
<td>Jun</td>
<td>-0.795* (-5.46)</td>
<td>-1.884 (-1.38)</td>
<td>-1.248* (-2.13)</td>
</tr>
<tr>
<td>Jul</td>
<td>-1.022* (-7.26)</td>
<td>2.111 (1.58)</td>
<td>3.776* (6.65)</td>
</tr>
<tr>
<td>Aug</td>
<td>0.179 (1.22)</td>
<td>4.815* (3.45)</td>
<td>1.634* (2.75)</td>
</tr>
<tr>
<td>Sep</td>
<td>-0.325* (-2.27)</td>
<td>2.559 (1.91)</td>
<td>6.010* (10.45)</td>
</tr>
<tr>
<td>Oct</td>
<td>-0.547* (-3.82)</td>
<td>3.060* (2.24)</td>
<td>1.633* (2.84)</td>
</tr>
<tr>
<td>Nov</td>
<td>0.549* (3.73)</td>
<td>3.000* (2.15)</td>
<td>0.875 (1.47)</td>
</tr>
</tbody>
</table>

* Significant at 5 percent level. T-values are in brackets.

Table 3.5: Parameter Estimation for Determinants of Root Squared Error Associated with Alternative Basis Forecasting Models for Hogs, Corn and Soybean Meal.
<table>
<thead>
<tr>
<th>Commodity</th>
<th>Forecasting Horizon (Weeks)</th>
<th>3-Year Average</th>
<th>4-Year Average</th>
<th>5-Year Average</th>
<th>SARIMA Futures Spread</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hog</td>
<td>1</td>
<td>89.9</td>
<td>89.4</td>
<td>89.4</td>
<td>89.9</td>
</tr>
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<td>89.9</td>
<td>89.4</td>
<td>89.4</td>
<td>89.1</td>
</tr>
<tr>
<td>Corn</td>
<td>1</td>
<td>75.0</td>
<td>78.2</td>
<td>78.2</td>
<td>94.2</td>
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<tr>
<td></td>
<td>2</td>
<td>75.0</td>
<td>78.2</td>
<td>78.2</td>
<td>90.6</td>
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<td>75.0</td>
<td>78.2</td>
<td>78.2</td>
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<td>78.2</td>
<td>78.2</td>
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<tr>
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<td>12</td>
<td>75.0</td>
<td>78.2</td>
<td>78.2</td>
<td>71.8</td>
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<tr>
<td></td>
<td>26</td>
<td>75.0</td>
<td>78.2</td>
<td>78.2</td>
<td>54.5</td>
</tr>
<tr>
<td></td>
<td>52</td>
<td>75.0</td>
<td>78.2</td>
<td>78.2</td>
<td>41.7</td>
</tr>
<tr>
<td>Soybean Meal</td>
<td>1</td>
<td>64.4</td>
<td>68.3</td>
<td>81.3</td>
<td>92.8</td>
</tr>
<tr>
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<td>68.3</td>
<td>81.3</td>
<td>89.9</td>
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<td>81.3</td>
<td>72.7</td>
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<td>64.4</td>
<td>68.3</td>
<td>81.3</td>
<td>68.8</td>
</tr>
</tbody>
</table>

Table 3.6: Expected Probability (in Percentage) of Correctly Predicting the Sign of Basis by Alternative Forecasting Models For Hogs, Corn and Soybean Meal by Henriksson-Merton (HM) Timing Test.
CHAPTER 4

CONTRACT DESIGN AND PRICING

As mentioned in Chapter 2, marketing contracts are increasingly used as risk management tools. Among them, window contracts, floor contracts and hog revenue insurance are of current or emerging interest among hog producers and hog sector agribusinesses. In this chapter Monte Carlo techniques developed in Chapter 3 are used to derive contract parameters for two types of window contracts and this effort is related to existing work in the exotic options pricing literature.

4.1. Methodology.

The effectiveness of window and other marketing contracts rests upon their price and design, which must be desirable to both producers and packers. However, there is little published research concerning the structure of window contracts. Thus there are not many clear criteria for their pricing and design. Unterschultz et al. (1998) propose a promising approach for the pricing and design of one type of contract called a fixed window contract, which is to view a window contract from the producer’s perspective as a European option portfolio that is long in puts and short in calls. The long put strike price is the floor price and the short call strike price is the ceiling price of the window.
Then, by using standard option pricing theory, one can easily calculate the premium the producer pays for buying the put option and receives for selling the call option. The difference of the premiums is the final price of this window contract. However, in real life a window contract is designed such that the cost to enter into it is assumed to be zero. Furthermore, window contracts typically specify a minimum delivery amount and, hence, likely provide efficiencies to the issuer (usually a processor) with respect to production scheduling. The question becomes, given the premiums a producer pays and receives are equal, how to design the window contract, namely, how to determine the floor and ceiling price of the window contract. Unterschultz et al. proposed two methods: a confidence interval approach, in which the floor price is determined by the lower bound of the confidence interval of the futures price distribution, and a break-even approach, in which the projected break even price for hog finishing is used to determine the floor price and then the width of the window was altered to equate the premiums paid and received. To help readers fully understand their method, which forms the basis for the research in the remainder of this chapter, the payoff functions for the option portfolio are shown as follows:

\[(4.1) \quad \text{Payoff for long put: } VP(T) = \max(KP - PT, 0);\]

where \(VP(T)\) is the payoff of the long put at the expiration of the option; \(PT\) is the delivery price of hog at the expiration and \(KP\) is the strike price of this put option.

\[(4.2) \quad \text{Payoff for short call: } VC(T) = \min(KC - PT, 0);\]

Where \(VC(T)\) is the payoff of the short call at the expiration of the option and \(KC\) is the strike price of this call option. \(KP\) should be less than \(KC\). Otherwise; there will be an
inverse window, which is unrealistic. Figure 4.2 shows the payoff for long a put and short a call.

The combined payoff for the option portfolio is derived by adding equations (4.1) and (4.2) as in equation (4.3) and shown in Figure 4.3.

\[ V(T) = 0, \text{ when } KP \leq P_T \leq KC, \]
\[ KP - P_T, \text{ when } P_T < KP, \]
\[ KC - P_T, \text{ when } P_T > KC. \]

The cash position the producer takes is exactly \( P_T \) as shown in Figure 4.1. So the final payoff for a hog producer who enters a window contract is the combination of the payoff of cash and option positions, namely, the sum of \( P_T \) and \( V(T) \):

\[ V = P_T, \text{ when } KP \leq P_T \leq KC, \]
\[ KP, \text{ when } P_T < KP, \]
\[ KC, \text{ when } P_T > KC. \]

where \( V \) is the final payoff for entering a window contract; this is exactly same with the definition of a window contract. The final payoff for a hog producer is shown in Figure 4.4.

However, Unterschultz et al.’s paper only examines short-term window contracts that involve delivery of hogs at one point in time. Furthermore, in the real world, the floor and ceiling of the window contract must also be adjusted with a basis forecast to localize the contract. This study forwards the literature by addressing both these issues, i.e., by examining window contracts involving multiple deliveries of hogs over the period of one calendar year. While window contracts are often specified for durations longer
than one year, the current effort can help shift the focus from short-term contract design to a longer-term contract design.

Unterschultz et al.’s method forms the basis for the pricing and design of a window contract with fixed floors and ceilings (hereafter, fixed window contracts). But fixed window contracts are but one type of hog marketing contract. Many contracts specify a floor price as a moving average of input prices. For example, the floor price may be a linear function of the six-month moving average feed price and the ceiling price is the floor price plus a fixed number. Thus, this window contract can be viewed as a combination of a long European-type Asian-Basket put option and a short European-type Asian-Basket call option.

This study provides another contribution to the current literature by designing and pricing a multiple period moving window contract. This contract can be decomposed as a combination of multiple long European-type Asian-Basket put options and multiple short European-type Asian-Basket call options.

Risk management tools involving Asian-Basket options have emerged from the public sector during the past few years. For example, livestock revenue insurance, which resembles an Asian-Basket put option, was introduced by the U.S. Department of Agriculture’s Risk Management Agency in 2002. Hart, Babcock and Hayes (2001) evaluate the performance of several potential livestock revenue insurance contracts and find that they outperform or are competitive with alternative risk management tools. Revenue insurance programs involving exotic options have been introduced in crop sectors these past years and are well accepted. Having the “right” price for these insurance contracts is very important because it can help the writer of the contract avoid
being inadequately hedged against the risk they are assuming or from overpricing these contracts. Several studies have been done on how to determine the actuarially fair premium for these insurance programs. Turvey and Amanor-Boadu (1989) examine the premium for a farm income insurance policy by using a crop insurance type model with normal assumptions for income and a Black-Scholes option pricing type model with lognormal assumption and found the two methods give substantially different results. Kang and Brorsen (1995) treat the target price support program as a put option and use both a GARCH average-option pricing model and a Black average-option pricing model to calculate its premium. Stokes (2000) studies the premium for crop revenue coverage insurance. Because it is similar to an Asian put option, an Asian option pricing model is used to determine a lower bound for the premium. In a risk neutral world, this lower bound is also the actuarially fair premium. Hart et al. outline several structures for hog revenue insurance based on an Asian-basket put option. The actuarially fair premium for the policy is the price of the option. They use lognormal and inverse gamma approximations to price the Asian part and Monte Carlo simulation to price the basket part of the option.

Results indicate the Monte Carlo based method provides unbiased pricing of fixed and moving window hog finishing contracts of one-year duration over the 1991 to 2000 time period in a risk-neutral world. The moving window may be more attractive than a fixed window because it takes advantage of co-movement of commodity prices, reduces volatility of price paid by issuers and performs better cumulatively.
4.2. Asian-Basket Option Type Window Contracts.

The payoff of an Asian option depends on the average price of the underlying asset during a specified period. The payoff from an Asian call is max\[A-K, 0\] and that from an Asian put is max\[K-A, 0\], where \(A\) is the average value of the underlying asset calculated over a predetermined averaging period and \(K\) is the strike price defined prior to entry into the option contract. Another type of Asian option is an average strike, or floating strike option. The payoff from an average strike call is max \[P_T - A, 0\] and that from an average strike put is max \[A - P_T, 0\], where \(P_T\) is the price of underlying asset at delivery. An Asian option can also be classified by its time to maturity. If its time to maturity is greater than or equal to the length of averaging period, it is called a forward-starting or a plain-vanilla Asian option. Otherwise, it is called a backward-starting Asian option. The pricing of these two types of Asian options follows the same general framework with only a few differences. The advantages of Asian options are that, unlike regular European type options, they can protect the option holder from dramatic price changes at the delivery day and reduce the chance of market manipulation in a thinly traded market. Also, Asian options are usually less costly than European options because the volatility of average price is less than that of price at delivery (Kemna and Vorst, 1990). The regular European option is just a special case of an Asian option when there is only one set point at the expiration; hence the price of a European option gives an upper bound for the price of an Asian option. The average price \(A\) can be specified in two ways. One is a geometric average \((P_1*P_2...*P_T)^{1/T}\) and the other is an arithmetic average \((P_1+P_2.....+P_T)/T\). In the real world the arithmetic average is more prevalent.
and is the target we are studying. Geometric averages are often used as a tool to help price arithmetic average Asian options.

The payoff of a basket option depends on the value of a portfolio (or basket) of assets. For a hog finisher, the basket of interest includes three assets for which liquid futures markets exist: market hogs, corn and soybean meal. Basket options can reduce the cost for risk management compared to hedging each of the three assets separately because it can take advantage of the price co-movement of the three assets which, in the case of hogs and corn, often involve some elements of a natural hedge. A spread option is a special case of a basket option, which involves the difference of multiple asset values.

An Asian–basket option is a combination of an Asian option and a basket option. Its payoff at maturity depends on the average value of multiple assets. In the hog industry, the Asian-basket option type window contract is the most popular among all types of Asian-basket option type risk management tools.

The window contract to be designed will last for one year and requires the hog producer to deliver the same number of hogs each week to the contract issuer. Thus, the window contract can be decomposed into 52 sub-window contracts. For each sub-window contract, the floor price is defined as:

\[
floor_t = \alpha + \frac{\beta_1}{m} \sum_{j=t-m+1}^{t} P_{c,j} + \frac{\beta_2}{m} \sum_{j=t-m+1}^{t} P_{s,j},
\]

where \( \alpha, \beta_1, \) and \( \beta_2 \) are parameters to be determined; \( P_{c,j} \) and \( P_{s,j} \) are corn and soybean meal cash price respectively at time \( j \); and \( m \) is the number of weeks used in calculating corn and soybean meal moving average price. A
representative value of $m$ observed in sample hog contracts is eight. Thus, the ceiling price is:

\[(4.6) \quad ceiling_t = floor_t + \Delta\]

where $ceiling_t$ is the ceiling price at $t$th week and $\Delta$ is the width of the window. Note, $\Delta$ is a constant term to be calculated by the option pricing method. It does not change across the 52 weeks. The specification of this window contract involves average prices and multiple assets; hence the use of the term Asian-Basket type window contract.

Following Unterschultz et al.’s method, each of the 52 sub-window contracts can be decomposed as a long put option and a short call option. Then the entire window contract can be decomposed as 52 long Asian-Basket type put options and 52 short Asian-Basket type call options. If it is a zero cost contract at the entry point, the premiums paid for buying the 52 put options should be equal to the premiums received by selling the 52 call options. Equation (4.7) illustrates this relationship:

\[(4.7) \quad \sum_{t=1}^{52} \exp(-rt/52)E[\max(floor_t - p_{h,t},0)] = \sum_{t=1}^{52} \exp(-rt/52)E[\max(p_{h,t} - ceiling_t,0)]\]

where $r$ is the risk-free interest rate at the start of the contract ($r$ is assumed to be constant over the entire year); $E$ is the expectation operator; and $p_{h,t}$ denotes the hog cash price at time $t$. The left-hand side is the present value of premiums paid for buying the 52 put options and the right-hand side is that of the premiums received by selling the 52 call options.\(^7\)

Option pricing methods are needed to solve equation (4.7) for the width of the window, i.e., $\Delta$. Before that, the floor price must be specified, particularly the parameters
\(\alpha, \beta_1\) and \(\beta_2\) in equation (4.5). Unterschultz et al. proposed a confidence interval approach and a projected break-even approach to determine the floor price. Here the projected break-even method is followed. In the real world, hog production technology and, hence, production parameters can vary considerably across hog producers and the exact provision in the contract differs across packers and even across contracts from the same packer depending on when the contract was signed as the nature and terms of these contracts have evolved over time. Thus, this particular contract can be only viewed as an approximation to a real contract and our method is just a basis for the design and price of similar contracts. The benchmark production parameters are taken from the 1999 Ohio State University Extension Livestock Budgets. These benchmarks assume that a hog is marketed at 250 pounds and that it consumes 8.5 bushels of corn and 84 pounds of soybean meal during its growth from a 50-pound feeder pig. \(\beta_1\) and \(\beta_2\) can be determined by this benchmark technology. For example, if the price of live hogs is expressed in $/cwt, that of corn in $/bushel and that of soybean meal in $/ton, \(\beta_1 = 8.5/250*100 = 3.4\) and \(\beta_2 = 84/2000/250*100 = 0.0168\). \(\alpha\) denotes the costs other than feed costs and it is decomposed into two parts. The first part is the average feeder pig price for next 52 weeks. A simple linear model is used to forecast this average price:

\[
(4.8) \quad \bar{p}_{f,t} = \gamma_0 + \gamma_1 \bar{f}_{h,t} + \gamma_2 \bar{f}_{c,t} + \gamma_3 \bar{f}_{s,t} + \gamma_4 \sigma_{h,t} + \gamma_5 \sigma_{c,t} + \gamma_6 \sigma_{s,t}
\]

where \(\bar{p}_{f,t}\) is the 52 week average feeder pig price from time \(t\); \(\bar{f}_{h,t}, \bar{f}_{c,t}\) and \(\bar{f}_{s,t}\) are the average observed futures price for next year at time \(t\) for hog, corn and soybean meal respectively; \(\sigma_{h,t}, \sigma_{c,t}\) and \(\sigma_{s,t}\) are annualized implied volatilities calculated by the Black-Scholes formula at time \(t\) for hog, corn and soybean meal respectively; and \(\gamma_0\) to \(\gamma_6\) are
parameters to be estimated by applying standard regression techniques to historical data (Table 4.1). The projected feeder pig price varies each week because the observed futures prices and calculated implied volatilities change each week. The second, less volatile part of $\alpha$ represents costs other than the feed and the feeder pig. This part is fixed at 25 dollars per head, which is representative of costs provided by several land grant university livestock budgets.

Note that the regression results are only used to help determine the floor price to be used in the window contract and not to price the window contract directly. That is, rather than trying to predict the average cost of feeder pigs for the upcoming year, an arbitrary industry expected average could be put in its place with no impact on the efficiency of the contract pricing, which takes place in the next section. Hence, the results of the regression do not impact on the pricing efficiency achieved by the methods detailed in the next section.

4.3. Asian-Basket Option Pricing: Application of Monte Carlo Simulation.

To price the Asian-Basket window contract described above, a stochastic process for commodity prices needs to be assumed. Following Chapter 3, the process assumed here is a random walk with drift, which implies the commodity price follows a lognormal distribution. In the case of Asian options and basket options, however, it is impossible to find a closed-form solution for call or put premiums. This stems from the following statistical fact: when the price of the underlying asset is assumed to be log normally distributed, the arithmetic average will not have a lognormal distribution. Hence, closed-form solutions in the spirit of Black-Scholes are elusive.
To solve this problem, various methods have been used, including Monte Carlo simulation methods, partial differential equation methods and analytic approximations. Boyle (1977) introduced a Monte Carlo approach with a variance reduction technique to price options. Since then, Monte Carlo simulation has become a more popular approach to option pricing because of its flexibility to fit various complicated options and various assumed distributions and because of the recent improvement in computation speeds. Kemna and Vorst (1990) follow this way to price a geometric average option and almost any study proposing alternative solutions for arithmetic average option uses Monte Carlo simulation results as benchmark to evaluate the proposed method. In the agricultural risk management field, Stokes (2000) applies a Monte Carlo simulation method to set the lower bound for premiums for crop revenue coverage insurance, which can be viewed as an Asian put option.

Partial differential equation (PDE) techniques comprise another set of promising methods to price arithmetic average options. The PDE approach is a traditional way to understand options (Black and Scholes, 1973; Merton, 1973). Kemna and Vorst (1990) introduced a PDE with two state variables: the price of the underlying asset and the average price over the relevant time period. Alziary et al. (1997) propose a one-state-variable differential equation by using a change of numeraire; the solution of this PDE gives the price of an arithmetic average Asian option.

The third method is to establish an analytic approximation for the price of arithmetic average Asian options. Although the sum of log normally distributed variables does not follow a lognormal distribution, it may be approximated by some known distributions. Turnbull and Wakeman (1991) and Ritchken et al. (1993) both use an
Edgeworth series expansion to approximate this distribution by a lognormal distribution with the first two moments. Compared with Monte Carlo simulation, their results perform very well except for deep in-the-money call options. Levy (1992) follows the same approach to approximate the sum of lognormals with a lognormal distribution. He extends Turnbull and Wakeman’s method by a Wilkinson approximation to approximate the arithmetic density function. This method is easily implemented and its results are a bit more accurate than Turnbull and Wakeman’s. When annual volatility is higher than 20 percent, which often happens in commodity markets, the method does not perform very well. Curran (1992) has developed an approximation for Asian option pricing by a lognormal distribution conditional on the geometric average; the author claims this method outperforms the previous two. A recent development of Asian option pricing theory is introduced by Milevsky and Posner (1998). The infinite sum of correlated lognormal random variables is an inverse gamma distribution, under suitable parameter restrictions. Thus the finite sum of lognormal variables can be approximated by an inverse gamma distribution. They derived a closed-form analytic formula for an arithmetic Asian option. The cumulative density function of the gamma distribution plays the same role as that of the standard normal distribution in Black-Scholes formula. Compared to Monte Carlo simulation and other methods, it is faster, intuitively more understandable and at least as accurate.

For basket option pricing, Monte Carlo simulation is one possible method. A basket option is quite similar to an Asian option. With an Asian option, the sum is across time for one asset. With a basket option, the sum is at one date but across multiple assets.
So it is also natural to use the approximation approaches used for Asian options to price basket options (Stulz, 1999).

To price an Asian-basket option, as usual, Monte Carlo simulation is the first natural choice. One alternative is to use one of the approximation methods mentioned above to price the Asian part and use Monte Carlo simulation to price the basket part (Hart et al., 2001). The opposite way also holds. Another alternative is to use approximation methods on both parts.

Due to the complicated specification of the Asian-Basket window contract detailed in the previous section, and because of a desire to incorporate practical issues such as basis risk, Monte Carlo simulation methods are used to price these contracts. This first requires specification of the joint distribution of hog, corn and soybean meal cash and futures prices. Namely, the mean, volatility and correlation of the six price series must be articulated for a one-year time period.

Following the simulation method which has been introduced in chapter 3, I will use futures prices to make point estimation. Implied volatility and historical volatility are used as near term and long term volatility forecasts. The simulated futures prices must be adjusted by expected basis, and this adjustment should account for basis risk if it is to yield realistic cash price paths because the reference prices of the contract are defined as cash prices rather than futures prices. Following results in chapter 3, the futures spread model works best for near term basis point forecasting and the five-year historical average works best for longer term basis point forecasting. The switches in forecasting methods occur after one week for hogs, eight weeks for corn and twelve weeks for soybean meal. To account for the uncertainty of basis, basis can be randomly generated.
from a normal distribution with a mean forecasted by the appropriate method (futures spread or historical average) and variance forecasted by historical variance specific to the time of the year. The basis correlation factors are set to zero. This also follows the results in chapter 3.

Now that the method for determining all mean, variance, covariance and basis terms has been established, Monte Carlo simulation proceeds by repeatedly generating sequences of random numbers following the specified multivariate normal distribution to get the cash price paths for the three commodities. For each simulated time series, the payoff of the Asian-Basket call and put options are calculated and their respective means are denoted as the option premium. Thus, equation (4.7) is solved for $\Delta$, the width of the moving window, by searching over candidate values for $\Delta$ until the value that solves equation (4.7) for the given time period is found.


The Monte Carlo simulation model is applied to historical data to test the performance of the model. Unterschultz et al. indicate that one problem of setting the floor for a window contract at the projected breakeven level is that it can cause the window to become inverted, i.e., the efficient value for $\Delta$ to be negative. Here an inverted window means the call strike price is below the put strike price. This is caused when many of the futures prices are below the projected breakeven price. In such a case, the hog producer is projected to lose money under the contract. Whenever the pricing algorithm yields an inverted window, the floor is re-specified as 90 percent of the projected breakeven price, which avoids all instances of the inversion problem.
For each week from 1991 to 2000 the simulation model is used to price the moving window contract for the next 52 weeks using information that would have been available before the first week of the contract. In total 520 contracts are priced. The performance of each contract is then evaluated by comparing the issuer’s expenditures if an equal number of hogs were purchased each week under the contract to the issuer’s expenditures if the same hogs were purchased at prevailing cash prices (without the contract). In a risk neutral world with a correctly priced window contract average expenditures should be equal. Most contract issuers are meat packers. Compared to hog producers, they may have a greater ability to weather short-term price risk than individual hog producers. Thus, the assumption of risk-neutral contract issuer (or at least less risk averse than the hog producer) is a reasonable one. The assumption of risk neutrality is important for pricing these contracts because the volatility used in this model is not constant; it switches from implied volatility to historical volatility at the 26\textsuperscript{th} week. Furthermore, basis is built into the model and basis can not be hedged by any currently traded instrument on market. These two issues would mean the pricing of the contracts would not be independent of the degree of risk aversion if risk aversion existed.

To assist comparisons to the existing literature (Unterschultz \textit{et al}.) a fixed window is also priced using these methods. The floor of this fixed window is determined by equation (4.5) except the moving average corn and soybean meal cash prices are replaced by average corn and soybean meal futures prices observed at the beginning of the contract. Thus, the floor and ceiling will be a constant number across all the 52 weeks. The width of the 520 moving and fixed window contracts are depicted by Figure 4.5 and some descriptive statistics are shown in Table 4.2. The widths of the window
contracts priced by the model vary dramatically over time, which is consistent with Unterschultz et al.’s results.

The prices paid by the contract issuer under the moving window and fixed window are formally compared to the price paid to procure hogs at the prevailing cash market price, by testing if the expected value of the differences are zero. Specifically, define the difference as

\[(4.9a) \quad e_{mw,t} = \sum_{i=t+1}^{t+52} P_{mw,i} - \sum_{i=t+1}^{t+52} P_{c,i} \quad \text{and} \]

\[(4.9b) \quad e_{fw,t} = \sum_{i=t+1}^{t+52} P_{fw,i} - \sum_{i=t+1}^{t+52} P_{c,i} \]

where \(P_{mw,i}, P_{fw,i} \) and \(P_{c,i} \) are the prices paid for per hundred weight of live hog at time \(i \) under the moving window, fixed window and cash market procurement strategies, respectively; \(e_{mw,t} \) is the total difference of price paid between the moving window and the cash market procurement strategy for one entire year starting from time \(t \) and \(e_{fw,t} \) is the total difference of price paid between the fixed window and the cash market procurement strategy for one entire year starting from time \(t \). If all the observations of \(e_{mw,t} \) and \(e_{fw,t} \) in the sample were independent, the central limit theorem would hold and a simple t-test could be applied. Note, however, the individual observations are autocorrelated because, within \(e_{mw,t} \) and \(e_{fw,t} \), there exists an overlap of \(P_{mw,i}, P_{fw,i} \) and \(P_{c,i} \) up to 51 time periods. To solve this problem, the assumption is made that the autocorrelation disappears after 52 weeks and the Harvey, Leybourne and Newbold test (HLN test, 1997) introduced in chapter 3 is applied. The test statistic is defined as:

\[(4.10) \quad S_i^* = \left[ \frac{n + 1 - 2h + n^{-1}h(h-1)}{n} \right]^{1/2} S_i \]
where \( S_1^* = \left[ V(\bar{e}) \right]^{-1/2} \bar{e} \), \( S_1^* \) is the HLN test statistic; \( n \) is the number of observations; \( h \) is the number of overlapping periods which is 51 here; \( \bar{e} \) is the sample mean of the difference and \( V(\bar{e}) \) is the asymptotic variance of \( \bar{e} \), which takes into account of the autocorrelation over 51 weeks. \( S_1^* \) follows a Student’s t-distribution with \( (n-1) \) degrees of freedom. The test results and descriptive statistic are shown in Table 4.3.

Neither of the two HLN test statistics is significant though the HLN statistic for the moving window contract borders upon the significant region at the 10 percent level. Hence, neither the moving window nor the fixed window significantly outperforms or significantly under-performs the cash market procurement strategy at traditional levels of statistical significance. That is to say, in a risk-neutral world, the model “correctly” designs the moving and fixed window such that a risk-neutral issuer is indifferent between the contract and a cash market procurement strategy, or that the Monte Carlo methods can in practice efficiently price complex window contracts using the assumptions and parameterizations previously outlined. Note that, while the fixed window shows a smaller absolute level of bias than the moving window ($0.09/cwt vs. $0.17/cwt), the standard deviation of the realized bias is smaller for the moving window contract, which is not surprising as moving average terms exhibit less volatile movements than the individual terms that comprise the moving average. While the contracts appear unbiased, the pricing for any particular period can result in large losses or gains for the issuer. The maximum deviations from cash-only procurement for any given 52-week period are rather large and represent a magnitude that is approximately 20 percent as large as the average hog price over this time period.
Because the fixed and moving window contracts appear ‘correctly’ priced, it might be imagined that a risk neutral firm would be indifferent between sourcing market hogs from the cash market, from a fixed window contract or from a moving window contract. That is, on average the price of procurement over the year that the contract covers will be no different across the methods investigated; however, the deviation in procurement price for any given period between a window contract and the cash market may be substantial. Furthermore, the deviation between a particular window contract and the cash market may be correlated over time. While this autocorrelation was accounted for in the statistical tests discussed above, there exists a separate issue concerning autocorrelation of relative procurement prices. Specifically, a run of ‘bad luck’ in signing contracts, i.e., paying contract prices above cash market prices, might cause the issuing firm to accumulate a level of debt that causes the firm to endure financial stress (e.g., require restructuring of debt and perhaps a higher cost of capital) or even firm failure.

Hence, while the tests above confirm that a risk neutral firm might indeed be indifferent among these three methods for the next year’s procurement of market hogs, it may hold preferences over the three methods if it intends to use one method over longer periods of time. To analyze this issue the cumulative deviations in procurement costs under both fixed and moving window contracts relative to cash market procurement costs are presented in Figure 4.6. Analysis is conducted for relative differences between window and cash procurement costs because the processing sector is generally considered a margin business, i.e., hog processors receive a flat margin for the service of procuring and processing hogs into pork products. Because this margin is generally
based upon the going cash market price, the biggest threat facing a processing firm would be if contract procurement prices were greater than cash market procurement costs for an extended period of time.

The dollar figures in Figure 4.6 are calculated under the following assumptions. I assume the firm slaughters 50,000 hogs per week and calculate the cost of hog procurement under fixed window contracts, moving window contracts and cash market procurement. The cost of procurement under a contract for any given week is calculated as follows. First, I assume that 1/52 of the hogs (about 1.9 percent or 961 hogs) are delivered under the specifications of a contract issued 52 weeks ago, another 1/52 of the hogs are delivered under the specification of a contract issued 51 weeks ago, and so on. So the firm may be paying 52 distinct prices for the hogs it procures in any given week, which is similar to saying the firms are paying a 52-week moving average of the conditional contract prices. The pricing parameters of each contract are those that were determined using the Monte Carlo methods described earlier in the chapter. The prevailing cash market price is then subtracted from this contract price for both fixed and moving window contracts. The cumulative sum of this difference is displayed in Figure 4.6.

Inspection of Figure 4.6 leads us to conclude that fixed window contracts may be more likely than moving window contracts to cause a firm to encounter financial stress if they are the contract is the sole means of hog procurement. Indeed, the moving window contract’s cumulative deviation lies below that of the fixed window contract for nearly the entire nine year period, which is more desirable from the issuer’s point of view. Particularly, after the historically low prices of 1998 and 1999, the cost of procurement
under both contracts is significantly higher than procurement from the cash market because the futures market, which was used to calibrate contracts signed before the price crash, did not predict the future collapse in prices and left contract prices significantly higher than cash prices. The relative disadvantage of contract procurement versus cash procurement, however, dissipated more rapidly if a moving window contract was employed than if a fixed window contract was used. This stems from the flexibility built into the specifications of the moving window contract; i.e., the contract can gradually lower the absolute level of prices paid to procure hogs in response to changes in price levels during the course of the contract. On the other hand, the fixed window has no such flexibility; once the window is set it remains as initially proscribed regardless of changes in market prices during the duration of the contract term.

This suggests that while firms may be indifferent between the two types of contracts for procuring hogs over the next 12 months, firms may not be indifferent between the two types of contracts if accumulated debt from high procurement costs over the course of several years could cause financial hardships. In such a case this analysis suggests that moving window contracts might be preferred. An alternative way to deal with this problem, however, would be to require a ledger account for fixed window contracts. Ledger provisions require that an account be maintained and that each time the price falls below (above) the window, the processors ledger account be credited (debited) with the balance of the account to be cleared at the end of the contract through cash transfer between the parties. Indeed, a small percentage of contracts have such provisions, though it is not as prevalent as one might expect. Alternatively, firms may
use a portfolio approach and chose to procure hogs under a variety of different contractual forms and under cash procurement to avoid such risk.

4.5. Results and Extensions.

Window contracts are an increasingly used risk management tool in U.S. hog sector. Because the payoffs of Asian-Basket type moving window contracts depend upon moving average prices rather than single period prices, the distribution of payoffs exhibits less volatility than a fixed window contract and, hence may be more attractive. However, designing and pricing moving window contracts is quite challenging because of the complex nature of price relationships. A Monte Carlo simulation model is used to price and design both moving and fixed window contracts. These methods provide unbiased pricing of fixed and moving window hog finishing contracts of one-year duration over the 1991 to 2000 time period. From the risk-neutral contract issuer’s perspective, the contract pricing is unbiased in that the average cost of hog procurement through the spot market was not significantly different than the cost of procurement via contracts for the duration of the year-long contract. The contract issuer could benefit from these contracts for reasons other than price, however. For example, the contract may specify a quality of delivered hogs or a delivery schedule that might be unobtainable from the spot market on a regular basis. Hog producers, who may have greater risk aversion than contract issuers, may benefit from such contracts because they limit price risk and provide a guaranteed market outlet for finished hogs. These additional benefits may suggest that observed window contract prices would not match risk-neutral prices. However, deriving the exact pricing implications of these additional benefits would
require comparing the risk-neutral price of window contracts to the contract prices revealed in real markets; such analysis is beyond the scope of the current study but should be the subject of future research.

The specification of the floor of the moving window remains a critical issue. When hog futures prices are quite low and the floor is specified as the breakeven price of hog production, the risk-neutral window tends to be inverted. In this chapter the floor is reduced to 90 percent of the projected breakeven in such cases and all instances of inverted windows are avoided. On the other hand, when hog futures prices are quite high, the floor seems to be too low, which causes the width of the window to be greater than window widths observed in real hog window contracts. For example, sample hog contracts mentioned in the agricultural press or posted on the Iowa Attorney General’s web page seldom have windows with width above $20/cwt on a live weight basis. However, Table 4.2 shows that about 15 percent of the moving windows and 18 percent of the fixed windows priced in this study have a width larger than $20/cwt. This also causes the problem that the cash price seldom hits the floor or ceiling of the window. Thus, the window seems not to play its risk management role to hog producers. One likely reason for this departure from observed window widths is that most observed contracts have durations of several years while those priced in this dissertation are of a single year in duration. Hence, one-year contracts priced at the top of a hog cycle may feature a very wide window because hog futures prices are quite high. If the contract were written for a longer duration, and hence included years projected to be in the downturn phase of a hog cycle, the optimal window width would probably be narrower. This leads to area of great importance for future research: the pricing of complex
contracts written for durations that include years for which no futures markets contracts are currently traded. While the futures-calibrated methods used in this study would still be applicable for simulating the early portion of longer contracts, other methods, e.g., forecasts from structural models calibrated with historical data or contingent window updating based on past market performance, appear to be the only alternative for pricing longer-run contracts.

Finally, to reduce the computational costs needed to design the Asian–Basket type moving window contract, analytical approximation might be an alternative to Monte Carlo simulation. Though the literature has proposed several approaches, it is not an easy task to price such a complicated contract solely by analytic approximation. Also, given the recent advances of the speed of computation and the lack of generalizability of many of the more complex contracts, the long-term efficacy of developing analytical pricing approximation techniques must be questioned.
Figure 4.1: The Payoff for Cash Position.

Figure 4.2: The Payoff for Long a Put and Short a Call Option.
The dashed line shows the payoff if both parties share 50 percent of price risk outside of the window.

Figure 4.3: Combined Payoff for Put and Call Options.
The bold solid line is the payoff for the window contract without risk sharing; the bold dashed line is the payoff of the window contract with 50 percent risk sharing.

**Figure 4.4: The Payoff to a Producer Entering a Window Contract.**
Figure 4.5: Fixed and Moving Window Width Determined by Simulation Model, 1991-2000.
* Cumulative difference in hog procurement costs between using a window contract and cash market procurement for a processing plant with a weekly capacity of 50,000 hogs. Assumes plant issued one-year window contracts and that an equal number of hogs were placed under contract during each week over the entire period.

**Figure 4.6:** Cumulative Difference in Procurement Costs: Window Contracts vs. Cash.
### Table 4.1: Regression Results: Feeder Pig Price Equation.

<table>
<thead>
<tr>
<th>$\gamma_0$</th>
<th>$\gamma_1$</th>
<th>$\gamma_2$</th>
<th>$\gamma_3$</th>
<th>$\Gamma_4$</th>
<th>$\gamma_5$</th>
<th>$\gamma_6$</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>-1.87</td>
<td>77.86*</td>
<td>-12.00*</td>
<td>0.07*</td>
<td>32.20*</td>
<td>24.97*</td>
<td>-17.67*</td>
<td>0.44</td>
</tr>
<tr>
<td>(2.94)</td>
<td>(6.04)</td>
<td>(1.06)</td>
<td>(0.02)</td>
<td>(4.28)</td>
<td>(6.30)</td>
<td>(5.91)</td>
<td></td>
</tr>
</tbody>
</table>

*Significant at 5 percent level. Standard errors are in parentheses.

### Table 4.2: Descriptive Statistics for Fixed and Moving Window Widths.

<table>
<thead>
<tr>
<th></th>
<th>Moving Window</th>
<th>Fixed Window</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average ($/cwt*)</td>
<td>13.40</td>
<td>13.91</td>
</tr>
<tr>
<td>Std. Dev. ($/cwt)</td>
<td>5.47</td>
<td>5.82</td>
</tr>
<tr>
<td>Min ($/cwt)</td>
<td>0.89</td>
<td>1.11</td>
</tr>
<tr>
<td>Max ($/cwt)</td>
<td>25.46</td>
<td>26.34</td>
</tr>
<tr>
<td>Percentage of Windows Wider Than $20 / cwt</td>
<td>15.23</td>
<td>17.97</td>
</tr>
<tr>
<td>Percentage of Windows Narrower Than $5 / cwt</td>
<td>6.05</td>
<td>6.84</td>
</tr>
</tbody>
</table>

*Cwt is hundredweight of live hog.
<table>
<thead>
<tr>
<th></th>
<th>$e_{mw,t}$</th>
<th>$e_{fw,t}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>$0.17 / \text{cwt}^*$</td>
<td>$0.09 / \text{cwt}$</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>$1.97 / \text{cwt}$</td>
<td>$2.49 / \text{cwt}$</td>
</tr>
<tr>
<td>Max</td>
<td>$5.36 / \text{cwt}$</td>
<td>$6.76 / \text{cwt}$</td>
</tr>
<tr>
<td>Min</td>
<td>$-6.73 / \text{cwt}$</td>
<td>$-8.32 / \text{cwt}$</td>
</tr>
<tr>
<td>HLN Test</td>
<td>1.66 (0.10)</td>
<td>0.72 (0.47)</td>
</tr>
</tbody>
</table>

*Cwt is hundredweight of live hog. P-values are in parentheses.

Table 4.3: Descriptive Statistic and HLN Test Results for Difference between Prices Paid under Moving Window, Fixed Window and Cash Market Procurement Strategy.
CHAPTER 5

NET REVENUE FORECASTS AND PROSPECTIVE EVALUATION

5.1. Net Revenue Forecasting.

The previous chapter focused on specifying the parameters of a marketing contract such that a risk neutral contract issuer would be indifferent between procuring hogs using the contract or via the cash spot market. In this chapter the same type of computational effort is harnessed to look at this issue from the point of view of the hog producer. That is, the hog producer may have several different methods available to market hogs and would like guidance as to the method or methods that would best meet profit and risk goals.

To forecast net revenue for hog producers under various marketing strategies, I apply the Monte Carlo simulation methods developed in chapter 3 to simulate a hog producer’s net revenue as defined by equation (2.2) and as parameterized by equation (2.3). Specifically, when I want to forecast the net revenue for the next $T$ periods, I generate $N$ groups of random numbers, which allow for the simulation of $N$ joint price series from which net revenue can be calculated. Each series contains three individual price series, thus I can calculate the net revenue by equation (2.2) for each of the $N$
draws. Simple summary statistics can then be used to characterize the distribution of
forecasted net revenue figures.

Again, as in Chapter 4, I choose each week from 1991 to 2000 as the starting
point of a 52-week forecasting period and forecast the net revenue for a hypothetical
Eastern Corn Belt hog producer who sells one hog and buys enough feeds for finishing
one hog each week. The sample size is 520 and the number of Monte Carlo simulation
trials (N) is 3,000 per period. As an illustrative example, the forecasted mean, standard
deviation and value at risk starting from the last week of 2000 is shown in Figure 5.1 and
Table 5.1 for the case where no risk management strategy is used (cash only strategy).
Value at Risk is defined as the maximum net revenue the hog producer will receive for a
particular probability and it is a key method for comparing alternative risk management
strategies. For example, Table 5.1 shows that the producer has a 35 percent chance of
earning a net revenue less than or equal to 34.52 $/cwt during next 52 weeks under this
particular marketing plan. We can see from the distribution that it is slightly skewed to
the right. The realized net revenue falls in the 95 percent prediction interval and the
interval one standard deviation away from the mean.

Summarizing all 520 cases for the cash only strategy, in 433 out of the 520 cases
(84.4 percent of the cases), the realized net revenue falls in the interval one standard
deviation from the mean. Only once did the realized net revenue falls out of the 95
percent prediction interval; in that case, the realized net revenue is lower than the lower
bound of the 95 percent prediction interval. This case occurred for a forecasting period
beginning in June of 1998; hog prices experienced a dramatic, unexpected drop in the
second half of 1998. In 226 cases (44.1 percent) the model overestimates the realized
value and in the other 294 times (55.9 percent) it underestimates the realized net revenue. On average, the model underestimates actual net revenue by 2.8 percent.

5.2. Prospective vs. Retrospective Evaluation.

In the hog industry, the prevalent way of evaluating risk management strategies is to use retrospective evaluation in which the historical performance of several strategies are examined over a sufficiently long time period (e.g., Zanini and Garcia, 1995; Lawrence and Wang, 1997; Lawrence and Vontalge, 2000). For example, Lawrence and Vontalge (2000) used this method to evaluate several risk management tools and packer contracts and found none of them can consistently outperform the benchmark cash strategy in terms of net returns (though, for pure risk reduction purposes, several tools and contracts are preferred). This is consistent with the efficient market hypothesis.

Retrospective evaluation methods do not take advantage of all the available information contained in futures prices and option premiums and potentially suffer the fate that undoubtedly lead to the ubiquitous disclaimers in investment commercials: Past performance does not guarantee future results. Prospective evaluation methods, such as the one proposed in this study, fully utilize all the market information and, thus, may provide more informed forecasts for hog producers choosing among risk management strategies. Interest in prospective (ex ante) assessment techniques is growing in other areas of commodity agriculture (e.g., Schnitkey and Miranda, 1998). I conduct prospective assessments of risk management strategies based on the net revenue forecasting model and explore the effect of typical risk management strategies on a producer’s net revenue over a twelve-month period.
To make a comparison between retrospective and prospective evaluation, I assume two different objective functions for hog producers. First is that of net revenue maximization. Second, following Garcia, Adam and Hauser (1994), I assume a simple mean-variance utility function and the objective of hog producers is to maximize utility. The mean-variance utility function is assumed as:

\begin{equation}
E[U(E(\tilde{R}), \sigma)] = E(\tilde{R}) - \frac{1}{2} A \sigma^2,
\end{equation}

where $E$ denotes the expectation; $U$ is the utility; $\tilde{R}$ is the net revenue; $\sigma$ is the standard deviation of the net revenue and $A$ is the risk aversion coefficient. I assume the hog producer is moderately risk averse and assign $A$ to be 0.01.

Under the objective of net revenue maximization, for retrospective evaluation, at the beginning of each forecasting period the producer observes the past performance of the alternative risk management strategies including the cash only strategy and various window contracts and calculates the average net revenue for all the past 52-week periods under these strategies for a given period of time. The producer chooses the risk management strategy which gives him/her the highest historical average net revenue over that period. Because prices fluctuate in a cyclical pattern that tends to repeat itself about every four years, which is typically referred to as a hog cycle, the historic period over which strategies are evaluated will be four years and the 1991-1994 data will be used as an initial base for making decisions. So the decision made under retrospective evaluation will start from the first week of 1995. Thus the hog producer needs to make decisions each week from 1995 to 2000; there will be a total of 312 decisions for this hog producer to make. For prospective evaluation, I forecast the mean of the net revenue under all of
these alternatives and the hog producer, who faces the same 312 decisions points, chooses the strategy that maximizes net revenue. After choosing the strategy predicted as optimal by the retrospective and prospective rules respectively, an ex post comparison of retrospective and prospective evaluation is made relative to blindly employing a cash only strategy. That is, I examine whether employing each rule yields the higher realized net revenue and lower volatility than would simply buying and selling under a cash-only strategy every period.

Under the objective of utility maximization, for retrospective evaluation, at the beginning of each forecasting period the producer observes the past performance of the alternative risk management strategies and calculates the mean and variance of the net revenue for all the past 52-week periods under these strategies for a given period of time. The producer chooses the risk management strategy that yields the highest utility calculated by equation (5.1) over that period. As in the net revenue maximization case, the 1991-1994 data will be used as an initial base for making decisions; hence, decisions made under retrospective evaluation will start from the first week of 1995. Thus the hog producer needs to make decisions each week from 1995 to 2000 and totally there will be 312 decisions for this hog producer to make. For prospective evaluation, I forecast the mean and variance of the net revenue under all of these alternatives and the hog producer’s choice is based on the same utility function (5.1). After choosing the strategy predicted as optimal by the retrospective and prospective rules respectively, an ex post comparison of retrospective and prospective evaluation is made relative to blindly employing a cash only strategy. That is, we examine whether employing each rule yields
the higher realized net revenue and lower volatility than would simply buying and selling under a cash-only strategy every period.

To conduct the comparison between retrospective and prospective evaluation, the hypothetical hog producer will face four different choice sets. The first choice set includes three choices: cash only strategy, a fairly priced fixed window and a fairly priced moving window. The second choice set includes five choices: cash only strategy, a fairly priced fixed window, a fairly priced moving window, an unfairly priced fixed window and an unfairly priced moving window. The third choice set is composed of three choices: cash only strategy, a fairly priced fixed window and an unfairly priced moving window contract. The fourth choice set is also composed of three choices: cash only strategy, an unfairly priced fixed window and a fairly priced moving window contract. A fairly priced contract is defined as one with parameters specified using the Monte Carlo pricing methods developed in Chapter 4. That is, a fairly priced contract has its parameters chosen such that a risk neutral contract issuer would be indifferent between issuing the contract and procuring hogs on the cash market. An unfairly priced contract is one in which the parameters are chosen to be unfair to the issuer or, in other words, advantageous to the hog producer. In general ‘unfair’ contracts are priced such that hog producers would, on average, expect to gain net revenue that is greater than a fairly priced contract. For simplicity, there is no risk sharing and no ledger account associated with these contracts.

More specifically, in the first choice set, the hog producer needs to choose among the cash only strategy, a fixed window and a moving window contract which are
efficiently or fairly priced and designed in Chapter 4. When a hog producer faces this choice set, he/she makes decisions by both retrospective and prospective evaluation.

In the second choice set, the hog producer needs to choose among the three strategies in choice set 1, plus an unfair fixed and an unfair moving window contract whose floor prices are two percent lower and ceiling prices are five percent higher than those of the fair fixed and moving window designed in Chapter 4.

The comparisons of retrospective and prospective rules by using cash only strategy for all periods as the benchmark under the objective of net revenue and utility maximization are shown in Table 5.2 and 5.3 respectively. It can be seen from these tables that, when the hog producer faces choice set 1, which is composed of the cash only strategy, fair fixed window and fair moving window, the prospective evaluation is marginally better than retrospective evaluation in terms of revenue enhancement and volatility reduction under the objective of both net revenue and utility maximization.

Because the 312 decision periods overlap, again, the HLN test (Harvey, Leybourne and Newbold, 1997) is used to see if the net revenue enhancement is significant. The results show that net revenues gained following either the prospective or the retrospective evaluation method are not statistically different from net revenues gained by blindly following a cash only strategy. This confirms the fairness of the fixed and moving window and is an additional piece of evidence for efficient market hypothesis.

To sharpen the comparison of the prospective vs. retrospective evaluation methods, Table 5.4 (Table 5.5) reports a head-to-head comparison of net revenues (utility) gained using the prospective and retrospective evaluation methods; again, the
issue of autocorrelation between returns in adjacent periods is controlled for by employing the HLN test. Realized net revenue and utility are not significantly different for prospective and retrospective evaluation methods for choice set 1.

When the hog producer faces choice set 2, which has five alternatives in it, choosing the marketing strategy based on both the retrospective and prospective evaluations allows the hog producer outperform the pure cash strategy by more than 1 percent each period on average; the HLN test results show both figures are significant (Tables 5.2 and 5.3). This is mostly because both retrospective and prospective advice allowed the producer to make the more profitable marketing decision before entering the periods with dramatic hog price drops. For example, both strategies guided producers to choose the window contract during the second half of 1998, in which the realized net revenue under the any of the four window contract is at least 30 percent higher than under the cash strategy. It might seem strange that the retrospective method could identify such a period of ‘unexpected’ low prices. However, the observed pattern in 1998 was merely an extremely exaggerated example of a typical, seasonal downturn in prices, and retrospective evaluations can easily identify such typical seasonal downturns. However, in the head-to-head comparison of the two methods (Tables 5.4 and 5.5), there is no significant advantage to employing prospective evaluation rather than retrospective evaluation in terms of net revenue or utility.

It seems that in choice set 2 both retrospective and prospective methods can create a money machine. A money machine stands for an arbitrage opportunity which can increase returns and reduce risk over cash only strategy at the same time by using the instrument. But keep in mind that there are two unfairly priced contracts in this choice
set. Hence this ability to create wealth only exists if a contract is designed in such an inefficient way that it systematically outperforms or underperforms the cash only benchmark. I need to further test whether the retrospective or prospective method has a stronger ability to identify such unfair contracts. To this end, I introduce the third and fourth choice sets. Each choice set involves three marketing strategies and one of them is a contract that is intentionally designed as biased.

In the third choice set, the hog producer needs to choose among (1) the cash only strategy, (2) an unfairly designed fixed window contract whose floor price is 5 percent higher than the fair fixed window designed in Chapter 4 and whose width is exactly same as the fixed window width solved in Chapter 4 and (3) a moving window contract which is efficiently or fairly priced and designed in Chapter 4. In the fourth choice set, the hog producer needs to choose among (1) the cash only strategy, (2) a fair fixed window contract that is efficiently designed in Chapter 4 and (3) an unfairly designed moving window contract whose floor price is 5 percent higher than the fair moving window designed in Chapter 4 and whose width is exactly same as the moving window width solved in Chapter 4. By design, the unfair fixed window contract in the third choice set and the unfair moving window contract in the fourth choice set will outperform the other two alternatives in their choice set respectively. I need to examine for these two choice sets whether the retrospective or prospective method has a better chance to help the hog producer choose the unfair window contract that is advantageous to the producer. These results are also contained in Tables 5.2 to 5.5. Basically, prospective and retrospective evaluations are very close in terms of net revenue enhancement, volatility reduction and the ability to identify the advantageous contracts. In choice set 3, under head-to-head
comparisons and utility maximization (Table 5.5), prospective evaluation outperforms retrospective evaluation in terms of its ability to identify the advantageous contract. In head-to-head comparisons of the two methods for choice set 4, the realized levels of net revenue under net revenue maximization (Table 5.4) and utility maximization (Table 5.5) are almost identical and, statistically, not different from one another.

Though prospective evaluation seems to only marginally outperform retrospective evaluation, the main advantage of prospective evaluation probably lies with its improved ability to forecast near-term volatility. Recall near term volatility in the prospective evaluation utilizes implied volatility while retrospective evaluation, by definition, relies upon historical volatility for all forecasting horizons. Recall from Chapter 3 that the forecasting ability of implied volatility was better than historical volatility in the near term. For a net revenue maximizer, the improvement in volatility forecasting is not critical because volatility does not play a role in the objective function. But for a risk-averse utility maximizer, the improved volatility forecasts can help hog producers who worry about higher moments of the distribution make risk management decisions that improve utility.

In summary, because the prospective method incorporates all contemporary market information and the retrospective method does not, and because prospective method uses better forecasts of near-term volatility than does the retrospective method, the former is preferred on informational efficiency and forecasting accuracy grounds. Empirical results show the prospective method performs marginally better than the retrospective method. Though the improvement in performance is statistically significant in only one of the eight cases investigated, prospective evaluation can compete with the
widely used retrospective evaluation in hog industry and any further forecasting improvements that become available through other advancements in the forecasting profession can be built into this model and can yield additional advantages over retrospective evaluation.
Figure 5.1: The Distribution of Forecasted Net Revenue for a 52-week Period Starting from the Last Week of 2000.
<table>
<thead>
<tr>
<th>Realized Net Revenue ($/cwt*)</th>
<th>Forecasted Net Revenue ($/cwt)</th>
<th>Standard Deviation ($/cwt)</th>
<th>95 percent Prediction Interval ($/cwt)</th>
<th>Value at Risk ($/cwt)</th>
</tr>
</thead>
<tbody>
<tr>
<td>33.80</td>
<td>36.93</td>
<td>5.01</td>
<td>(28.31, 47.34)</td>
<td>5 percent, 29.38</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>20 percent, 32.73</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>35 percent, 34.52</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>50 percent, 36.44</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>65 percent, 38.74</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>80 percent, 41.23</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>95 percent, 45.88</td>
<td></td>
</tr>
</tbody>
</table>

*Cwt is hundredweight of live hog.

Table 5.1: The Forecasted Mean, Standard Deviation and Value at Risk for a 52-Week Period Starting from the Last Week of 2000.
<table>
<thead>
<tr>
<th>Choice Set</th>
<th>Rule</th>
<th>Average Gain Over Benchmark</th>
<th>Volatility Reduction Over Benchmark</th>
<th>Times Choosing Net Revenue Maximizing Strategy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Prospective</td>
<td>0.6 percent (1.41)</td>
<td>13.9 percent</td>
<td>39.7 percent</td>
</tr>
<tr>
<td></td>
<td>Retrospective</td>
<td>0.2 percent (0.44)</td>
<td>12.9 percent</td>
<td>40.0 percent</td>
</tr>
<tr>
<td>2</td>
<td>Prospective</td>
<td>1.6 percent (3.03)*</td>
<td>20.3 percent</td>
<td>24.9 percent</td>
</tr>
<tr>
<td></td>
<td>Retrospective</td>
<td>1.3 percent (2.97)*</td>
<td>15.5 percent</td>
<td>24.6 percent</td>
</tr>
<tr>
<td>3</td>
<td>Prospective</td>
<td>2.3 percent (4.80)*</td>
<td>18.1 percent</td>
<td>42.3 percent</td>
</tr>
<tr>
<td></td>
<td>Retrospective</td>
<td>2.2 percent (4.26)*</td>
<td>18.0 percent</td>
<td>42.6 percent</td>
</tr>
<tr>
<td>4</td>
<td>Prospective</td>
<td>3.4 percent (4.86)*</td>
<td>26.6 percent</td>
<td>61.3 percent</td>
</tr>
<tr>
<td></td>
<td>Retrospective</td>
<td>3.4 percent (4.85)*</td>
<td>26.5 percent</td>
<td>61.6 percent</td>
</tr>
</tbody>
</table>

* Significant at 5 percent level. t-values are in brackets.

Table 5.2: Summary of Results of Prospective and Retrospective Evaluation vs. Cash Only Benchmark for Four Choice Sets under Net Revenue Maximization, 1995-2000.
<table>
<thead>
<tr>
<th>Choice Set</th>
<th>Rule</th>
<th>Average Gain Over Benchmark</th>
<th>Volatility Reduction Over Benchmark</th>
<th>Times Choosing Net Revenue Maximizing Strategy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Prospective</td>
<td>0.7 percent (1.42)</td>
<td>15.4 percent</td>
<td>40.7 percent</td>
</tr>
<tr>
<td>1</td>
<td>Retrospective</td>
<td>0.3 percent (0.60)</td>
<td>14.3 percent</td>
<td>41.3 percent</td>
</tr>
<tr>
<td>2</td>
<td>Prospective</td>
<td>1.6 percent (3.02)*</td>
<td>20.3 percent</td>
<td>25.6 percent</td>
</tr>
<tr>
<td></td>
<td>Retrospective</td>
<td>1.4 percent (2.82)*</td>
<td>17.8 percent</td>
<td>21.3 percent</td>
</tr>
<tr>
<td>3</td>
<td>Prospective</td>
<td>2.3 percent (4.74)*</td>
<td>18.4 percent</td>
<td>42.6 percent</td>
</tr>
<tr>
<td></td>
<td>Retrospective</td>
<td>2.1 percent (4.22)*</td>
<td>18.0 percent</td>
<td>43.0 percent</td>
</tr>
<tr>
<td>4</td>
<td>Prospective</td>
<td>3.4 percent (4.86)*</td>
<td>26.6 percent</td>
<td>61.3 percent</td>
</tr>
<tr>
<td></td>
<td>Retrospective</td>
<td>3.4 percent (4.85)*</td>
<td>26.5 percent</td>
<td>61.6 percent</td>
</tr>
</tbody>
</table>

* Significant at 5 percent level. t-values are in brackets.

Table 5.3: Summary of Results of Prospective and Retrospective Evaluation vs. Cash Only Benchmark for Four Choice Sets under Utility Maximization, 1995-2000.
<table>
<thead>
<tr>
<th>Choice Set</th>
<th>Average Gain: Prospective over Retrospective</th>
<th>Volatility Reduction: Prospective over Retrospective</th>
<th>Unfair Window Contract Chosen by Prospective</th>
<th>Unfair Window Contract Chosen by Retrospective</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.4 percent (1.15)</td>
<td>2.4 percent</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>2</td>
<td>0.3 percent (1.17)</td>
<td>6.0 percent</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>3</td>
<td>0.1 percent (1.20)</td>
<td>0.0 percent</td>
<td>91.8 percent</td>
<td>90.2 percent</td>
</tr>
<tr>
<td>4</td>
<td>0.0 percent (0.34)</td>
<td>0.1 percent</td>
<td>97.0 percent</td>
<td>100.0 percent</td>
</tr>
</tbody>
</table>

*t-values are in brackets.

Table 5.4: Summary of Results of Prospective vs. Retrospective Evaluation for Four Choice Sets under Net Revenue Maximization, 1995-2000.

<table>
<thead>
<tr>
<th>Choice Set</th>
<th>Average Gain: Prospective over Retrospective</th>
<th>Volatility Reduction: Prospective over Retrospective</th>
<th>Unfair Window Contract Chosen by Prospective</th>
<th>Unfair Window Contract Chosen by Retrospective</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.4 percent (1.35)</td>
<td>1.3 percent</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>2</td>
<td>0.2 percent (1.42)</td>
<td>3.1 percent</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>3</td>
<td>0.1 percent (1.94)**</td>
<td>0.4 percent</td>
<td>91.3 percent</td>
<td>87.5 percent</td>
</tr>
<tr>
<td>4</td>
<td>0.0 percent (0.34)</td>
<td>0.1 percent</td>
<td>94.9 percent</td>
<td>97.8 percent</td>
</tr>
</tbody>
</table>

** Significant at 10 percent level. *-values are in brackets.

Table 5.5: Summary of Results of Prospective vs. Retrospective Evaluation for Four Choice Sets under Utility Maximization, 1995-2000.
CHAPTER 6

CONCLUSIONS

The objectives of this research are (1) to price and design risk management contracts frequently used in the hog industry, especially window contracts and (2) to forecast hog producers’ net revenue distributions under alternative risk management strategies to help hog producer make better hedging and marketing decisions. The former is important as hog processing firms increasingly seek ways to attract hog producers to commit to longer term contracts while simultaneously holding hog procurement costs at competitive levels. These firms need an efficient way to price and design these contracts to make sure that they are fair to both parties and so that large, unexpected losses can be avoided. The latter is increasingly important to hog producers as more alternatives to cash-only marketing strategies are being offered by various hog processing and agribusiness firms.

A Monte Carlo simulation model in which thousands of paths for commodity prices are simulated is developed to achieve the above two goals. I assume these commodity prices follow a random walk process with drift which implies a log-normal distribution. To calibrate the means of the expected joint distribution of prices for hogs, corn and soybean meal – the key determinates of net revenue from hog finishing - I
assume the efficient market hypothesis holds and, hence, use the futures prices to estimate future spot prices. To calibrate future volatility of prices, I examine the relative forecasting power of three frequently used forecasting methods: historical volatility, implied volatility and GARCH-based volatility. Consistent with recent research, the performance of these three methods is both commodity and horizon specific. However, implied volatility performs well for near term forecasting horizons while historical volatility performs well for longer term horizons. Thus, I use implied volatility to forecast near term future price variance and historical volatility for longer term variance. Historical correlation is introduced to capture the co-movement of the three price series. I also compare alternative basis forecasting approaches and find the futures spread model outperforms others in near-term forecasting in terms of accuracy and convenience and the five-year historical average is the best for long-term forecasting.

Window contracts are an increasingly used risk management tool in North American hog sector. This type of contract can be viewed as a portfolio of option contracts. Following Unterschultz et al. (1998), the simplest window contract is, from the producer’s perspective, the combination of a long European put option and a short European call option. Thus option pricing methods can be applied to price and design this type of contract. However, most window contracts involve moving average prices of multiple commodities and multiple delivery dates. This type of contract can be decomposed in multiple long European-type Asian-Basket put options and multiple short European-type Asian-Basket call options. The Monte Carlo simulation method is used to price and design both a moving and a fixed window contract. The results show that, over the 1991 to 2000 time period, this method provides unbiased pricing of both fixed and
moving window hog finishing contracts of one-year duration. From the risk-neutral contract issuer’s perspective, the contract pricing is unbiased in that the average cost of hog procurement through the spot market was not significantly different than the cost of procurement via contracts for the duration of the year-long contract. Because the payoffs of Asian-Basket type moving window contracts depend upon moving average prices rather than single period prices, the distribution of payoffs exhibits less volatility than a fixed window contract and, hence may be more attractive to a contract issuer. Also, the cumulative performance of these contracts, which takes into consideration the fact that sequential contracts’ performances often feature serial correlation, did tend to suggest that firms might favor moving window contracts.

This same Monte Carlo method is also used to forecast net revenue for hog producers. I examine the out-of-sample forecasting performance of the forecasting model for a 52-week time horizon using data from 1991 to 2000. I found that this model provides very accurate forecasts when comparing the realized with the forecasted net revenues. More specifically, for 84.4 percent of the cases, the realized net revenues fall in the interval one standard deviation from the forecasted means and for only one case did the realized net revenue falls out of the 95 percent prediction interval. For 44.1 percent of the cases, the model overestimates net revenue and for the other 55.9 percent of the cases, it underestimates the realized net revenue. On average, the model underestimates actual realized net revenue by 2.8 percent. The relatively high forecasting power of this model provides a foundation for risk management tool evaluation.

Based on this forecasting model, the mean and variance of net revenue distributions under various risk management strategies can be derived. Thus, the
hypothesised hog producer can choose the appropriate risk management strategy whether his/her objective is simple net revenue maximization or a more involved utility maximization that involves higher moments of the distribution such as variance. This method for choosing strategies is called the prospective evaluation method, and it is compared to a retrospective method which uses only the historical performance of different strategies to guide producers’ decisions. Comparing prospective evaluation with retrospective evaluation in four different hypothetical choice sets the producer might face, the former is marginally better than the latter in terms of net revenue enhancement and risk reduction and is generally preferred because it incorporates all market information.

The Monte Carlo simulation method shows great promise for marketing contract design in the hog industry and as a decision tool for hog producers making hedging and marketing decisions. However, there is room for improvement. First, in this model, the stochastic processes for commodity prices are assumed as Geometric Brownian Motion. This process is the most frequently used assumption in financial world. But the actual process for commodity prices may be far more complicated than Geometric Brownian Motion. For example, jumps and spikes, such as the dramatic drop in hog prices that happened in the second half of 1998, may require a departure from simple Brownian Motion. A jump process proposed by Merton (1976) and generalizations developed thereafter are good candidates that could be incorporated into the model. Second, though the prospective evaluation based on the Monte Carlo simulation method often outperforms retrospective evaluation in terms of predictive capability, the difference is not always statistically significant. Any improvement based on the current model will
further increase the power of prospective evaluation. For example, a more accurate point estimation of future spot price, a more accurate forecast of volatility term structure or a better realization of commodity price co-movement will enhance the forecasting power for the model and make it a more useful decision tool. Retrospective evaluation, which depends solely on past historical information, does not have much room to improve because all past information is known and the information does not speak much for the future, while the prospective evaluation has much more room to improve when newer and more accurate stochastic process and forecasting methods are developed.
LIST OF REFERENCE


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Wright, M., 2001. *Informational Efficiency and Routine Bias: Three Studies Involving Corn, Soybean, Hog and Cattle Futures Markets.* *Masters Thesis*, Ohio State University, Columbus, OH.


Endnotes

1 Note that marketing contracts are distinct from production contracts. The former primarily focus on issues of guaranteed price-quality schedules for finished hogs while the latter often involve a shift of asset ownership from producers to contractors as well as a loss of autonomy concerning husbandry practices.

2 Note that a large portion of hog marketing contracts do not isolate the producer from systematic risk in the price of finished hogs but, rather, are merely mechanisms to guarantee the producer access to a slaughter outlet. In such formula and basis contracts the price received by the producer is linearly related to either cash or futures prices for hogs and, as such, these contracts do little to transfer risk between parties.

3 Note the discount factor is ignored in this definition of profit and net revenue because of prevailing low interest rates and the short horizon considered in the model.

4 Production risk and quality risk are assumed to be zero in this study. If these sources of risk are orthogonal to price risk, the relative analyses of price risk management tools will be unaffected by such considerations.

5 The futures price and option premium used to calculate implied volatility may not have been determined at the same exact time, which can affect the quality of the implied volatility estimates.

6 Cash and futures price are highly correlated and usually move in the same direction and by a similar amount. The Black’s option pricing model uses a European option. But the futures options for hog, corn and soybean meal are American type, which can be exercised before the expiration date. This causes a slightly upward-biased estimate for the true implied volatility for an American option. Shastri and Tandon (1986) stated the bias is trivial for a short-term at-the-money option. Also, because the at-the-money option is the most actively traded option among options with different strike prices, I use at-the-money put and call options to calculate implied volatility and take the average of the two as the forecasted implied volatility. When the futures price is not the same as an option strike price, the just-out-of-the-money option is used as an alternative.

7 Transaction costs for the contract are ignored to simplify the study. So the contract price derived in this study is the actuarially fair price and it can serve as a boundary for the real price. Most window contracts are over-the-counter contracts. Over-the-counter contracts usually have lower transaction costs than futures and options contracts traded in an exchange and the bid-ask spread data for an over-the-counter contract is hard to obtain. Hence, the preference for over-the-counter contracts might be overstated because their bid-ask spread is ignored.

8 The quality of hogs procured under contract and in the spot market is assumed to be the same. While somewhat unrealistic, this assumption is made because hog quality-pricing issues are not the central theme of this dissertation.