University of Alberta

An Evaluation of Value at Risk in the Alberta Pork Production Industry

by

Joffre Conan Hotz ©

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CHAPTER 1: Introduction

The agriculture industry, especially the livestock sector, is currently undergoing dramatic changes (Boehlje and Lins 2002). These changes are transforming traditional family farms into large, specialized, highly technical, and management intensive farms This has been classified as the 'Industrialization of Agriculture' (Boehlje and Doering 2000). This process of becoming larger and more specialized has been the current trend of hog production in Alberta[1], as the production per Alberta hog farm has grown almost 300% from 1996 to 2001 (Alberta Agriculture, Food, and Rural Development 2001).

As agricultural operations become larger and more specialized, they are able to take advantage of economies of size (Boehlje and Lins 2002). However, this specialization exposes firms solely to the risks of their specific industry. For example, in 2001 hogs were the primary source of income for about one third of Alberta hog producers (Alberta Agriculture, Food, and Rural Development 2001). If no risk management was used, the income of these Alberta hog producers would have been heavily exposed to the large losses reported in 2002 for the hog industry, which reached levels of -$87.95 per hog sold during Sept. 2002 (Toma and Bouma Management Consultants 2003). Traditionally, this risk was managed using farm diversification, where both livestock and crops were produced.

Considering the changing structure of the Albert hog production industry, as well as the large losses that have been experienced, new and innovative risk management tools need to be developed and implemented. If new and innovative risk management tools can be developed, producers will be better equipped to measure and manage their risk exposures. This may help to maintain the long-term financial sustainability of the Alberta hog production industry. Thus, the purpose of this study is to develop and test the risk management tool of Value at Risk (VaR) and determine if it can provide a new and effective approach to manage risks in the Alberta hog industry.

1.1 Value at Risk (VaR)

Originally created as a method of managing risk in financial asset portfolios, Value at Risk (VaR) provides a statistical measure of the potential downside risk of the

[1] See Chapter 2 for a review of the Alberta hog production industry.

portfolio over a specified time horizon and given level of confidence. This statistical measure is a single value reported in dollars, providing an easy to understand and intuitive value. The initial VaR calculations used in the financial industry were concerned with how much the value of a portfolio of assets could decline over a holding period if it was marked to market[2]. This focused mainly on price risk, and dealt with determining the adverse effect of unexpected price changes over a short period of time.

The transparency of VaR for reporting risk and its ability to easily be understood by both management and shareholders are some of the reasons for its quick adoption by the financial industry (Jorion 2001). VaR has become a standard risk measure in the financial industry, and in the mid 1990's it became an accepted measure used by the Basel Committee[3] for regulating the banking industry. The Basel regulations are intended to ensure that banks carry enough capital to cover a loss to their portfolio during an extreme circumstance (Jorion 2001). The Securities and Exchange Commission (SEC)[4] also approved VaR as one of three acceptable quantitative methods for disclosing market risks derived from derivatives and other financial instruments (Jorion 2001).

More recent applications of the VaR framework have attempted to incorporate a wider range of risk exposures, not just those derived from marking assets to market. The range of application now includes risks derived from lending (Credit Risk) and risks derived from entire business operations [Cash Flow or Corporate Risk] (Corporatemetrics Technical Document 1999). These new applications still maintain the original objectives of portfolio VAR used in the financial industry in that it attempts to produce a statistical measure of the downside risk for the specified time period. However, instead of focusing on marking assets to market, the end measure includes risks derived from other sources such as sales, production, and credit risk, while using a metric such as cash flow to measure the potential downside risk.

[2] Mark to market is the process of adjusting the value of a security, financial instrument, or portfolio to reflect their fair value (RiskMetrics Group 1999 – CorporateMetrics)
[3] The Basel Committee is a group of regulators created to monitor the risk exposures and capital levels held by banking institutions (Jorion 2001).
[4] The SEC is a US federal agency that oversees the US security market and regulates financial reporting practices of public corporations (Jorion 2001)

1.2 Literature on VaR and Non-financial Firms

Papers written on the subject of VaR have focused mainly on the theory and application of VaR to financial portfolios[5]. Although this is the area where VaR originated and is mainly used, few papers have been written addressing the needs and requirements for the application of VaR to non-financial firms. Manfredo et al. (1998, 2001, and 2003) and Sanders and Manfredo (1999) have addressed some of the specific issues of applying VaR to non-financial firms, performed some quantitative applications of VaR to non-financial firms, and have compared the VaR measures to other more traditional mean-variance risk measures. All of Manfredo's work has focused specifically on the application of VaR to agribusiness. Odening and Hinrichs (2002) also address the application of VaR to non-financial firms, with a focus on applying VaR to the hog production industry. Other than these articles mentioned above, to date, few other articles have been found that specifically address the use and application of VaR by non-financial firms.

1.2.1 Limitations of the Literature

Although the work by Manfredo et al. (1998, 2001, 2003) and Odening and Hinrichs (2002) has moved forward the application of VaR to non-financial firms, the results are limited. The combined literature mentioned above addresses three of the main concerns of applying VaR to non-financial firms, however, each individual paper fails to address all three at once. These three concerns are; to address the need of non-financial firm's to evaluate VaR measures over long time horizons, such as quarterly, semi-annual, or even annual; include non-financial sources of risk into their model as these may have large impacts on a firm's risk exposures; and to validate the performance of the VaR model.

1.3 Statement of Research

The purpose of this research is to determine how the risk management framework of Value at Risk (VaR) can be applied to the Alberta hog industry and if it will provide a useful and effective tool for managers to identify, measure, and manage their risk exposures. Specifically, this will be accomplished by completing the key objectives of;

[5] See the website www.gloriamundi.org for an extensive list of VaR articles

evaluating different price forecasting models and choosing the forecasting model that best reflects agricultural price risks; modeling production risk using distributions created from actual historical production data; validating the VaR model using statistical tests; and determining how much production risk contributes to the overall downside risk of the modeled hog operation. Completing these objectives, the research will attempt to overcome the VaR limitations of previous research in that it will use longer time horizons, include both price and non-price risk sources, and will statistically test the validity of VaR results.

After the initial VaR model is constructed and validated, the research will be extended and risk management strategies will be included into the model. Including the risk management strategies into the model is done in order to evaluate the ability of VaR to rank the best performing risk reduction strategies when compared to the ranking results of alternative decision criteria. The potential downside risk reduction ability of the various risk management strategies will also be briefly discussed.

1.4 Theoretical Methods

The research will use Monte Carlo simulation to derive the distributions of operating cash flows that may potentially occur over specified time periods. The Monte Carlo simulation will simulate both price and production risk and then capture the interaction of these risk exposures with the non-stochastic model components. The stochastic price and production factors will be simulated in the student version of @RISK 4.5 using parameters estimated from historical data and pseudo-random numbers. The simulation then produces thousands of hypothetical operating cash flow results, enabling for the construction of operating cash flow distributions. The cash flow distributions are then used to estimate the downside risk to operating cash flows for a specified confidence level and time horizon.

The Random Walk, Auto Regressive, and Vector Auto Regressive price forecasting models will be estimated and evaluated. Based on the results, the best price forecasting model will be used in the Monte Carlo simulation to represent prices.

1.5 Empirical Methods

As mentioned above, the Monte Carlo Simulation model relies on the parameters estimated from historical information. Two different types of data must be collected. The first type of data are historical price data for both the modeled operation's input and output prices. These data are used to determine the parameters of the three price forecasting models and are also used to test which model performs the best. The second type of data required are production data. These data are used to determine the parameters and distributions used to simulate the stochastic production factors. Combining both the production and price simulations with the non-stochastic model components enables the simulation model to analyze the combined effects of the risk sources and estimate the potential impact these may have on operating cash flows.

1.6 Thesis Structure

Chapter 2

This chapter reviews the Alberta hog production industry. It provides statistics showing the rapid change of the industry in Alberta and the economic contribution it provides to the Alberta Economy.

Chapter 3

This chapter reviews definitions of risk and a basic process of risk management. Value at Risk will then be defined and literature regarding where and why VaR started, how it is calculated, and its application to non-financial firms is discussed. Finally the potential to use VaR in agriculture is discussed.

Chapter 4

This chapter defines the type and location of the hog operation used in the VaR model, as well as the underlying VaR measure or metric. The data and methods used to simulate and evaluate price within the model are first discussed, followed by the data and methods used to simulate production. Finally, the non-stochastic components and the structure of Monte Carlo model are discussed.

Chapter 5

This chapter reviews the results of the model. First, the results of the initial price data tests are reviewed, followed by the performance results of the forecasting models.

Next, the production data and forecasting results are discussed. Finally, the VaR model results are given along with the model back testing results.

Chapter 6

This chapter discusses continued research regarding the implementation of risk management strategies into the VaR model, how the model can be used to evaluate the risk management strategies, and how the rankings of the model results compare to alternative decision criteria rankings.

Chapter 7

This chapter reviews the overall results, the potential impact of the risk management strategies, and the potential use of VaR by hog operations. Limitations of the research and suggestions for further research will also be discussed.

CHAPTER 2: The Alberta Hog Industry

The Alberta hog production industry has experienced rapid growth and change over the last several decades. These changes include larger farms, increased production, and a larger capital and debt structure. This chapter will discuss these changes, how they have impacted hog operations, and the contribution of the hog production industry to the Alberta economy.

2.1 Trends in Agriculture and Hog Production

As factors such as technology, price, and demand continue to change, businesses have been forced to respond, growing larger in order to remain efficient and viable. Business growth and increased concentration has dominated many industries over the past decade, such as the retail grocery industry (Baldanza et al. 2002), oil and gas industry (Snieckus 2001), and the dairy processing industry (Agriculture and Agri-Food Canada 2001). Canadian farms are no different and have also followed this trend. From 1951 to 1996, the number of Canadian farms decreased from 623,091 to 276,548, while farm size during this same time period grew from an average of about 359 to 608 acres (Brinkman 2001). The capital value of farms also grew from 1951-1996, with the average capital farm value increasing from $15,200 to $565,793 (Brinkman 2001).

Hog operations in Alberta have also followed this pattern of increased concentration. The number of farms with hogs has dropped from 26,204 in 1971 to 1,950 in 2001 (Figure 2.1). Despite the drop in farm numbers, hog production in Alberta has increased, with total hog production for Alberta growing from about 2 million in 1971 to almost 3.5 in 2001 (Alberta's Pork Production Industry 2002). Two main factors have contributed to the increased pork production in Alberta; first, the gains in productivity, such as larger litters, better genetics, and improved housing, feeding, and farrowing technology; second, the increase in farm size (Alberta Agriculture, Food, and Rural Development (AAFRD 2001). With both farm size and production increasing, the average farm has gone from selling 90 hogs in 1971 to selling 1788 hogs in 2001 (Figure 2.1). Since 1996 alone, the average number of hogs sold per farm has increased from 622 to 1788 (Figure 2.1]).

The increase in farm size and the increased number of hogs produced per farm has resulted in hog operations becoming more capital intensive. From the period of 1971 to 2001, the total capital value of Alberta hog farms has increased from $37,177,000 to $224,925,000 (Figure 2.2). On a per farm basis, the average long-term assets per Alberta hog farm have increased from $547,561 to $1,804,970 over the period of 1993 to 1999 (Figure 2.3). This capital growth has mainly been due to an increase in the amount spent on buildings and equipment (AAFRD 2001), with new investment often financed with debt (Bressee 1997). During this same period (1993 to 1999), the average long-term debt per Alberta hog farm has increased from an average of $111,658 to $425,154 (Figure 2.3).

2.2 Increased Financial Sensitivity of Hog Operations

As capital and debt increases, so does the financial sensitivity of operations as a larger portion of costs become fixed and financial leverage is increased. Thus, we can expect Alberta hog operations to have an increased financial sensitivity as their capital and debt levels are increasing. Also, the high degree of specialization by hog operations has allowed them to take advantage of economies of size, but the lack of diversification has resulted in increased financial sensitivity to industry specific risk exposures.

2.2.1 Increased Capital and Debt's Contribution to Increased Financial Sensitivity

According to basic accounting principles, increased capital levels and debt can increase the financial sensitivity of a firm. In general, increases in capital levels of operations often result from changes in technology and automated systems (Garrison et al. 1996). The introduction of these types of systems, such as automated feed systems in hog barns, tends to reduce the amount of the operation's variable costs[6] (e.g. labor) and increases the proportion of fixed costs[7]. Increase proportions of fixed costs will often produce higher net incomes during high revenue periods, but will have the opposite effect during low revenue periods (Garrison et al. 1996). Thus, as hog operations become more consolidated, more capital intensive, and adopt new technologies and automated systems, fixed costs will likely make up a larger portion of their cost structure, increasing the financial sensitivity of the business.

[6] Variable costs – change as the level of operation activity (production) changes (Garrison et al. 1996)
[7] Fixed costs – do not change as the level of operation activity (production) changes (Garrison et al. 1996)

Using the long-term debt to equity ratio (LD/E) and the 1993-1999 values from Figure 2.3, the average portion of a hog operation that is financed with long-term debt, relative to amount of equity held, can be determined. According to the LD/E ratio calculations for 1993 and 1999, there is only a slight increase in the long-term debt relative to equity, as the ratio has increased from only 20.4% to 23.6%. This does not show a substantial increase in the level of debt used by hog operations, and is likely due to the ratios being based on average values. However, Ellison and Lang (2003) indicate, debt to equity levels for hog operations will rarely exceed 100%, but some larger operations may have debt to equity levels as high as 150%. As a result, debt obligations will be significantly higher, and because debt payments are generally fixed, the increased debt obligations may be difficult to pay during periods with little cash flow. Because the trend in the Alberta hog industry is toward larger sized operations, it is expected that debt and financial sensitivity will also continue to increase.

2.2.2 Specialization's Contribution to Increased Sensitivity

As Alberta hog operations become more industrialized, they are also becoming more specialized and less diversified. This specialization exposes them entirely to the risks generated from producing hogs, with traditional on-farm diversification as a means to manage risk no longer relevant. Thus, due to structural changes of the hog industry, it is increasingly important to manage the industry risks (Snitynsky 2001).

2.3 Impact of Hog Production on Alberta Economy

As shown by the increasing number of pigs born in Alberta (Figure 2.4), the Alberta hog production industry has steadily grown over the last several decades. This growth in hog numbers has also contributed to the Alberta economy, as gross farm cash receipts for Alberta hog farms increased from $78,623,000 in 1971 to about $570,062,000 in 2001 (Figure 2.5).

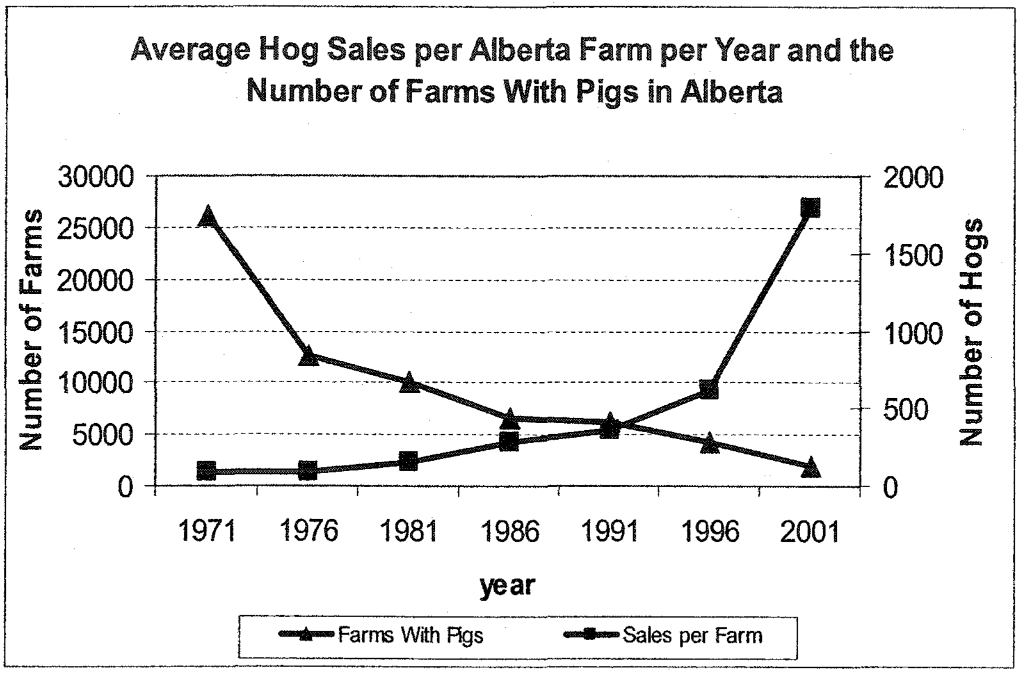
The dollar value of pork and live hog exports has also steadily increased (Figure 2.6) and has gone from a total dollar value of $95,855,000 in 1992 to a value of about $350,976,000 in 2000. There are several key countries to which Alberta exports pork, but the dominant buyer is the United States. In the year 2000, roughly $120 million, or 100% of Alberta's live exports were purchased by the US, along with 63% of Alberta's pork exports. The other major importer of Alberta pork is Japan, which accounts for another 30% of Alberta's exports. Russia, Hong Kong, and South Korea are the remaining significant importers of Alberta Pork (AAFRD 2001). These exports bring foreign dollars into Alberta's economy.

2.4 Chapter Summary

The growing pork production industry has positively contributed to Alberta's economy; however, it has also become more sensitive financially because of the increased capital and debt levels and the increased exposure to only pork industry specific risks. In order to maintain the continued growth and strength of the industry, emphasis must be placed on developing and implementing new risk management tools that address the needs of the changing industry. If new risk management tools, such as Value at Risk, can be applied and deemed effective, this may help to improve the financial stability and sustain the growth of the pork production industry. Value at Risk, and its application to the hog production industry are discussed in the remaining chapters.

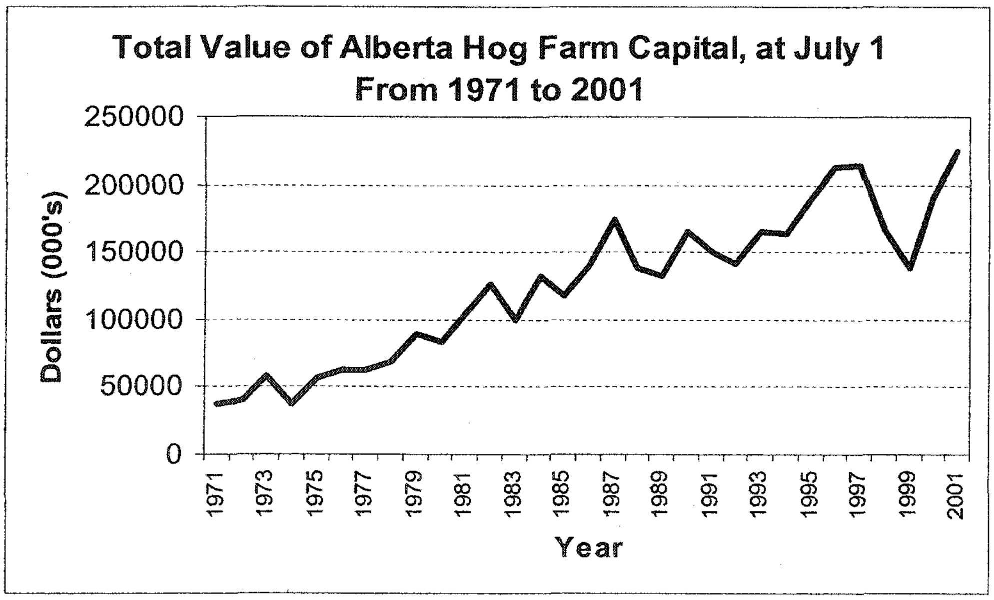
2.5 Chapter 2 Figures

Figure 2.1 Average Hog Sales per Alberta Farm per Year and the Number of Farms with Pigs in Alberta



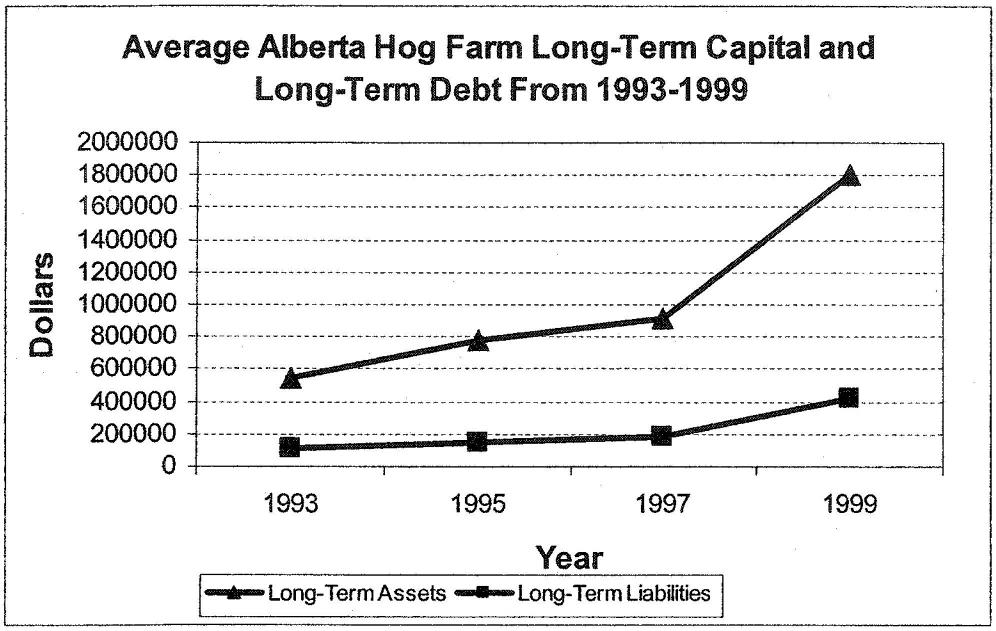
(Source: AAFRD 2001)

Figure 2.2 Total Value of Alberta Hog Farm Capital from 1971-2001 at July 1st



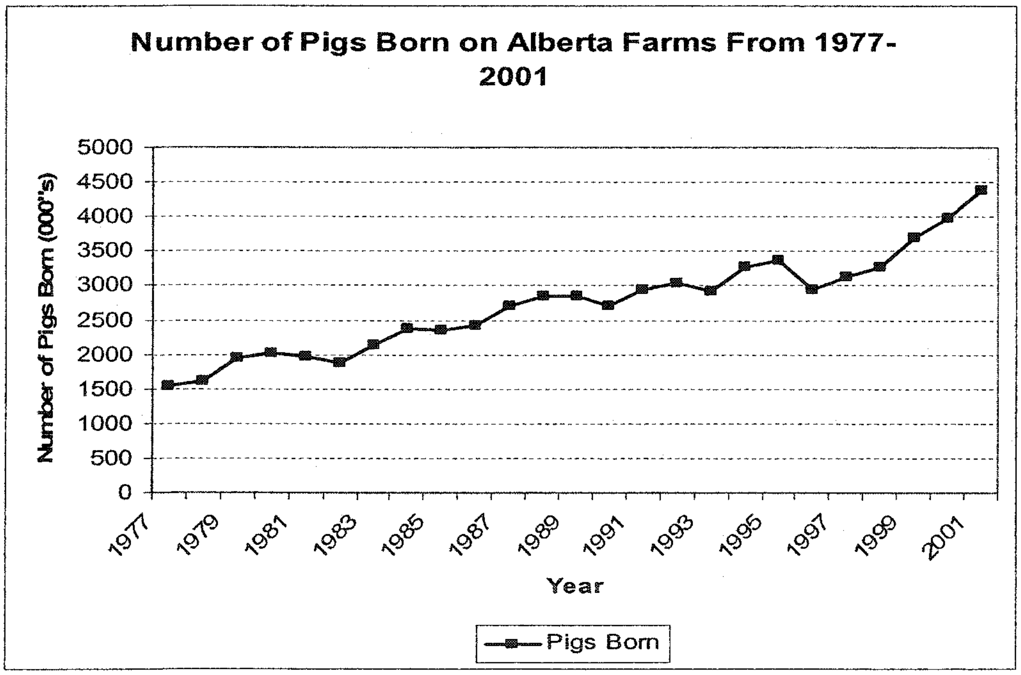
(Source: CANSIM II Series V1312650)

Figure 2.3 Average Alberta Hog Farm Long-Term Capital and Debt from 1993-1999



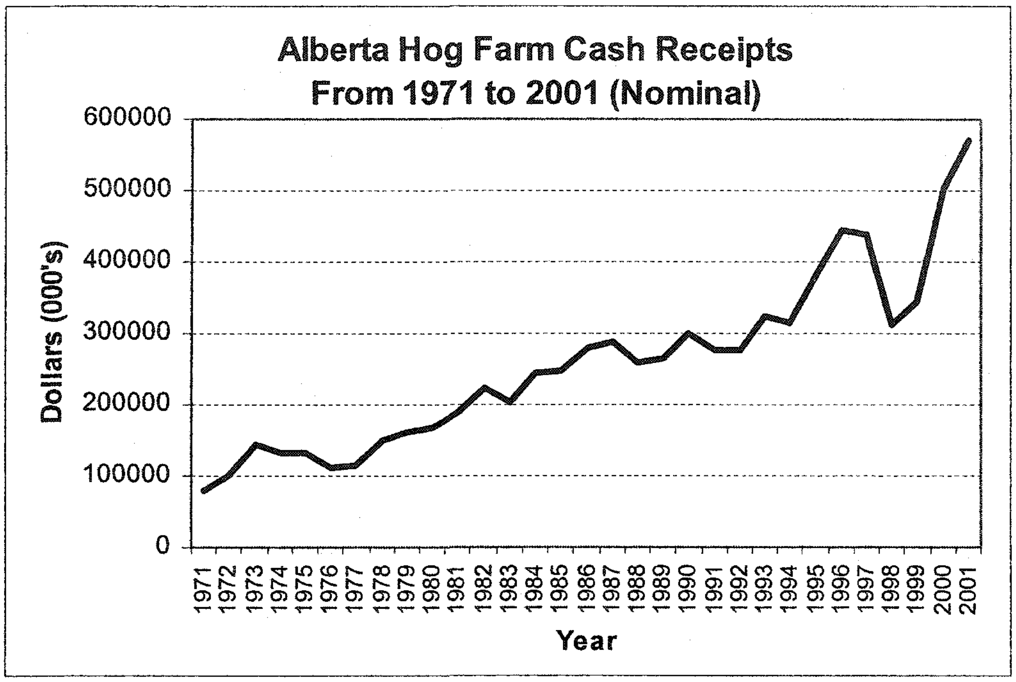
(Source: Statistics Canada, 1998 and 2000 Farm Financial Survey)

Figure 2.4 Number of Pigs Born on Alberta Farms From 1977-2001



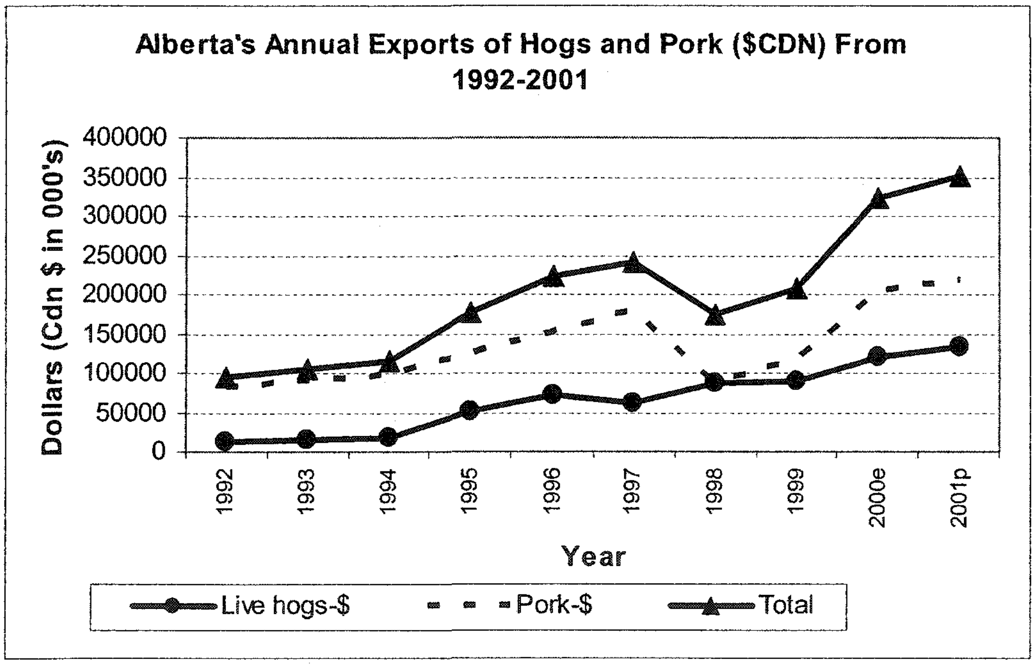
(Source: CANSIM II Series V721532)

Figure 2.5 Alberta Hog Farm Cash Receipts from 1971-2001 (Nominal)



(Source: CANSIM II Series V170878)

Figure 2.6 Alberta's Annual Exports of Hogs and Pork From 1992-2001



(Source: AAFRD 2001)

CHAPTER 3: Review of Risk, Risk Management, and Value at Risk

This chapter will review some definitions of risk and the process of risk management. Several simple risk management decision criteria are then discussed, followed by an introduction to Value at Risk. Next, various methods of calculating VaR are discussed, along with its application to non-financial firms. Finally, the distinction of Cash Flow at Risk (CFaR) is made, its potential use in agriculture, as well as some reasons for performing this research.

3.1 Definition of Risk

Hardaker et al. (1997, p. 5) defines risk as "uncertain consequences". Although risk has both an upside and a down-side, the focus has generally been on downside risk as it is often viewed as more relevant, especially for risk analysis in agriculture (Hardaker et al. 1997). From a business perspective, risk is the possibility of loss to a metric of concern, such as asset value, cash flow, or some other type of financial measure. The risks that may impact an operation can be classified into a variety of different types, and are explained next within the context of agriculture.

3.2 Types of Agricultural Risk

Depending on the industry being discussed, or the specific situation, the same classification of risk can have different definitions. For example, Jorion (2001) defines *financial risk* as the possible losses in financial markets, where as Hardaker et al. (1997) defines *financial risk* as the potential losses due to the way in which the business is financed. Because of the discrepancy in definitions, this section will define the various risk types that are used in this thesis according to Hardaker et al. (1997) as these definitions of risk apply more specifically to agricultural. The following definitions are presented.

Production Risk: The risk due to variation in the production performance of livestock or crops, which occurs as a result of natural factors such as disease, weather, and genetics.

Market Risk (Price Risk): The risk due to the uncertainty surrounding the price of both input and outputs used or produced by the operation.

Institutional Risk: The risk due to changing government policy such as trade policy, environmental regulations, and drug use (antibiotics).

Human Risk (Personal Risk): The risk due to the potential of becoming injured or killed while on or off the operation, as well as a major personal event such as a divorce which may impact the operation.

Business Risk: Business risk is considered by Hardaker et al. (1997) to be the uncertainty that the sum of risks above potentially have on the financial performance of the operation.

Financial Risk: As mentioned above, Hardaker et al. (1997) defines financial risk to stem from the way the firm is financed. If there is no debt in the operation then the firm is not exposed to financial risk.

3.3 Three Basic Steps of Risk Management

Risk management, as defined by Jorion (2001), is the process of identifying sources of risks, measuring them, and then managing them. The process of risk management for an agricultural business also follows these three basic steps: 1. Identify the major sources of risk that may impact the total risk of the operation. 2. Measure the risk sources by determining the probability of their occurrence and the severity of their consequences. 3. Manage or control the risk by understanding where current risk management practices or strategies fail to adequately address the source of risk, and then implement more effective strategies.

Choosing the most effective, or the best risk management strategy is not straight forward. There are a variety of methods that can be used to rank between various risk management strategies, however, there is no overwhelming support for any particular method (Nydene 1999). Some of the risk management ranking procedures or decision criteria are discussed next.

3.4 Risk Management Decision Criteria or Ranking Tools

Because the focus of this thesis is on the evaluation of VaR, and not on the evaluation of the other various risk management tools, only a few simple and more traditional risk management decision criteria are described below. The alternative decision criteria used in this research are first degree stochastic dominance (FSD), E-V efficiency (mean-varaince), and the Sharpe ratio, and will be compared to the results of the VaR measure. These alternative decision criteria were chosen as they have been used in other agricultural literature to rank risk management strategies (e.g. Nydene 1999, Bresee 1997, Hardaker et al. 1997, Manfredo et al. 2003)

One economic theory used when making decisions under uncertainty is that all individuals will seek to maximize their expected utility of wealth, whether risk averse or not (Copeland et al. 2005). The framework of expected utility maximization "integrates the information about a decision maker's preferences and expectations in order to identify preferred choices under uncertainty" (Barry 1884, p. 68). However, it is often difficult to accurately measure a decision maker's preferences and problems often occur in application. Some of the problems can be overcome by using efficiency criterion to partially order the decision alternatives into an efficient or inefficient set (Barry 1984, p.68-69), such as the FSD, Mean-Variance (E-V) analysis, and the Sharpe Ratio used in this research. These decision criteria will not necessarily produce the same efficient or inefficient sets as they have different assumed underlying utility restrictions. The underlying expected utility restrictions for VaR and each of the decision criteria are given in their respective section below.

3.4.1 Stochastic Dominance

The First order stochastic dominance (FSD) decision criterion holds for all decision makers who have a positive marginal utility (Barry 1984 p.70), or simply where more wealth is preferred to less. Thus, FSD will identify the efficient strategies between risky alternatives when the wealth of one strategy is greater than the wealth of another in all states of nature (Copeland et al. 2005).

The FSD efficient set of risk management strategies can be determined by comparing the cumulative distributions of various outcomes. When all risk management strategies are plotted together, the cumulative distribution farthest to the right is the most dominant. If two or more cumulative distributions that are furthest to the right cross, then the FSD is indifferent and none of the strategies can be considered dominant over the other (Hardaker et al. 1997). For example, in Figure 3.1, Alternative Z is further to the right of Alternative X, and the two alternatives do not cross. Thus, Alternative Z is dominant over Alternative X. However, Alternative Y crosses Alternative Z, thus we can not determine if either Alternative Y or Z is more dominant.

The FSD measure can be extended to second order (SSD) or third order stochastic dominance (TSD). Both of these measures consider mean and variance of the various risk management decisions. These processes are more likely to identify one specific strategy when FSD is indifferent. However, this research will only use FSD.

3.4.2 E-V Efficiency (Mean Variance)

E-V efficiency is based on mean - variance criterion, where the basic concept used to identify efficient strategies is to choose more over less wealth and less risk over higher risk alternatives (Hardaker et al. 1997). This measure will identify the efficient set of risk alternatives based on the expected utility assumption that the decision maker is risk averse (Barry 1984, p.72). However, E-V also requires that the outcome distributions are normal or that the decision maker's utility function is quadratic (Barry 1984, p.72).

The efficient set is identified by the risk management choices that are the highest and the most left when plotted in x-y space, where variance values compose the x-axis and mean values compose the y-axis (Hardaker et al.1997). This basic E-V analysis can identify the efficient set of risk management choices, but may not identify the single most efficient choice when there are several choices in the efficient set. For example, in Figure 3.2, A and B are both more efficient than C as both of these points lie above and to the left of C. However, we are unable to determine which is more efficient between A and B as neither points are above and to the left of one another. Thus points A and B make up the efficient set.

However, if the utility function of a specific individual is known, then the choice(s) that lie(s) on the upper and left most utility curve indicates the most efficient risk management choice(s) for that individual. Again looking at Figure 3.2, Utility Curve 1 is the upper and most left utility curve, thus, point A is the most efficient choice as it lies on this curve. The steeper the gradient of the utility curve, the more risk averse the individual is (Hardaker et al. 1997, p. 142), as the individual will increasingly demand higher expected returns in order to compensate for risk. However, this research will not go as far as identifying specific utility curves and will only identify the most efficient set, unless one specific point can be identified as most efficient.

3.4.3 Sharp Ratio

The Sharp ratio is more commonly used in finance, however, it can be used to rank risk management decisions in agriculture, as was done by Nydene (1999) and Manfredo et al (2003). The underlying information of this ratio is the mean and the standard deviation of various risk management scenarios when compared to a base case scenario. The higher the ratio value, the better the relative ranking the risk management strategy receives. This decision criterion is consistent with expected utility maximization for individuals who make choices consistent with mean-variance utility functions (Gloy and Baker 2001). The Sharpe Ratio, as used by Nydene (1999), is defined by Sharpe (1994) as:

$$S \equiv \frac{\overline{D}}{\sigma_D} \qquad [3.1]$$

where:

$$\overline{D} \equiv \frac{1}{T}\sum_{t=1}^{T} D_t \quad \text{and} \quad \sigma_D \equiv \sqrt{\frac{\sum_{t=1}^{T}(D_t - \overline{D})^2}{T-1}} \qquad [3.2]$$

$D_t \equiv R_{Ft} - R_{Bt}$

$R_{Ft} \equiv$ the return on the fund (portfolio) of interest

$R_{Bt} \equiv$ the return on the benchmark portfolio

$T \equiv$ the time period

3.5 Value at Risk (VaR)

Although a brief definition of Value at risk was given in Chapter 1, it will again be defined. Next, a brief history will be given describing some incentives that made the adoption of VaR popular, as well as some of its potential uses. Both the definition and the history of VaR will be given with respect to the financial industry. Its application to non-financial industries and agriculture will be discussed in sections 3.7 and 3.8.

3.5.1 Value at Risk Defined

Within the framework of financial portfolios, VaR can be defined as "a single, summary, statistical measure of possible portfolio losses. Specifically, value at risk is a measure of losses due to 'normal' market movements" (Linsmeier and Pearson 1996, p.

3) and "summarizes the worst loss over a target horizon with a given level of confidence" (Jorion 2001, p. 22). Thus, VaR focuses on measuring the downside loss of portfolio returns for a specified probability and time horizon. The general form of VaR is described by Jorion (2001) as:

$$1-c=\int_{-\infty}^{W^*} f(w)\,dw = P(w \leq W^*) = p \tag{3.3}$$

where:

W^* = is "the Quantile of the distribution (for the portfolio return), which is the cutoff value with a fixed probability of being exceeded." (Jorion 2001, p.110)
$f(w)$ = the future portfolio value
c = given confidence level
p = probability, which must sum to 1-c

VaR has been criticized that it is a "safety first measure of risk and ignores the inherent trade-off between risk and return" (Manfredo et al. 2003, p. 15) and can not be derived from maximizing utility (Barry 1984, p.64). Instead, safety first measures generally focus on minimizing bad outcomes. However, the underlying expected utility assumption of VaR is considered to be consistent with the expected utility of First Order Stochastic Dominance (FSD) when portfolio returns are elliptically distributed or when the risk management strategies can be ranked by FSD (Yamai and Yoshiba 2002). Therefore, if these conditions hold VaR can be considered consistent for individuals with a positive marginal utility

The process of calculating and using the VaR framework can be achieved by following the three steps of risk management identified in section 3.3. First, the risk sources that may have a downside effect on the portfolio value must be identified. Second, the identified individual risk sources and the combined effects they may have on the portfolio must be measured. Finally, the calculated measures should be used to understand where current risk management practices or strategies fail to adequately address the sources of risk, and then implement more effective strategies.

3.5.2 Key Components of VaR

Two key components of VaR, the "target time horizon" and the "level of confidence", are user specific. The confidence level should be chosen to reflect the level of risk the individual is concerned about (Jorion 2001). In general, the confidence levels used in the financial industry are high as VaR is generally used to measure extreme losses. The probability (confidence) levels most commonly used in literature are 1% (99%) and 5% (95%), however this has ranged from 0.1% (99.9%) to 10% (90%).

The target time horizon should reflect the length of time needed to make corrective actions and adjust the risk of the portfolio (Jorion 2001). Because most applications have been to the financial industry, the time horizon have generally been short, such as 1 day to 1 month. The shorter time horizons used in the financial industry are due to the nature of financial portfolios, which are often derived from very liquid and frequently traded assets, where corrective actions can be made quickly to adjust the risk of the portfolio.

3.5.3 Why Value at Risk has Become Popular in the Financial Industry

History has provided many incentives for the financial industry to adopt the risk management strategy of VaR. With the increase in international trade, international business linkages, and foreign currency exposures, companies' portfolios have become very complex, with the risk exposures less than obvious (Linsmeier and Pearson 1996). This lack of clarity regarding company wide risk exposures, and a lack of company risk management policies, has led to several financial disasters.

Two such examples are; Metallgesellschaft[8], where rolling hedges meant to offset the risks on long term oil contracts accumulated large margin calls that could not be met, and led to a loss of about $1.3 billion; and Barrings[9], where one individual in the bank was responsible for a loss of over $1 billion due to many speculative positions taken on the Nikkei 225. Both of the extreme losses mentioned above were due to a lack of risk management and poor risk management policies, where the risk exposures of these firms were not identified.

The growing complexity of portfolios and the lessons learned from major disasters led to the general consensus in the financial industry that a more transparent, firm wide risk management tool was needed. Thus, VaR, which had already been in use by some firms, became increasingly popular. In early 1995 the Basel Committee on banking supervision deemed VaR an acceptable measure for banks to measure their

[8] See Jorion (2001) for a more detailed description of how and why these losses occurred.
[9] Also see Jorion (2001) for a more detailed description of how and why these losses occurred.

capital requirements (Linsmeier and Pearson 1996). In 1997, the US Securities and Exchange Commission also allowed VaR to be one of the three allowed corporate risk disclosure measures (Jorion 2001)[10].

One final reason for the growth in popularity of the VaR measure is due to its simplicity. Jorion (2001, p.107) states "perhaps the greatest advantage of value at risk (VaR) is that it summarizes in a single, easy to understand number the downside risk of an institution". This single number then portrays the downside risk to both investors and management regarding the risk exposure of the operation, from which they can determine if this is an acceptable level of risk. Before this VaR, shareholders only had a vague idea of the trading risks held by financial institutions (Jorion 2001).

3.5.4 The Different Uses of Value at Risk

Value at Risk has three basic uses; a benchmark measure, a potential loss measure, and capital requirement measure (Jorion 2001). The benchmark measure is the simplest, where the firm uses the measure to compare its risks across different time periods in order to gauge if their exposures have changed, and if so, why. This would include determining if risks have changed due to an increased volatility of the market or a larger position taken in the underlying risk source.

Using VaR as a loss measure is intended to identify the loss a firm may be exposed to subject to changes in market conditions. This is to help the firm identify potential losses and allow it to address those risks through changes in its portfolio and risk structure. The measure can then be used to determine how the potential changes impact the downside risk to the portfolio.

Finally, VaR is used to establish a capital requirement level in financial institutions. This is how VaR fulfils the requirements of the Basel Committee, as the banking industry must maintain a level of capital that will cushion the bank against an extreme loss.

3.6 Methods for Calculating Value at Risk

In general, the literature describes three main methods that can be used to calculate VaR (Jorion 2001, RiskMetrics Technical Document 1995, Linsmeier and

[10] See Jorion for more examples of regulation committees who recommend the use of VaR

Pearson 1996). Although there are several variations and extensions of VaR that have been developed, only the three basic methods will be described below.

3.6.1 Variance – Covariance Method (Parametric Valuation)

The Variance-Covariance (V-C) VaR calculation method is also referred to as the Parametric or Delta Valuation method. This method is considered easy to implement, and it assumes that all assets returns comprising the portfolio are normally distributed (Jorion 2001). Because all of the assets in the portfolio are assumed normally distributed, the portfolio returns will also be normally distributed, allowing for two main calculation simplifications:

1. The standard deviations corresponding to a specific confidence level can be easily determined using a normal distribution table, such as those provided in the back of statistics text books.
2. The square root rule[11] can be used to adjust the standard deviation of a portfolio for any time period.

The simplest method for calculating VaR using V-C can be accomplished by measuring the variance and correlations of the assets in the portfolio and then multiply them by the exposure levels of the asset returns, the time horizon of interest, and the confidence interval of interest. This process can be shown as (Manfredo and Leuthold 2001):

$$VAR = \sigma_P \alpha \sqrt{t} \qquad [3.4]$$

where:

t = the time horizon of interest (must be in the same time units used to measure the volatility and variances of assets in the portfolio, such as daily, weekly etc...)
α = the number of standard deviations corresponding to the confidence level

$$\sigma_P = \sqrt{\sum_i^n \sum_j^n \rho_{ij} x_i x_j \sigma_i \sigma_j)} \qquad [3.5]$$

where:

σ_p = future standard deviation of the portfolio returns
x_i = the exposure level, or amount invested in the asset i…n
ρ_{ij} = the future correlation coefficient between asset returns i…n and j..n
σ_i = future standard deviation of asset returns i…n

[11] The use of the square root rule to adjust variance for different time periods can be viewed in Hull 2002 on page 334.

Although this is a simple V-C method for calculating VaR, it displays the basic principles of the V-C approach.

Advantages of Covariance-Variance Method

The V-C method is computationally fast, can handle large portfolios, and is also considered easy to implement, even though it is somewhat mathematically intensive. The V-C method also has the ability to test alternative assumptions about distributions, variances of markets, correlations between assets, or extreme occurrences (non-normal market movements) (Linsmeier and Pearson 1996). Testing these other situations is also referred to as stress testing and scenario analysis.

Disadvantages of Covariance-Variance Method

The distribution of financial assets returns often have fat tails (leptokurtic), therefore the normal distribution assumptions, which provides the foundation of the V-C approach, often under estimates risk. Another disadvantage of the V-C approach is that it has a limited ability to measure non-linear risks, such as those stemming from options or mortgages (Jorion 2001). If the non-linear risks can be mapped out into linear exposures, and the VaR time horizon is very short, small non-linear risks may be represented. However, as the length of the time horizon and the number of non-linear exposures grows, then the V-C method will provide unreliable results (Linsmeier and Pearson 1996).

3.6.2 Historical Simulation (HS)

Unlike the single estimate given by the V-C method, the historical simulation (HS) method generates the entire distribution of portfolio returns. Therefore, the HS method is considered a full valuation method. The (HS) method is also considered to be a non-parametric method because it places no specific assumptions on the distribution of portfolio assets, and instead uses the distribution information directly observed from historical data.

The method of calculating HS is also considered to be quite simple. First, all of the risky assets comprising the portfolio must be identified, and then historical data must be collected for each asset. The daily returns of each asset, in a percentage form, are then calculated from the historical data. Next, the historical returns (in %) of each asset are applied to the current value of each respective asset held in the current portfolio. For example, if 100 days of data were used, then 100 returns would be applied to the current portfolio assets, generating 100 hypothetical daily portfolio returns.

Jorion (2001)[12] describes the HS calculation process as:

$$R_{p,k} = \sum_{i=1}^{N} x_{i,t} R_{i,k} \qquad \text{k=1,...t} \qquad [3.5]$$

where:

$R_{p,k}$ = Portfolio return for simulation k

$R_{i,k}$ = Return for asset i...N for simulation k

$x_{i,t}$ = The exposure level, or amount invested in the asset i...N at the current time t

Finally, the portfolio returns $R_{p,k}$ are ordered from greatest to least, where the VaR level of concern can be measured. Out of the 100 simulated returns, a 5% VaR would be the 5th lowest in the ordered returns. These results can also be plotted in the cumulative distribution, where similar results can be extracted.

Advantages of Historical Simulation Method

The HS method is simple to calculate because it directly relies on historical time series data and does not require the calculation of the variance covariance matrix. The HS is able to account for non-linear components, such as those derived from options or mortgages. Also, the HS method does not make specific assumptions about the distribution of returns, therefore it accounts for fat tails in the distributions, unlike the V-C approach.

Disadvantages of Historical Simulation Method

Because the HS method relies strictly on historical data, there must first be adequate amounts of data available for each portfolio asset. If 1000 daily returns were desired, it would take 4 years of data. If the time horizon of concern was monthly, then we would need over 83 years of monthly returns for 1000 data points. Also, because only a single historical price path is used in HS, it is assuming that the future market movements will follow the same behavior that has occurred during the chosen historical

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[12] Jorion 2001 (page 221) uses $w_{i,t}$ in stead of $x_{i,t}$. This slight variation was made in order to make equation 3.5 more consistent with 3.3.

time period (Godfrey and Espinosa 1998). Also, because only historical results are used, this VaR methodology cannot be used for stress testing or scenario analysis.

3.6.3 Monte Carlo Simulation (MC)

Similar to Historical simulation, Monte Carlo simulation is a full valuation approach as it generates the entire distribution of potential portfolio outcomes. However, instead of using actual historical results to generate simulations, random draws from pre-specified distributions are used. The parameters for the pre-specified distributions can be calculated from historical data or extracted from markets.

Once the sources of portfolio risks have been identified, the first step in Monte Carlo simulation is to choose stochastic models that reflect the behavior of the risk sources. This step is considered by Jorion (2001) to be the most critical, and Linsmeier and Pearson (1996) state that this requires a large amount of expertise and judgment. The sources of risk may be represented using the various parameters, independent distributions, and time dependent stochastic processes, such as a series of prices when analyzing financial portfolios. The stochastic variables are then simulated over the span of the target time horizons. In the case of a financial portfolio, the simulated prices are then applied to the specific portfolio assets, as though they were marked to market. Finally, this process is repeated a large number of times, from which a distribution of all the portfolio values can be compiled. From this distribution, the VaR for any level of confidence can be determined.

Advantages of Monte Carlo Simulation Method

The Monte Carlo (MC) simulation method is considered by Jorion (2001, p. 225) as "by far the most powerful method to compute VaR". The MC method does not have the linear restrictions of the V-C approach. Also, the MC method has less historical data restrictions when compared to the HS approach as the MC approach uses distributions based on the historical data rather than the actual data itself. This makes the MC approach a very flexible simulation method. This flexibility is the MC method's biggest advantage, as it allows for the inclusion of nonlinear risks, model risks, volatility risk, and can account for fat tails in the distribution (Jorion 2001). Thus, the MC VaR framework is almost limitless with regards to the types and sources of risk that it can account for. Also, like the V-C approach, MC can be used for stress testing and scenario analysis.

Disadvantages of Monte Carlo Simulation Method

There are also several drawbacks to the Monte Carlo method. Because financial portfolios can be very complex, with many assets, this can create a very large number of variables that must be simulated. For example, 100 variables (portfolio assets) simulated 10,000 times for a single time period would be 1,000,000 simulations. If price paths for the 100 variables were simulated over a time horizon, the number of simulated variables would grow dramatically. Thus, developing and running a model can be very timely and expensive (Linsmeier and Pearson 1996, Jorion 2001), requiring sophisticated computer hardware and software. Also, because a stochastic model has to be chosen to represent each portfolio asset, there is the risk that an incorrect model will be chosen (Jorion 2001). This introduces model risk and the chance of misspecification, which is a result of the MC simulation inadequately representing the risks of the portfolio.

3.7 Application of VaR to Non-Financial Firms

Although substantial literature exists regarding the use of VaR in the financial industry[13], only small amounts of literature addresses the VaR needs of non-financial or corporate firms(Sanders and Manfredo 1999). The reason for this lack of literature is due to the unique challenges and problems that come as a result of trying to extend the VaR theory to account for the needs of non-financial firms.

3.7.1 Problems of Applying VaR to Non Financial Firms

The first concern regarding the application of VaR to non-financial firms is the underlying measure of the VaR calculation. For financial firms, the underlying concern is the value of the portfolio that would occur if the assets were marked to market at the end of the target horizon. However, non-financial firms also need to include other business factors, such as "changes in consumer demand, the outcomes of R&D programs, and competitors' pricing decisions" (Linsmeier and Pearson 1996, p. 24). Therefore, to account for these other types of business factors, the underlying measure used should be cash flows (Linsmeier and Pearson 1996) or earnings (Corporate Metrics Document,

[13] See www.gloriamundi.org for an extensive list of VaR literature.

1999). Thus, the application of VaR to non-financial firms can be called "Cash Flow at Risk" (CFaR) or "Earnings at Risk" (EaR).

Modeling Cash Flow

The application of CFaR to non-financial (corporate) firms has not been straightforward, and according to Spinner (1996), the use of CFaR to measure non-financial firm's risk exposures is plagued with difficulties. Including multiple sources of risk, such as forecasted sales and balance sheet and economic exposures, into the VaR analysis and refining these complex items into a series of cash flows is a problem (Spinner 1996). This can be a major undertaking in itself (Linsmeier and Pearson 1996).

Data Restrictions

Another considerable problem regarding the application of VaR to non-financial firms is the lack of data (Stein et al. 2000). This problem arises due to the longer target time horizon that non-financial firms require when calculating CFaR. As the time horizon increases, the available data points to estimate parameters and market behavior decreases. For example, one can look at the historical cash flows of a corporate firm in order to determine the main factors that influence cash flow variability; however, these figures are often only reported quarterly. This creates the problem of very few data points to use in order to determine and replicate the likelihood of events affecting the firm's cash flow. Although some firms have been around for many years, the manner in which these businesses operate and perform have most likely changed considerably over time, making historical data beyond the most recent years extraneous (Stein et al. 2000).

There are two specific approaches that can be taken regarding the construction of a CFaR model, each with entirely different data requirements. The first approach, which is the approach used for in this research, is the bottom up approach. The bottom up approach develops the CFaR model by identifying specific risk sources that impact cash flow, collecting data for each specific risk source, and then using data to determine the appropriate method to represent the risk source. All of the specific risk sources are then interacted together in order to determine the CFaR. However, collecting data is often very difficult for non-financial firms (Spinner 1996). For this reason Stein et al. (2000) developed a method for calculating "C-FaR" (Cash Flow at Risk) that uses the top down approach. The Stein et al. (2000) approach uses aggregated cash flow data from many non-financial firms, categorizes it according to size of firm and specific industry, and then uses the aggregated data to estimate the likelihood of extreme cash flow events occurring for a similar type of firm.

The data problems associated with using a bottom up approach may not be as significant when applying CFaR to agriculture due to four main reasons. First, the majority of price risks in agriculture are commodity based, and in general there is good historical commodity price data. Second, commodity products are considered homogeneous, thus, all products that fall under the commodity quality category should receive their respective market price. This means that factors such as competitor prices do not have to be considered. Third, there is no need to forecast the supply and demand effects of individual producer decisions, as each producer is only a small component of any total commodity market and individual production decisions will not have an impact regarding price (Purcell and Koontz 1999). Fourth, many operations, such as hog operations, are beginning to keep track of production data using computer software. This historical production data can then be used to determine the variability of production variables. Thus, the application of CFaR to agriculture may be simpler and lack some of the problems identified above, providing an advantage over the CFaR application to other types of non-financial firms.

Backtesting Problems

Using longer time horizons also creates data problems, as there will be limited data that can be used for testing (backtesting) the validity of the model. Backtesting is the process of systematically comparing the CFaR results with actual subsequent cash flow results (Jorion 2001). This can be achieved using statistical measures, such as the LR test or the Z-stat, which are defined in Chapter 4 (section 4.9).

The LR and Z-stat tests rely on actual subsequent data to test the CFaR model performance, thus the statistical power of the tests are limited by the amount of subsequent out of sample data available. There are two main problems that limit the amount of data; the length of the time horizon and the probability level being tested. Longer time horizons reduce the number of subsequent observations that can be used for comparison. Low probability test levels (high confidence levels) reduce the expected number of observations that can be observed in the out of sample data. Both of these data restrictions lower the statistical power of the LR and Z-stat tests (Jorion 2001). Thus, shorter time horizons and higher probability levels will produce more powerful tests.

In the financial industry, lack of backtesting data is generally not a problem as the time horizons are usually short, such as daily or weekly. These shorter time horizons provide sufficient backtesting data, and also allow for testing at very low probably levels. Because the application of VaR to non-financial firms requires longer time horizons, this creates the problem of statistically testing (backtesting) the performance of the model as there will be limited data points that can be used for backtesting. Thus, due to these limitations, the backtesting results of VaR when applied to non-financial firms may be difficult to perform and may lack statistical power.

3.8 Potential of VaR in Agriculture

Despite the above challenges of applying VaR to non-financial firms, Manfredo and Leuthold (1998) identified that the application of VaR for risk management in agriculture may be very practical. There are two reasons for the potential use of VaR in agriculture: First, realistic portfolios can be developed which reflect agricultural production, such as the cattle feeding margin created by Peterson and Leuthold (1987), and second, the availability of agricultural price data corresponding to agricultural portfolios. Also, "the use of agricultural prices will bring new data to the empirical evaluation of Value at Risk" (Manfredo and Leuthold 1998, p. 10). With the potential being identified, research has begun in this area which tests various VaR calculation methodologies and their ability to measure risk in the cattle industry (Manfredo and Leuthold 2001), hog industry (Odening and Hinrichs 2002), and how VaR compares to other risk management techniques when used by agricultural cooperatives to analyze risk management strategies (Manfredo et al. 2003).

Manfredo and Leuthold (2001) and Odening and Hinrichs (2002) used a simple portfolio approach using weekly input and output prices to generate a gross margin value to be used for the VaR measure. Using the portfolio approach allows for the gross margin calculation to be simplified as it assumes that it is derived from a firm being long and short in various assets. Their approach also assumes that production technology remains constant.

Although the portfolio approach is used to calculate the VaR measure in both papers, Odening and Hinrichs (2002) indicate that their methodology is measuring Cash-Flow-at-Risk. Although there is no distinction in the calculation method of CFaR and VaR, the distinction occurs when making the economic interpretation of the results as CFaR has implications with regards to the flow of cash into the firm, where as VaR quantifies the loss of asset value (Odening and Hinrichs 2002).

Manfredo and Leuthold (2001) use the portfolio approach to evaluate a multitude of weekly VaR calculation methods, both parametric (variance-covariance method) and non-parametric (simulation), for the cattle feeding margin. Their paper tests the historical simulation method as well as a variety of methods for estimating the volatilities and correlations to be used in the V-C calculation, including long run historical averages, 150 week historical moving average, GARCH (1,1)[14], exponential smoothing (RiskMetrics 1995), and implied volatilities from option contracts. Of all the methods tested, the RiskMetrics approach and the Historical Simulation method consistently produced the best results across the tested 90%, 95%, and 99% confidence levels for weekly VaR measures. Both the Z-stat and the LR-stat were used to validate each VaR approach at each specific confidence level, along with the minimum, maximum, and average violation size. The results that both parametric and nonparametric methods provide acceptable measures mirrors those of other financial papers (Manfredo and Leuthold 2001), and is most likely due to the absence of non-linear assets in the portfolio.

Odening and Hinrichs (2002) test three methods of calculating VaR. These methods are the V-C approach using GARCH (1,1) to estimate volatility and correlations, historical simulation, and VaR with the addition of extreme value theory (EVT). Odening and Hinrichs (2002) use weekly price data and calculate weekly VaR measures for a farrow operation, a finishing operation, and a farrow to finish hog operation. They then extend the time horizon from one week to 12 weeks by using the square root rule for the V-C and HS method, and the alpha-root-rule[15] for the VaR with EVT. This paper did

[14] GARCH stands for Generalised Autoregressive Conditional Heteroskedastic and is a model that can be used to forecast time series data. The GARCH process is capable of forecasting volatility and estimating model parameters (Levy 2001).
[15] See Odening and Hinrichs (2002) for explanation of the alpha-root-rule. In general, it leads to smaller VaR calculations for longer forecast horizons, eliminating some of the overestimation problems associated with the square root rule.

not statistically validate any of the methods due to their data restrictions, and all results were relative to each other. However, the results are that weekly V-C underestimates risk over a 1 week horizon when compared to the HS and EVT methods, and that the V-C and HS overestimates risk for a 12 week horizon when compared to the EVT.

Manfredo et al. (2003) use a somewhat different approach regarding the use of the VaR measure. Instead of comparing different methods of calculating VaR, this paper tests the ability of VaR to rank risk management strategies when compared to more traditional mean-variance risk measures. Using Monte Carlo techniques, 5000 simulations were conducted in order to develop the distribution of the Return on Assets (ROA) for three different sizes of agricultural cooperatives. Stochastic Dominance, the Sharp Ratio, and VaR were then used to rank 11 different potential risk management strategies[16], or a combination of risk management strategies, that these various size cooperatives could take part in. The cash market only scenario was used as the base case scenario. Although the biggest difference in rankings was between the VaR and the mean-variance approaches, the overall results were quite consistent between all the different risk measures and across the different firm sizes (Manfredo et al. 2003). This paper did not report the use of any statistical measures to test the validity of the VaR model.

3.9 Chapter Summary

This chapter discussed Value at Risk, giving a general definition and the three standard methods used to calculate VaR. VaR has become widely used in the financial industry, and is now gaining interest regarding its application to non-financial firms.

Despite several difficulties with applying VaR to non-financial firms, several studies have evaluated the potential of VaR when used by agricultural firms. These studies have evaluated the effectiveness of different VaR methods when used by agricultural firms, as well as how VaR compares to more traditionally used risk measures. Overall, these initial applications of VaR to agricultural firms have helped support the point made by the Manfredo (1998) in that there seems to be a potential to use VaR in agriculture. However, no single paper completely addresses the non-financial firm's

[16] A cash only strategy is included in these 11, and is used as the base scenario.

CFaR application requirements of longer time horizons, production risks, and model validations. Thus, this research project will address all three of these issues, while evaluating if CFaR will provide a useful tool for agricultural managers to identify, measure, and manage their risk exposures.

3.10 Chapter 3 Figures

Figure 3.1 Example of First Degree Stochastic Dominance

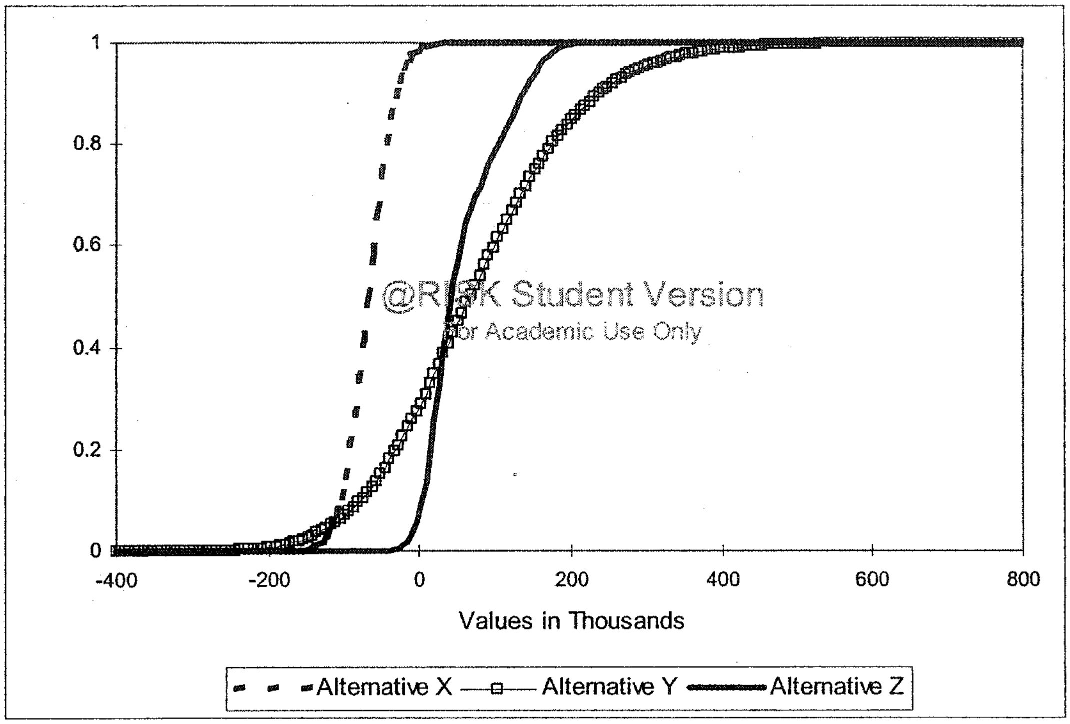
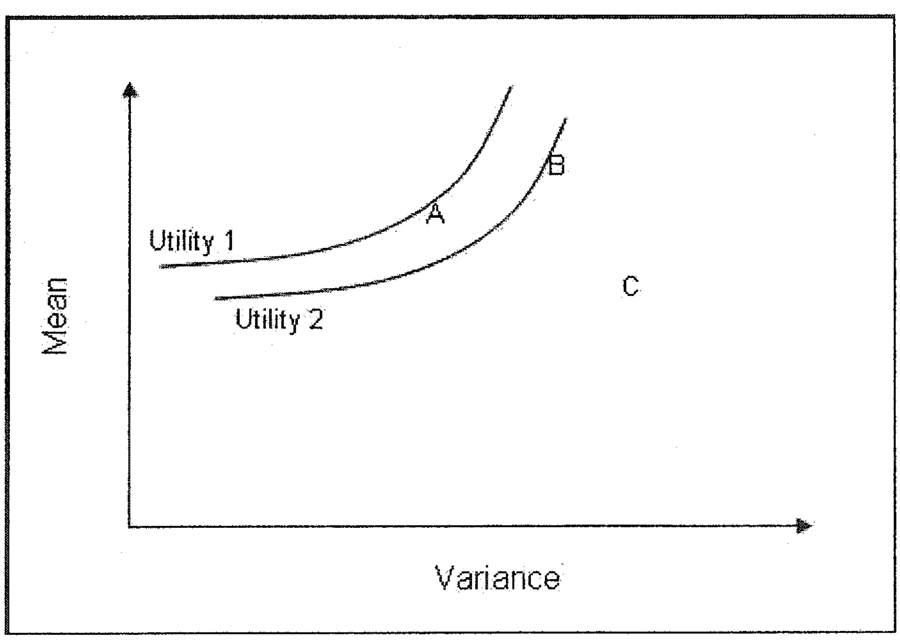


Figure 3.2 Example of E-V Space Analysis with Utility Assumptions



Chapter 4 – Data and Methods

This chapter will first define and explain the type of operation that was chosen for the research's VaR application and justify why it was chosen. The VaR methodology that was used is then identified and explained, followed by a description of the data and how they were tested and transformed. Next, the chapter explains how the various sources of risk are forecasted or simulated in order to calculate the end VaR measure. Finally, the structure of the Monte Carlo Simulation is explained, as well as how the model performance was verified (backtested).

4.1 Operation Type and Location

The operation that will be used in this VaR research as the example agri-business is a 1000 sow farrow to finish operation, which is assumed to be located in south central Alberta. There are several reasons for choosing the size and location of the operation. First, although there continues to be more specialized production units, such as only farrowing operations or finishing operations, farrow to finish operations still make up the majority of operations in Alberta (B. Denning 2003, and M. Soloman 2003). Second, as discussed in Chapter 2, the hog industry in Alberta is undergoing rapid changes with regards to the increasing size and production capacity of individual operations. Thus, because the trend is for larger firms, a 1000 sow farrow to finish operation was chosen. The future importance of operations of this size was also confirmed by Alberta hog industry experts (B. Denning 2003, and M. Soloman 2003), as their opinion was that a minimum of 800-1000 sows would be needed in order for a farrow to finish operation to be economically sustainable.

The southern Alberta area was chosen for the operation's location due to its recent growth in hog production, large average farm size, and the fact that this area is responsible for a large percentage of Alberta's total pork production (AAFRD 2001). Lethbridge, Drumheller, and Medicine Hat hog herds grew (number of pigs on farms) approximately 20%, 47%, and 67% respectively from the year of 1996 to 2001. These three areas alone also had the largest average number of hogs per farm, and are responsible for over 38% of Alberta's total production.

4.2 Underlying VaR Measure and VaR Components

This section identifies the underlying VaR measure (metric) as operating cash flow and gives the rationale for why it has been chosen. Several key components that are necessary for the application of VaR, such as the risk factors, time horizon, and confidence level, are then discussed.

4.2.1 Operating Cash Flow as Underlying VaR Measure

Cash flow will be used as the underlying measure (metric) of the VaR calculation due to its importance in non-financial firms, the impact it has previously had on hog producers, and the importance it holds with financial lenders. As discussed in section 3.7.1, non-financial firms, such as agri-businesses, are generally concerned with the risk factors related to cash flow. This is due to the fact that cash flow is considered to represent a clearer picture of a company's performance when compared to earnings (Fink 2002), and financial troubles will often first be revealed by cash flow (Kieso et al. 1997).

Managing cash flow is important in order to ensure bills are paid, unnecessary debt and interest is avoided, and to protect the liquidity[17] and solvency[18] of the business (Gibbins 1998). Thus, it is important for non-financial firms to have a good understanding of the cash flow they can expect to obtain for an upcoming period in order to protect the overall liquidity and solvency of the business.

During the 1998-99 period of low hog prices, low cash flows were a problem for hog producers. Producers had very little cash coming into their operations, while still having the regular cash outflows associated with production. This lack of positive cash flow caused problems, such as increased debt, prolonging principle payments, and a decline in firm equity (Western Producer 1998[a], 1998[b], 1998[c], 1999).

Finally, cash flow is a very important measure for creditors who lend to hog operations. Ellison (2003), who is the Alberta hog industry loans specialist for Farm Credit Canada, indicated that cash flow is their primary concern. The ability of an operation to generate cash shows the ability to service the debt, with equity only becoming a concern when cash flow has declined such that equity levels begin to decline (Ellison, 2003).

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[17] Can be defined as " the excess of very short term assets over short-term debts, and so the measure of a company's ability to pay its immediate obligations in cash at the present moment" (Gibbins 1998, p. G-21)
[18] Can be defined as "the condition of being able to meet all debts and obligations" (Gibbins 1998, p. G-30)

The equation below describes how the operating cash flows used in this research are calculated.

$$CF_t = \tilde{Q}^m \tilde{P}^m + \tilde{Q}^{cs} P^{cs} + Q^{cb} P^{cb} - \sum_{j=1}^{2} \tilde{Q}^w \tilde{R}^j - \sum_{h=3}^{6} \tilde{Q}^h \tilde{R}^h - \sum_{k=1}^{K} Q^s OC^k - \tilde{Q}^{rs} P^{rs} - Q^{rb} P^{rb} \quad [4.1]$$

where:
CF_t = quarterly cash flow from operations
Q = quantity of pigs
P = price
R = Ration cost of all feed consumed during specific stage (j,h)
OC = operating costs
m= market hogs
w = weaned piglets
j = different feed rations for weaners {j=1,2}
h = growth stage of pigs and respective feed ration {h=3,4,5,6}
s = sows
k = various operating costs (were k=1,2…10 from Table 4.1)
cs = culled sows
cb = culled boars
rs = replacement sows
rb = replacement boars
$\tilde{}$ = indicates variables that are stochastic

The stochastic variables $\tilde{P}^m$, $\tilde{R}^j$, and $\tilde{R}^h$ are dependent of time, and variables $\tilde{Q}^m$, $\tilde{Q}^{cs}$, $\tilde{Q}^w$, $\tilde{Q}^h$, and $\tilde{Q}^{rs}$ are independent of time.

All components of the operating cash flow, both stochastic and non-stochastic, are calculated on a monthly basis and then aggregated into longer time horizons such as quarterly, semiannual, and annual. It is important to note that because operating cash flow will be used as the underlying measure, Cash Flow at Risk (CFaR) is actually being measured, and is only referred to as CFaR from this point on.

4.2.2 CFaR Calculation Methodology

Monte Carlo simulation was chosen as the CFaR calculation method for several reasons. First, Monte Carlo is very flexible and can include both linear and non-linear risk exposures. This is important for the research, as some non-linear risk management strategies are evaluated in Chapter 6. Second, Monte Carlo is generally used when Cash Flow is the underlying metric (Linsmeier and Pearson 1996). This is again due to its flexibility and ability to include many different types of risks and analyze longer time horizons. Third, because Monte Carlo simulation is a full-valuation approach, it will generate the entire distribution of potential cash flows, allowing for the measurement of CFaR at any confidence level.

Similar to the definition given by equation 3.2, we can define the general equation for calculating CFaR as:

$$1 - c = \int_{-\infty}^{CF*} f(cf)\ dcf = P(cf \leq CF*) = p \qquad [4.2]$$

where:

CF* = is "the Quantile [of cash flow] of the distribution, which is the cutoff value with a fixed probability of being exceeded." (Jorion 2001, p.110)
f(cf) = the future cash flow value
c = given confidence level
p = probability, which must sum to 1-c

In general, CFaR is calculated by holding probability (*p*) fixed (e.g. 5%) and determining *CF**. However, CFaR can also be used by holding *CF** fixed (e.g. Cash Flows = 0) in order to determine the corresponding probability (*p*). Both of the above CFaR calculation methods are used in this research.

4.2.3 Risk Factors

With the underlying measure of operating cash flow being determined, the risk sources that will have the greatest influence on cash flow variability must be identified. Only the most important risks should be identified as this enables the operation to focus on carefully managing the important risk sources, while minor risks should receive less attention (Godfrey and Espinosa 1998). This stage is an important part of risk management and is consistent with the first risk management step listed in section 3.3.

Hog operations are exposed to a variety of risks, such as those defined in section 3.2.1 to 3.2.6. Choosing which specific risk factors to include in the CFaR analysis was based on two important factors; first, the risk sources that have been identified by producers and industry personnel as important; and secondly, the risk sources can be quantified using historical data.

In the survey performed by Patrick et al. (2000), U.S. hog producers in Indiana and Nebraska ranked fourteen different risk sources that affect income using a scale from 1-5, with 1 representing the least risky and 5 the most. A list of the risk sources and their rankings are shown in Table 4.2. Although these results are from American hog producers, these help identify the major sources of risk to be included into the model, as the U.S. and Canadian pork production industries share similarities.

The risk sources used in this research are shaded gray in Table 4.2 and include; hog price variability, changes in input costs (feed), and variability in performance of hogs. Personal communication with several Alberta hog industry personnel (Willis 2003, Solomon 2003, Elison 2003, Denning 2003) confirmed that these three specific sources of risk were also important sources of risk to Alberta hog producers' operating cash flows.

These identified sources of risk were also chosen as they could be quantified using historical data. As stated in section 3.6.3, choosing a model to represent the behavior of the variable is very important, thus its behavior must be quantified so that it can accurately be represented and simulated. The behavior of prices in Alberta, both input and output, can be determined using historical data obtainable from Alberta Agriculture, Food, and Rural Development's data base AGDATA. The performance variability of hogs can also be obtained from historical data, such as the data collected by producers using programs such as PigCHAMP.

In total, there are 10 individual sources of risk that will be incorporated into the simulation model: hog, barley, canola meal, and corn prices, the number of piglets weaned/sow/litter, number of litters/sow/year, culling rate of sows, and the death loss of sows, growers, and finishers (Table 4.3). Alberta hog industry personnel (B. Denning 2003 and M. Soloman 2003) also identified utilities as a growing source of input risk; however, this variable will not be included in the research.

4.2.4 Time Horizon

As mentioned in section 3.5.2, the time horizon is user specific. When using CFaR to measure and manage risk, the minimum time period chosen should reflect the planning horizon of the operation and the time needed to make corrective actions related to the operations risks. The maximum time horizon chosen can be any length that is of management's interest, but it is not extended past 2 years in this research. Overall, the time horizons chosen should generate useful CFaR measures for management and reflect the planning horizon(s) of the operation.

For the CFaR application to hog production, the time horizons used need to be longer than the daily or weekly horizons used by financial firms. In the paper by Gjolberg and Bengtsson (1997), the planning horizons for piglet producers, finishers, and farrow to finish operations were identified as 6-7 months, 3-4 months, and 9-10 months, respectively. Thus, we can expect the minimum time horizon of a farrow to finish producer to be 3-4 months, as this is the shortest time horizon or planning horizon for one stage of the production lifecycle.

Also, because the underlying measure of CFaR is cash flow, longer time horizons must be used. Weekly and monthly cash flows may be of some interest, but it is the longer-term cumulative cash flows that will have a greater impact on an operation. If negative cash flows persist over long time periods, problems such as an inability to pay bills, excess debt, or erosion to equity may begin.

Based on the above reasoning, longer-time horizons will be used in this research, with a quarterly CFaR time horizon (3-month) the minimum time horizon analyzed. The minimum quarterly time horizon was chosen as this is the minimum amount of time needed to make changes to the finishing aspect of the farrow to finish operation. Also, cash flow results that are negative for an entire quarter will likely create the problems mentioned above that are associated with a lack of cash flow. Periods of 6-months, 9-months, 1-year, 1.5-years, and 2-years will also be analyzed in order to evaluate the potential downside risk to operating cash flow over longer time periods.

4.2.5 Confidence Level Choice

Choosing the confidence level for the research is not straightforward, as there is no specific confidence level that reflects the level of risk all producers are concerned with. "In most agricultural risk management situations, there is not a clear economic justification for selecting the probability level at which VAR is evaluated" (Gloy and Baker 2001, p.39). This research will evaluate 95% and 80% confidence levels, as well as find the confidence level associated with cash flows >$0.

Typically in financial literature, as well as VaR literature applied to agriculture, a confidence level of 95% has been used. Because there is no general confidence level that is regarded as best for agricultural use, three different confidence levels will be used in this research. First, the 95% confidence level (5% probability) is used as this level has been extensively used in both financial and agricultural literature. This level may not actually have any economic importance to Alberta hog operations, but it will be tested in order to determine if it can be used to set a liquid capital (e.g. cash on hand or operating loan access) requirement that could protect against extreme cash flow losses, similar to what is done in the banking industry to fulfill the Basel Committee requirements.

Secondly, a lower confidence level of 80% (20% probability) is used and tested in order to determine if lower confidence levels will provide better decision making information in agriculture, at least when compared to the higher confidence levels (95%) often used in the financial industry. Because these lower confidence levels (such as 80%) measure the losses to operating cash flows that are more likely to occur (20% probability), it is suspected that these will be of more interest to producers. Because producers are generally risk averse (Hardaker et al. 1997, Hardwood et al. 1999), they would generally want to manage risks that are more likely to occur, not just those that occur in extreme cases.

Finally, the confidence level (probability) is determined when cash flow is held fixed ($CF^* = 0$ in equation [4.2]). Holding the cash flow level fixed at zero, the CFaR measure will calculate the probability of the 1000 sow operation not achieving the economic target of cash flows breaking even. Using the measure in this respect is anticipated to be of most use to producers as they can evaluate a specific economic goal. The fixed cash flow chosen may be the amount of their debt obligations, living expenses, or perhaps cash flow >$0 as used in this research. However, the ultimate choice for a confidence level is producer specific, and should be chosen to best suit the individual's risk preference and operation's needs.

With the exception of the 95% confidence level, no research has been found that tests and evaluates the use of the 80% confidence level and probability of cash flows less than zero when applying VaR to agriculture. Comparing the performance and potential use of these measures in agriculture is unique to this research.

4.3 Price Data

This section will discuss where the data were obtained, how and why it was transformed, and the basic statistical tests that were used to analyze it.

4.3.1 Source of Price Data

All time series price data used to represent the various market risks (Table 4.3) were for the time period of Jan. 1979 to Dec. 2002 and were obtained from the Alberta Agriculture and Rural Development database AGDATA. The AGDATA series are #301, #35, #3, and #2 respectively for hogs, barley, corn, and canola meal. Because the operation in the model is based in southern Alberta, spot prices (hogs and barley) for Alberta and southern Alberta are used in order to take into account local basis. If no price data were available for the immediate area (canola meal and corn) then the closest available location was chosen.

4.3.2 Data Transformation

Two simple transformations were performed to the price data. First, the data obtained were in weekly time periods, so it was transformed to monthly periods by using the second week's price of each month. Monthly prices are needed as the time horizon of the price forecasts in the model are monthly.

Second, the data were transformed into its logged form using natural logs. Using the logged form of the price data will prevent the price forecasts from being negative, allowing them to range from zero to infinity (Hull 1989). The data were left in nominal terms and analyzed directly, such as done by Higginson et al. (1988). Also, any inflation effects that might impact prices will be minimal as the maximum time horizon forecasted and analyzed is only two years.

4.3.3 Statistical Testing of Data

Before the data were transformed into its logged form, basic descriptive statistics were taken. These statistics, such as the mean, minimum, maximum, and variance are reported in Chapter 5 and are used to compare and analyze the accuracy of the simulation price forecasts. Unit root tests were then performed to the log-transformed data in order to determine if the logged data were stationary. The importance of stationary data and the unit root tests used are discussed next.

Stationarity of Data

The stationary property ensures the mean, variance, and covariance of the data are constant over time (Judge et al. 1988). The stationarity property also has implications regarding the choice of methods that can be used to estimate the forecasting models.

If the time series data for a certain price variable is found to be stationary, then the price behavior of that variable can be considered to follow a mean reversion pattern instead of a random walk (Baker et al. 1998). This identifies that the use of simple mean reverting forecasting models, such as the Auto Regressive [AR(n)] and Vector Auto Regressive [Vector AR(n)] models (n = the number of lagged periods in the model), can be used to forecast the price path of the respective variable. This mean reversion pattern is often displayed by commodity prices, such as those used in this research, due to the supply and demand relationships that eventually bring the price back towards the commodities long run marginal cost (Baker et al 1998).

Also, the data should be stationary if Ordinary Least Squares (OLS) regression is going to be used to estimate the AR(n) and Vector AR(n) model parameters. Judge et al. (1988) and Griffiths et al. (1993) state that the regression of non-stationary data on non-stationary data may cause spurious regression, potentially leading to wrongly estimated coefficients, high R-squared values, and autocorrelation in the error terms. If the time series data are found to be stationary using a unit root test, then the data does not have to be transformed into a stationary state (Diebold and Kilian 2000). However, if the data are found to be non-stationary, it can be transformed into a stationary form using either a trend stationary process (TSP) or difference stationary process (DSP) (Griffiths et al 1993).

Unit Root Tests

The two unit root tests used in this research to determine data stationarity are the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron test. Diebold and Kilian (2000) found that using the Dickey-Fuller unit root test to determine if the data are stationary, and whether it needed to be differenced or not, improved AR(1) forecasting results.

Two variations of the ADF tests are used and are calculated using Shazam 8.0 (1997) for both a constant and no-trend:

$$\Delta Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \sum_{j=1}^{p} \gamma_j \Delta Y_{t-j} + \varepsilon_t \qquad [4.3]$$

and for a constant and trend:

$$\Delta Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 t + \sum_{j=1}^{p} \gamma_j \Delta Y_{t-j} + \varepsilon_t \qquad [4.4]$$

where Δ refers to the first difference of variable Y, ε_t is assumed to be the Gaussian white noise (independent and identically distributed errors (i.i.d.)), and p is the number of lagged terms chosen to ensure uncorrelated errors (Shazam 1997). The null hypothesis of this test is $\alpha_1 = 0$, which indicates that a unit root is present and that the data series is non-stationary. Testing the null hypothesis is accomplished using an adjusted critical t-test statistic, and if the observed ADF value is lower than the critical t-test then the null is rejected and we assume the data series is stationary ($\alpha_1 \neq 0$). The formulation of the Phillips-Perron (P-P) unit root test used can be viewed in Shazam (1997). Although the results of both unit root tests will be used, if conflicting results occur then priority will be given to the ADF test as its ability has been discussed and tested more extensively in other literature (Judge et al. 1988, Griffiths et al. 1993, and Diebold and Kilian 2000). The P-P unit root test is used to help confirm the ADF results.

4.4 Price Simulation

As mentioned by Jorion (2001), specifying the model to represent the risk factors is a crucial part of Monte Carlo simulation. However, because there is no universally approved forecasting model, several simple price forecasting models will be tested in order to choose the one that performs best.

When choosing potential price forecasting models, a number of objectives should be considered, such as the perceived accuracy in specifying the distribution of prices that will occur in the future, ease of implementation, closeness to market views, the ability to include factors such as market relationships, test extreme events, incorporate current market information, and account for macroeconomic conditions (RiskMetrics 1999). The three models that have been chosen and tested in this research are the Random Walk, the AR(n), and the Vector AR(n), and are explained below. All models are based on financial time series data and were chosen due to their ability to reflect commodity prices, their ease of implementation, and ability to reflect correlation relationships between markets.

4.4.1 Random Walk Forecasts Model

The random walk model is one of the most basic, yet one of the most widely used forecasting models in financial literature. This model is assumed to represent the movement of stock prices well, as it is consistent with weak-form efficiency theory (Cleary and Jones 2000). Efficiency theory states that prices today reflect the fair or present value of their economic worth as the current price includes and accounts for all current and relevant information (Ross et al. 1995). Thus, prices changes are due to new information being introduced into the market, and not based on past price changes. The random walk process can be shown as:

$$P_{t+1}^{m} = P_{t}^{m} + \varepsilon_{t+1} \qquad [4.5]$$

where the expected price P^m in period $t+1$ for commodity m is equal to the current price of P^m plus the unsystematic component or random shock ε_{t+1} (Gjolberg and Bengtsson 1997). Thus, prices for commodities m (hog, barley, canola meal, and corn) are derived from the current price plus the introduction of new information. When simulating, the random price change $\varepsilon_t \sim N(0,\sigma)$ is estimated such that (Risk Metrics 1995):

$$\sigma = \sqrt{\frac{\sum_{t=1}^{T}(P_t^m - P_{t-1}^m)^2}{T}} \qquad [4.6]$$

Although this is a popular model for simulating stock prices, it generally does not represent the behavior of commodity prices well (Baker et al. 1998). Despite this fact, this model will still be tested as it is a very simple, commonly used, and provides naive predictions that can be used to compare against the predictive ability of the AR(n) and Vector AR(n) models.

4.4.2 Auto Regressive Forecast Model

The AR(n) models (n = number of lags in AR model) can be used to forecast prices that return to the mean (Bewley 2000), however, there are several steps that must be taken in order to ensure that correct number of lags are included in the model, and that the OLS estimation of the coefficients are not biased.

The AR(1) process can be defined as:

$$P_{t+1} = \alpha + \phi_g P_{t-g} + \varepsilon_{t+1} \qquad [4.7]$$

where P_t is the logged price in period t, α = the constant, ϕ = the coefficient estimate, g= the number of lags, and ε_{t+1} = the random shock.

Estimation of AR(n) Coefficients Using OLS

Ordinary least squares regression can be used to estimate the AR(n) parameters as long as; the data have been determined stationary, or transformed into a stationary state; and that the disturbance or error terms (ε_{t+1}) are independently and identically distributed (i.i.d.) (Bewley 2000). Assuming the data are stationary, OLS estimates can then be calculated for AR(n) models of various lag lengths. The i.i.d. property of the OLS estimated AR(n) error terms can then be verified by using the Box-Pierce-Ljung (B-P-L) and LM-stat tests to determine if autocorrelation exists between the error terms. If small levels, or no autocorrelation exists between the errors, then the i.i.d. property can be assumed to exist. Although Shazam 8.0 (1997) recommends using the LM test over the B-P-L test when there are lagged dependent variables, both tests will be used as was done in the research by Higginson et al. (1988) and Unterschultz (1996).

AR(n) Lag Determination

Determining the correct AR lag structure for each commodity price forecasting model was accomplished using four different tests: The Akaike Information Criterion (AIC), the Schwartz Criterion (SC), coefficients t-tests, and adjusted R^2.

The AIC and SC tests are calculated according to Judge et al. (1988), and can be shown as:

$$AIC(n) = \ln \tilde{\sigma}_n^2 + 2n/T \qquad [4.8]$$

$$SC(n) = \ln \tilde{\sigma}_n^2 + n \ln T/T \qquad [4.9]$$

where $\tilde{\sigma}_n^2$ is the residual variance, n is the number of lags, and T is the number of observations. The selection criterion for both of the above tests is the number of lags that minimizes each of the measures (Judge et al. 1988). The AIC test tends to favor longer lag periods when compared to the SC. Although longer lag periods may produce inefficient estimators, the argument can be made that it is better to have an inefficient estimator with over parameterisation instead of a biased estimator with under parameterisation (Bewley 2000). Thus, the AIC decision criterion will be given more weighting than the SC decision criterion if conflicting results occur.

The t-test of coefficients and the adjusted R-squared tests are also used, as these are more standard OLS tests for model specification. The t-test are used to test whether the coefficient values of ϕ for the lagged variables are significantly different than zero, with the null hypothesis of $\phi=0$. The t-tests are performed by; first, start by using a large number of lags and test the longest lagged coefficient, second, reduce the number of lagged periods by 1 and retest the longest lagged coefficient estimate, third, keep doing this until the t-test indicates the last lagged coefficient to be significantly different than zero (Bewley 2000). When the last lagged ϕ estimate is found significant then this is the correct number of lagged periods to include in the AR(n) forecasting model. For the adjusted R-square test, the maximum value is the decision criteria for choosing the best number of lags to include in the AR(n) forecast model.

When choosing the proper lag structure, the AIC decision criteria will be given the most decision weight overall and is used when conflicting results occur between the various tests. The purpose of using the other lag length tests is to help check the decisions based on the AIC and to make sure they are not substantially different than the other tests.

Estimating as a System and Accounting for Correlation

After the lag length selection of each individual AR model is chosen (hogs, barley, canola meal, and corn) and the i.i.d. property has been shown to hold, the individual AR(n) models will be re-estimated together as a system of equations (Seemingly Unrelated Regression) using the Shazam 8.0 econometrics program. Although the individually estimated models can be used, the system approach will be used to estimate the coefficients, conditional variance/covariance matrix, and the conditional correlations, as this approach is more efficient than OLS (Judge et al. 1988).

The conditional correlation estimates obtained from the system estimation are used to incorporate the relationships between price movements in the simulation. This is accomplished by adjusting the error components in the simulation model using an extension of the bivariate normal distribution method described by Hull (1989):

$$\begin{aligned} E_1 &= X_1 \\ E_2 &= \rho_{i,j} X_1 + X_2\sqrt{1-\rho_{i,j}^2} \end{aligned} \qquad [4.10]$$

where E_1 and E_2 are the correlation adjusted errors for their respective AR(n) model, $\rho_{i,j}$ is the correlation between E_1 and E_2, and X_1 and X_2 are the independent random draws from a univariate standardized normal distribution (Hull 1989). The total formulation used to account for the correlation relationships in the AR models is (Miller 2002):

$$\begin{aligned} E_1 &= X_1 \\ E_2 &= \alpha_{21} X_1 + \alpha_{22} X_2 \\ E_3 &= \alpha_{31} X_1 + \alpha_{32} X_2 + \alpha_{33} X_3 \end{aligned} \qquad [4.11]$$

where:

$$\begin{aligned} &\alpha_{21} = \rho_{12} \quad and \quad \alpha_{22} = \sqrt{\rho_{12}^2} \\ &\alpha_{31} = \rho_{13} \quad and \quad \alpha_{32} = \left(\frac{\rho_{23} - \rho_{13}\rho_{12}}{\sqrt{1-\rho_{12}^2}}\right) \quad and \quad \alpha_{33} = \left(\sqrt{1-\rho_{13}^2 + \left(\frac{\rho_{23} - \rho_{13}\rho_{12}}{\sqrt{1-\rho_{12}^2}}\right)}\right) \end{aligned} \qquad [4.12]$$

Once the random draws for each specific price forecast are adjusted to include correlation relationships, they are then adjusted by their respective standard deviation.

$$\varepsilon_i = E_i * \sigma_i \qquad [4.13]$$

The corresponding standard deviations (σ_i) are extracted from the conditional variance/covariance matrix as calculated by the SUR.

4.4.3 Vector Auto Regressive Forecast model

The differences between the AR(n) model and a Vector AR(n) model is that the latter has a richer dynamic structure which allows it to capture the interaction between variables and causal relationships (Bewley 2003). This ability to capture the interaction can sometimes produce better forecasts for hog prices when compared to the AR(n) models, as was shown by Gjolberg and Bengtsson (1997) when forecasting hog prices in four Scandinavian countries. The process of choosing the best Vector AR(n) model is similar to that of the AR(n) model, and is described below.

The Vector Auto Regressive Model

Since the development of the Vector AR(n) model, several variations have been developed, however, a simple version is evaluated in this paper and can be shown as:

$$\begin{aligned} Y_t &= \alpha_0 + \phi_1 Y_{t-1} + \phi_i Y_{t-n} + \varphi_1 X_{t-1} + \varphi_i X_{t-n} + \beta_1 Z_{t-1} + \beta_i Z_{t-n} + \varepsilon_t \\ X_t &= \alpha_1 + \gamma_1 Y_{t-1} + \gamma_i Y_{t-n} + \kappa_1 X_{t-1} + \kappa_i X_{t-n} + \pi_1 Z_{t-1} + \pi_i Z_{t-n} + \varepsilon_t \\ Z_t &= \alpha_2 + \lambda_1 Y_{t-1} + \lambda_i Y_{t-n} + \psi_1 X_{t-1} + \psi_i X_{t-n} + \tau_1 Z_{t-1} + \tau_i Z_{t-n} + \varepsilon_t \end{aligned} \qquad [4.14]$$

where n= number of lags in system of equations [n = 1,2...6], t = time period, $\alpha,\phi,\varphi,\beta,\gamma,\kappa,,\lambda,\psi,\tau$, are the coefficients, X,Y,Z are the logged time series price variables, and ε_t is the error term. Thus, the impact of a change, whether through the error term ε_t or the lagged dependant variables, will be felt throughout the entire model as all the equations are linked.

Estimating the Vector AR(n) Model Coefficients

Once the data stationarity requirement is fulfilled, Seemingly Unrelated Regression will be used to estimate the coefficients, conditional variance/covariance matrix, and the conditional correlations system of equations using Shazam 8.0.

Lag Determination and Accounting for Correlation

The Vector AR(n) model will be estimated for n=1-6 and then subjected to the AIC and SC tests. However, a slight adjustment has to be made to the previous AIC and SC measures because we are now specifying the lag length for an entire system of equations and not just one single forecast variable, as was done with the AR(n) models. When determining the Vector AR(n) lag length, Judge 1988 defines the two measures as:

$$AIC(n) = \ln\det\tilde{\Sigma}_n + 2M^2 n / T \qquad [4.15]$$

$$SC(n) = \ln\det\tilde{\Sigma}_n + M^2 n \ln T / T \qquad [4.16]$$

where $\tilde{\Sigma}_n$ is an estimate of the residual covariance matrix, n is the number of lags, M is the number of variables in the system, and T is the number of observations (Judge 1988). The minimum test value is again the lag length selection criteria for these two measures. These are the only tests used to specify lag length for the Vector AR(n) model. Once the model is specified, the coefficient estimates can then be used in @RISK 4.5 to forecast prices. Accounting for the correlation relationships between prices will be accomplished in the Vector AR(n) forecasting models using the same method that was used in the AR(n) forecasts.

4.4.4 Price Forecasting Model Tests

Three different comparative tests will be used in order to determine which of the three forecasting models performs best. The three tests are the Mean Square Error (MSE), Mean Absolute Percent Error (MAPE), and a test for directional bias of the forecast (BIAS). These tests will be calculated by comparing the forecast values against the most current 12 months of out of sample data (Jan.-Dec. 2003). This process will be completed 10,000 times for each of the 12 months and for each forecasting model. The average values of the MSE, MAPE, and BIAS for the 10,000 simulations are then collected for each of the forecasting models, and are then used to rank them according to their performance.

The MSE and MAPE tests are hard to interpret in an economic sense (Gjolberg and Bengtsson 1997), and are instead used only to compare and rank the models relative to each other. If conflicting results occur between the measures, the MSE will be used as it focuses on choosing the forecast model with the lowest average squared prediction errors. The MSE, MAPE, and BIAS measures are calculated respectively as:

$$MSE = \sum_{i=1}^{T} \frac{(\widetilde{P}_i^F - P_i^A)^2}{T-1} \qquad [4.17]$$

$$MAPE = \sum_{i=1}^{T} \frac{Absolute((\widetilde{P}_i^F - P_i^A)/P_i^A)}{T-1} \qquad [4.18]$$

$$BIAS = \sum_{i=1}^{T} \frac{(\widetilde{P}_i^F - P_i^A)}{T-1} \qquad [4.19]$$

where i= month[i=1,2..T], $\widetilde{P}_i^F$ = forecasted monthly price, and P_i^A = actual observed monthly price.

4.5 Production Data

The production data used are based on Alberta and Canadian producers. Three different sets of data are used to derive the production simulation parameters. All three sets of data are either directly obtained from PigCHAMP, or are based upon PigCHAMP statistics.

The first set of data (Production Data set #1) are obtained directly from PigCHAMP[19] and are the production statistics for a single 1300 sow operation. The data are weekly averages of the number of piglets weaned per sow per litter obtained by the 1300 sow operation, are for the duration of 24 weeks (April 26-October 4, 2003), and are used to determine the distribution parameters for simulating this variable. Using a single operation to derive this production factor, instead of aggregated data, will allow the model to represent the actual variation in piglet production that might be obtained in a single operation of this size.

The second data set (Production Data set #2) are also obtained directly from PigCHAMP and are the production statistics for 19 Alberta producers. These data report average production results of for the number of litters per sow per year, the rate that sows are culled (%), and the death rate of sows (%) for each of the 19 Alberta producers. The producer's sizes range from about 150 to 700 sows, and the specific time and duration the data were collected for is not known. The parameters and distributions for the specific variables stated above are determined from this data set. Data Set #1 was not used for these production factors because it's time frame was not long enough and representative distributions and parameters could not be accurately estimated.

The third set of data (Production Data set #3) used to determine some of the model's production variables are obtained from the Vol. X, October 2001 Bacon Bits article. These data are the worst, average, and best results from 7 different Canadian producers, and are used as the parameters for producing the triangular distributions for % death loss of grower and finished hogs. These statistics are based upon aggregated PigCHAMP data from the year of 1999.

4.6 Production Risk Simulation

The individual production risk factors that will be simulated are: piglets/sow/litter, litters/sow/year, % death loss of sows, % of sows culled, % death loss of growers, and %

[19] PigCHAMP is a computer software package that can be used to store production statistics. The manufacturers of PigCHAMP also collect individual producer statistics which is used to generate a data base and average production statistics for various countries.

death loss of finishers. The simulation of these production risks are accomplished in two stages.

The first stage focuses on determining the number of piglets produced per sow/month, death loss of sows/month, and the number of sows culled/month. The production simulation parameters derived during this stage will then be transferred over to the second stage of the simulation, where they will be combined with grower and finisher death loss, price simulations, and the non-stochastic model inputs.

To accomplish the production simulation, various distributions will be used to represent different production risks, such as binomial, triangular, lognormal, and logistic distributions. The distributions and parameters are chosen for each production risk based on the respective data set and how well the distribution represents the individual source of risk. The different distributions chosen and their corresponding parameters are discussed in Chapter 5 (5.4.1 and 5.4.2).

4.7 Non-Stochastic Model Components

Although the non-stochastic components are not sources of risk in the model, their inclusion is important in order for the model to reflect the cash flow of the operation. The Manitoba Agriculture, Food, and Rural Initiatives (MAFRI) website was used as the source of the non-stochastic cash flow components due to its detailed breakdown of the cash flow statement for a farrow to finish operation. The non-stochastic operating costs are included into the model on a sow per year basis and are shown in Table 4.1. Other non-stochastic values used in the model include the price for cull boars ($110), cull sows ($90), replacement boars ($800), replacement sows ($250), average dressed carcass weight (88kg), and the number of cull boars sold and new boars purchased (10/year, which is 50% of 50 to 1 sow to boar ratio). These values were determined from recommendations and hog production consulting models given by Denning (2003). The number of sows held by the operation remains fixed at 1000 sows.

The MAFRI was also used as the source of the feed ration components, the feed rations for each production stage, the number of days spent in each production stage, and the amount of feed consumed during each stage. A list of the different feed rations, the time spent on each ration, and the total amount of feed consumed per ration stage are shown in Table 4.4.

4.8 Monte Carlo Structure

The Monte Carlo simulation model is capable of accounting for specific events during the specific months in which they occur. Because the model is focused on cash flows, the simulation model must keep track of when cash is flowing in or out of the operation at the corresponding time. This is important as the timing of operating cash flows can have a significant impact on the firm's viability and financial performance.

Due to the flexibility of the Monte Carlo approach, specific events that influence operating cash flows can be accounted for in the simulation at the approximate time they are occurring (a monthly basis). This includes keeping track of the stochastic or simulated production factors such as the number of pigs being born, the number of finished hogs sold, the number of sows purchased and sold, all during the specific month in which they occur. The model also combines these stochastic production components with the non-stochastic components in order to keep track of the flow of pigs through the different production stages and the total amount of feed the pigs are consuming at each stage each month. There are a total of 9 different feeding rations used, which reflect the different feed components and the composition of the ration for the stages of production. The rations used and the time an animal spends on each ration can be seen in Table 4.4. Thus, the model accounts for the number of pigs flowing through each production stage each month and how much feed they consume, reflecting the flow of an actual operation.

Finally, the model must combine the stochastic and non-stochastic components already mentioned with the price simulations and the remaining non-stochastic operating cash flow components. This is accomplished in order to reflect the operating cash flows that are occurring for each specific month. Simulating the entire model over and over (10,000 times) then allows for the collection of the CFaR results for the chosen time horizons and confidence levels. The simulation of the Monte Carlo model will be achieved using the Palisade Corporation student version of the software @RISK 4.5.

4.9 Backtesting Methods

The two statistical tests used to validate or backtest the model are the LR and Z-stat tests. The LR test is used to determine if the CFaR model results are significant. The null hypothesis is $\delta = \delta *$, where δ is the stated probability (5% CFaR) and $\delta *$ is the realized probability. The LR statistic can be calculated as:

$$LR(\delta) = 2\left[\ln(\delta *^{X} (1-\delta *)^{N-X}) - \ln(\delta^{X}(1-\delta)^{N-X})\right] \qquad [4.20]$$

where X is the number of realized violations (when the observed cash flows are less than the CFaR value), N is the number of out of sample data points, and $\delta *$ is calculated as X/N (Manfredo and Leuthold 2001). More specifically, X is obtained when the actual subsequent results observed violate the CFaR results. This test is then compared to the chi-square distribution with 1 degree of freedom.

The Z-stat can also be used, and determines whether the CFaR model significantly over or under estimates the downside risk, and is calculated as (Manfredo and Leuthold 2001):

$$Z_c = \frac{X - N(1-\delta)}{\sqrt{N\delta(1-\delta)}} \qquad [4.21]$$

where X, N, and δ are the same as described above for the LR test. If the results are significantly positive (negative) when compared to a critical Z value then the VaR results underestimate (overestimate) the potential downside risk.

4.10 Chapter Summary

This chapter discussed the type of operation that is used as the underlying business of the VaR application, and why it was chosen. The distinction was then made that the model is actually calculating CFaR as the underlying measure and economic interpretation of the measure is operating cash flow and not asset value. The initial setup and transformation of the price data was discussed, along with the various forecast models and tests used to determine the best model. The production data were then introduced along with the production risk factors that are simulated. Finally, a basic description was given regarding the overall structure of the Monte Carlo Simulation model and how it is developed in order to account for the flow of production and the timing of operating cash flows. Combining the production and price simulation with the non-stochastic components into the Monte Carlo model then allows for the estimation of CFaR measures for various time horizons and confidence levels. The results of the price forecast models, production simulation components, and the final CFaR results are discussed next.

4.11 Chapter 4 Tables

Table 4.1 Sow/Year Operating Costs used in CFaR Model

Non-Feed Operating Costs (Per Sow/Year)		
1. Vet. Med. & Supplies	$	47.27
2. Maintenance & Repairs	$	23.12
3. Hydro & Propane	$	50.86
4. Insurance	$	43.50
5. Manure Costs	$	83.32
6. Office Supplies	$	2.00
7. Marketing & Transport	$	127.03
8. Property Tax	$	22.05
Labour		
9. - Farrow to wean	$	187.20
10. - Grower to finish	$	93.60
Total Non-Feed Operating Costs	$	679.95

(Source: MAFRI[a] 2002)

Table 4.2 Risk Sources that Affect Income

Risk Sources that Affect Income	Rank of Importance
Hog price variability	1
Changes in environmental regulations	2
Disease in hogs	3
Market access	4
Changes in input costs	5
Changes in arrangements with those who purchase your production	6
Variability in performance of hogs	7
Changes in social or community acceptance of hogs	8
Changes in government programs	9
Changes in demands of management due to changes in structure and/or technology	10
Changes in attitudes of lenders	11
Possibility of an environmental accident	12
Labor/personnel	13
Possibility of a contractor failing to fulfill the terms of the contract	14

Source: Patrick et al. (2000)

Table 4.3 Specific Sources of Risk Included in This Research

Market Risk	Production Risk
- Hogs - Barley - Canola Meal - Corn	- Piglets weaned/sow/litter - Litters/sow/year - Culling rate of sows - Death loss to: - sows - growers - finishers

Table 4.4 Feed Rations (kg/day), Number of Days on Feed, and Feed Consumption per Production Stage

Production Stage	kg/day	Days on Feed	Total Feed Consumption per Stage
Dry Sow Ration	2.30	316.6	728.2
Nursing Sow Ration	6.00	48.4	290.4
Boar Ration	2.50	365.0	912.5
Creep Feed	0.14	22.0	3.0
Starter Ration 1	0.67	21.0	14.0
Starter Ration 2	1.00	14.0	14.0
Grower 1	1.76	40.0	70.2
Grower 2	2.59	37.0	96.0
Finish	2.53	43.0	108.9

(Source: MAFRI[b] 2002)

Chapter 5 – Results

This chapter will explain the results and the calculations that were performed in order to create and test the Cash Flow at Risk (CFaR) model. This will include the initial data tests, forecasting model lag selection and performance tests, the CFaR model results, and the CFaR backtesting results.

5.1 Testing the Price Data

Basic descriptive statistics were calculated for the initial monthly data and are reported in Table 5.1. These values are used later in the chapter to compare the output results of the forecasting models chosen to represent prices in the CFaR model. The data were then logged transformed and tested for unit roots to ensure data stationarity.

5.1.1 Unit Root Tests

The Dickey Fuller (DF) and Phillips-Perron (P-P) unit root tests are used to determine if the data are stationary. Both tests are calculated for a constant and no-trend, as well as a constant and trend, and are tested at a 10% significance level. The Dickey-Fuller results (Table 5.2) for all the individual prices are less than the critical DF values, thus, the null hypothesis is rejected, indicating that no unit roots exist in the hog, barley, canola meal, and corn price data. With the exception of barley, the P-P test results (Table 5.2) are also less than the critical values, again indicating the data are stationary. Although unit roots were found in the barley data by the P-P test, this research concludes that no unit roots exist in the barley data as the Dickey Fuller test is given the most decision weighting when conflicting results occur. This indicates that the prices used likely follow a mean reversion pattern, and that the logged price data and ordinary least squared regression (OLS) can be used to estimate the coefficients of the AR(n) and Vector AR(n) forecasting models.

5.2 Price Simulation

Three models developed and tested are the Random Walk (Equation [4.5]), AR model (Equation [4.7]), and Vector AR model (Equation [4.14]). The models are simulated 10,000 times on a monthly basis for a 5-year period[20]. The simulated monthly prices are transformed from logged prices back into actual prices, where data regarding the minimum, mean, maximum, and variance is gathered and compared against historical data statistics.

5.2.1 Random Walk Model

As mentioned in Chapter 4, the random walk model is commonly used to represent stock prices. However, because our unit root tests indicated that the price data are stationary, we can hypothesize that this model will poorly represent the CFaR price inputs as it is not mean reverting. Despite this hypothesis, we will still use the model as a naïve model that can be compared to the performance of the other forecast models.

The random walk model (equation [4.5]) is simply the last observed price plus a random component. The random component is assumed to have a normal distribution with a mean of zero and a standard deviation calculated according to equation [4.6]. The standard deviations calculated for logged hogs, barley, canola meal, and corn data are 0.1074, 0.0628, 0.0766, and 0.0962 respectively (Table 5.3).

Using December 2002 prices as the starting point, the Random Walk forecasting model is simulated monthly 10,000 times over a 5-year period. The simulated monthly prices are transformed from logged prices back into actual prices, where data regarding the minimum, mean, maximum, and variance for the hogs, barley, canola meal, and corn price forecasts are gathered. Because we are simulating the model 10,000 times, we can expect the minimum simulation values to be somewhat lower and the maximum simulation values to be somewhat higher than the historical values as the simulation is capturing potential prices that have not been observed over the short 288 historical observations. However, if the model is performing well, the simulated min, mean, max, and average variance values should be close to those that have been observed historically. The min, mean, max and average variance results of both the simulations and historical data are shown in Table 5.4.

In general, when comparing the Random Walk forecasts to the historically observed values (Table 5.4); the minimums are substantially lower; the mean values are

[20] A 5-year time horizon is used to gather the min, mean, and max information in order to provide more data points to analyze the forecasting models, but only two years is used for the CFaR analysis.

moderately different (both above or below); and the maximums and average variances are substantially higher. For example, the minimum, mean, maximum, and average variance for the simulated hog prices are 0.065$/kg, 1.357$/kg, 12.157$/kg, and 0.3695 respectively, which are different than the observed min, mean, max, and average variance of 0.601$/kg, 1.468$/kg, 2.130$/kg, and 0.0726. Using these basic stats, the conclusion is made that the Random Walk models perform poorly for forecasting the CFaR model price inputs, as the forecasted minimum, maximum, and variance are very unlikely to actually occur.

5.2.2 AR Forecasting Model

Various AR(n) models (n = number of lags in the model) are estimated using OLS (Equation [4.7]). In total, six different lag structures are estimated for each price, with the lag structures ranging from 1 to 6 lags [AR(n) where n = (1,2...6)].

Optimal Lag Structure

The optimum lag structure for each of the AR(n) price forecasting models are identified using the AIC, SC, coefficient significance test, and Adjusted R^2. As mentioned in Chapter 4, the AIC test is given the most decision weight when conflicting results occur. The coefficient t-tests and the adjusted R^2 tests are also used, but only to help confirm the results of the AIC test. The results of these tests are shown in Table 5.5.

According to the AIC test, the optimal AR models are the AR(3), AR(3), AR(1), and AR(2) for hogs, barley, canola meal, and corn respectively, as these lag structures produced the smallest AIC values (Table 5.5). All of the lag structures chosen by the AIC test are also confirmed by the coefficient t-test results, as each of the lagged variable coefficients was found to be significantly different than zero.

The SC test confirms the lag structures chosen for canola meal and corn, but differs from the AIC test results for hogs and barley. The adjusted R^2 value confirms only the AIC results for hogs, and adds no value for choosing the optimal lag structure for the other prices as it differs completely from all other tests.

Tests for Autocorrelation

Before the OLS estimates can be used, the error terms of the various AR(n) models are tested for serial autocorrelation (e.g. the i.i.d. property). The Box-Pierce-Ljung (B-P-L) test indicates (Table 5.6) that autocorrelation exists in the hog and barley error terms at 12 plus lags and 9 plus lags respectively. These results are most likely due to some seasonality in the price data. However, this test is not recommended by Shazam (1997) when lagged dependent variables are included and is therefore given less decision weighting. Also, because the auto correlation exists only for lag lengths significantly longer than those of the AR(n) models, the autocorrelation identified by the B-P-L test is ignored.

The LM-stat, which is recommended by Shazam (1997) when lagged dependent variables are included, fails to reject the null hypothesis that no autocorrelation exists in the AR(n) error terms for barley, canola meal, and corn. The LM-stat identifies autocorrelation only at the 12^{th} lag for hogs, as the LM-stat of 4.83 is greater than the 5% critical chi-square value of 3.84. However, we will assume that the impact of the autocorrelation in hogs is negligible for the purpose of this research, because its occurrence in the 12^{th} lag period is considerably greater than the lag periods used in the AR(n) models and because it only occurs once. Thus, we will assume that there is little to no autocorrelation and that the OLS estimations of all the AR(n) coefficients are adequate.

Estimating the AR(n) Models as a System

Now that the previous tests have been completed, the AR(n) parameters are re-estimated as a system using seemingly unrelated regression (SUR). Estimating an AR(3) for hogs, AR(3) for barley, AR(1) for canola meal, and an AR(2) for corn in a system provides new error correlations and standard deviations estimates (Table 5.7) and new AR(n) coefficient values (Table 5.8). As shown in Table 5.7, the correlations between hogs and the other variables are low, thus the correlation relationships between hogs and the other variables are not taken into account when forecasting. Only the correlation relationships between the error terms of the barley, canola meal, and corn AR(n) models are included into the model estimation as these correlations are stronger (Table 5.7). This is accomplished using equations 4.10-4.13 from Chapter 4.

The correlations, standard deviations, and coefficients reported in Tables 5.7 and 5.8 are the final values used to simulate prices in the Monte Carlo model. Simulating prices 10,000 times over a 5-year period, the min, mean, max, and average variance values of the AR(n) simulations are collected and compared to historical values. The

AR(n) models performed better than the Random Walk as the AR(n) min, mean, max, and average variance values are much closer to the historically observed values (Table 5.4). Thus, we can conclude that the AR(n) models out perform the Random Walk models and are better suited to the price simulation needs of this research. The AR(n) models are also compared to the Vector AR(n) models described next.

5.2.3 Vector AR Forecasting Model

The optimum lag structure for the Vector AR(n) models are determined using the AIC and SC tests described in equations [4.15] and [4.16]. These tests are applied to a total of 6 different Vector AR(n) lag structures ranging from 1 to 6 lags (n = 1,2...6).

After running SUR for the various lag structures, the AIC and SC tests are calculated and shown in Table 5.9. The AIC test indicates the Vector AR(3) as the optimal lag structure as it produced the minimum value of about –20.23. The SC test indicates the Vector AR(1) as the optimal lag structure of the Vector AR model as it produced the minimum value of about –19.98 (Table 5.9). Unlike the AR(n) models, no literature was found which specifically stated which test may produce better results for choosing the appropriate Vector AR(n) model. To be consistent with the AR(n) models the AIC test should be used as the main decision criteria. But to make sure which lag structure is best, several Vector AR(n) models ranging from 1-4 lags will be tested in the next section in order to see which produces the best forecasting results.

The coefficient estimations of the Vector AR(n) models are shown in Table 5.10 and the estimation of the error standard deviations and error correlations are shown in Table 5.11 and Table 5.12 respectively. As the number of lags in the Vector AR(n) model increase, the standard deviation of the errors decrease (Table 5.11), which is likely due to more of the price movements explained by the added lagged variable.

Although the best Vector AR(n) model has not yet been determined, we can still compare the min, mean, max, and average variance values obtained for the Vector AR(n) with lags from 1-4 for 10,000 5-year monthly simulations (Table 5.4). Comparing these results (Table 5.4), the Vector AR(n) models are much closer to the historically observed values than the Random Walk model, and perform very similar to the AR(n) models. The results in Table 5.4 do not provide enough information to determine if the Vector AR(n) models perform better than the individual AR(n) model. Thus, further testing is performed and discussed next.

5.3 Simulation Comparative Tests

Now that the coefficients and lag lengths of the Random Walk, AR(n), and the 4 Vector AR(n) forecast models have been estimated, their forecasting ability is compared using several performance measures. The coefficients for these models are estimated using the price data from 1979 to 2002. To test the performance of their forecasts, out of sample monthly data for the year of 2003 will be compared against the 10,000 one year monthly simulated forecasts from each of the models, enabling for the calculations of the MSE, MAPE, and BIAS measures (Equations [4.17, 4.18, and 4.19] respectively).

As reported on Table 5.13, the MSE ranks of the models are compared using a scale from 1 to 6, where 1 is smallest MSE value (best) and 6 is the largest MSE value (worst). The AR(n) models produce the best total average MSE rank of 1.25, with hogs, barley, and corn all receiving a rank of 1 and canola meal receiving a rank of 2. According to this measure, the AR(n) model outperforms most of the other models for all price variables. The next best model is the Vector AR(2) model, which received a total average MSE rank of 1.75. The Vector AR(2) results are interesting as they do not agree with either of the Vector AR(n) lags chosen by the AIC and SC selection criteria. As stated in section 5.2.3, the AIC test identified three lags and the SC identified one lag as the best structure. The Random Walk produced the worst estimates and received a total average MSE ranking of 6, supporting the statement in Chapter 4 that Random Walk models tend to poorly represent commodity prices.

The results of the MAPE test are shown in Table 5.14, and are very similar to the MSE results. Again, the AR(n) models outperform the others and receives a total average MAPE ranking of 1.25. Hogs, barley, and corn each received the top rank of 1 while the canola meal AR(1) model receive a rank of 2. The Vector AR(2) model was the second best performing forecasting model and received a total average MAPE rank of 1.75

The BIAS ranking results (Table 5.15) are used to identify if a forecasting model is generally over or under estimating price, and to what extent. These results also rank the AR(n) models as best (1.5) and the Vector AR(2) models second best (2.5). As shown in Table 5.15, all of the forecasting models biases are positive, with the exception of the Random Walk model for hogs. With only this one exception, all of the forecasting models tended to estimate prices that were higher than those obtained over the 2003 test period, producing an overall positive bias in the price forecasts.

The results of the three forecasting performance tests identify the AR(n) models as the best performing forecasting models. Based on these results, the AR(n) forecasting models will be used to derive the stochastic price forecasts in the CFaR Monte Carlo simulation model.

5.4 Production Data and Simulation

As mentioned in Chapter 4, three different sets of production data are used to derive the parameters and distributions of the various production risks in the CFaR model. The data sets were chosen for each specific risk factor based on its ability to provide appropriate and representative distributions and parameters. The production parameters are then used to simulate production risk using two separate simulation stages.

There are two main reasons for simulating the production variables in two different stages. First, the production factors in Stage 1 are transformed from annual and percentage forms into a monthly and discrete forms. This is important as all values are simulated on a monthly basis in Stage 2 of the simulation. Secondly, the interaction of several production distributions can be simplified and represented by a single monthly distribution. This simplification still incorporates the influence of original production risk factors, but reduces the complexity and run times of the Monte Carlo Simulation used in stage 2.

5.4.1 Simulation Stage One

The first stage of the simulation determines the distributions and parameters for the production factors of; the number of piglets weaned/month, how many sows die/month, and how many sows are culled/month. These are calculated on a monthly basis so that they can be included into the Stage two of the simulation.

Piglets Weaned/Month

The production factor of piglets weaned/month for the 1000 sow farrow to finish operation is derived by combining the stochastic production components of litters/sow/year, piglets weaned/sow/litter, and the % of sows that die/year. The distribution and parameters of litters/sow/year were estimated using the @Risk 4.5 Best-fit results of data set #2 (Figure 5.1). The distribution and parameters for piglets weaned/sow/litter (Figure 5.2) are estimated using @Risk 4.5 Best-fit results and data set #1. The % death loss of sows/year is calculated using data set #2 and a triangular distribution, using the 10% data low (2%), the mean (4.98%), and an upper value of 6.9%[21] as the triangular distribution parameters.

The three stochastic production components mentioned above were included into simulation Stage 1 and run 10,000 times. The output data for the number of piglets weaned/month was then collected and tested using the @Risk 4.5 Best-fit function. The resulting distribution and parameters for piglets weaned/month are displayed in negative values in Figure 5.3. The piglets weaned/month were transformed into negative values in order to determine the most appropriate Best-fit analysis, as there were no appropriate best fit distributions when the piglets/month were in their positive form. The distribution and parameters from the negative piglets/month best fit results are then used in simulation Stage 2, but are transformed into there positive values (multiplied by –1) before they are used in the simulation Stage 2 CFaR calculations.

Number of Sows/Month that are Culled or Die

The estimated number of sows that die or are culled each month are transformed from annual percentage forms (Table 5.16) into monthly discrete forms. This is accomplished by combining each of the triangular distributions from Table 5.16 separately with litters/sow/year (Figure 5.1), the total number of sows (1000), and dividing by 12 to get a monthly value. Next, the output data from the 10,000 simulations (stage 1) is collected for how many sows died and how many were culled each month. The simulation data are then analyzed using @Risk 4.5 Best-fit, where the discrete monthly distributions of Figure 5.4 and Figure 5.5 are determined as the best, and are used to represent these factors in simulation Stage 2. Both of these production factors are represented by a binomial distribution in order to produce the discrete values for use in Stage 2.

[21] The data set 10% high of 8.7% was considered to be too high when compared to the rest of the data and not representative of the operation used in the model. Thus the next observed % death loss of 6.9% was used instead as the upper triangular distribution parameter.

5.4.2 Simulation Stage Two

Stage 2 of the simulation combines the monthly production parameters derived from Stage 1 (piglets weaned/month, number of sows culled per month, and number of sows that die per month) with the remaining production parameters and stochastic price components. The remaining two stochastic production factors included in Stage 2 are the death loss to growers and finishers, and are represented by triangular distributions (Table 5.17). Combining these production risks, simulation Stage 2 is able to estimate and keep track of the number of market hogs that flow through the operation (CFaR model) from birth until sold. Stage 2 also estimates and keeps track of the number of sows culled, died, and replaced, with the assumption that a 1000 sow level is always maintained. Interacting these components with the other stochastic and fixed components allows for the complete CFaR results to be estimated.

5.5 Cash Flow at Risk

Combining all stochastic and non-stochastic components into the Monte Carlo simulation model (simulation Stage 2) and running it 10,000 times, the Cash Flow at Risk results for the 1000 sow farrow to finish operation are estimated. Although the Monte Carlo approach develops the entire distribution, the estimated CFaR results are reported at the 5% and 20% probability levels, as well as the probability of operating cash flows being less than zero (CF < 0). These results are collected for a quarterly, semi-annual, tri-quarterly, 1-year, 1.5 years, and 2 years time horizons and are reported on Table 5.18 and displayed in Figure 5.6. Because the CFaR results are forward looking into the year of 2003 to 2004, the prices used to start the AR(n) forecasting models are the monthly observed prices from Oct. to Dec. 2002 (Table 5.19). These prices are the last observed prices of the price data set used to estimate the AR(n) price forecasting models.

5.5.1 5% CFaR Results

The estimated 5% CFaR results reported for all time horizons are negative, indicating a large potential loss to the operations cash flow. These results continually decline (become more negative) up until the 2-year horizon (Table 5.18), at which point the cumulative cash flows begin to improve (become less negative). This indicates that the downside risk to cash flow continues to increase until the 1.5-year horizon. However, if the CFaR values for the various time horizons are calculated based on the expected number of market hogs that will be sold[22] over the time horizons, the 5% CFaR results begin to improve immediately as time increases (Table 5.18). Thus, the loss to operating cash flow per market hog sold improves overtime, which intuitively indicates that the probabilities of receiving low operating cash flows are decreasing over time. Despite the improvement shown by the 5% CFaR results per market hog sold, the increasing loss to the cumulative 5% CFaR measure should be the concern of management, as it is the cumulative negative cash flows that will cause the operation to have problems meeting operating cash flow commitments.

As mentioned in Chapter 4, the best anticipated use of the 5% CFaR measure would be to provide an estimate of a liquid capital level that could be used to protect against a large loss to operating cash flow. For example, for the first 6-months of 2003 (semi-annual), the manager of the 1000 sow operation would want to maintain access to, or a level of liquid capital (e.g. cash or operating loan) of about \$264,000 in order to protect against the potential downside loss to operating cash flow of -\$264,000 at the 5% level (Table 5.18). The \$264,000 worth of liquid capital would help ensure that the operation could continue paying its bills and meet their operating cash requirements 19 out of 20 times for the six-month period. A more conservative, or more risk adverse manager may want to choose a longer time horizon, such as 1-year, in order to protect against the risk that poor operating cash flows may occur for longer than 6-months.

Now suppose that the 5% CFaR measure is going to be violated and operating cash flows are going to fall below the semi-annual value of -\$264,000, what would be the expected loss to operating cash flows? In order to determine this, the average was taken of all the forecasted CFaR values that fell below the semi-annual 5% CFaR value of -\$264,000. The expected CFaR losses for the semi-annual 5% CFaR level, as well as all the other time horizons and the 20% CFaR levels are shown in Table 5.20. Continuing with the semi-annual time horizon example used previously, the expected CFaR results indicate that if operating cash flow falls below -\$264,000, then the expect loss to cash flow will be -\$311,449 (Table 5.20). This is a significantly greater loss than the 5%

[22] The expected number of hogs sold corresponds to the specific time horizon being analyzed. For example, the CFaR per hog sold for Quarter results is calculated by dividing the quarterly 5% CFaR measure (-\$150,086) by the expected number of hogs that will be sold over the quarter (5286).

CFaR value given, indicating that the liquid capital level held of $264,000 would not adequately meet the cash flow requirements of the operation if the 5% CFaR level was violated.

Overall, the 5% CFaR model anticipated very large losses to operating cash flow over 2003 and 2004. For example, the 5% quarterly CFaR results indicate a potential loss to cash flow of about -$28.39 per hog marketed (Table 5.18). Subtract another $20.74 for operating loan interest, investment, and other fixed costs (MAFRI[a]) to the -$28.39, and the 5% CFaR is predicting a total potential loss of -$49.13 or lower per hog sold for the first quarter of 2003. Although this loss may seem extreme, it is fairly close to the average loss of -$41.65[23] reported for Alberta producers from July 15th, 2002, to about March 2003 (Toma & Bouma Management Consultants 2003). These results are conservative when compared to the highest reported loss of -$87.95 per hog sold in September 2002 (Toma & Bouma Management Consultants 2003). If the 5% CFaR model was actually used by producers for decision making in December 2002, they should have realized that the 5% CFaR results could occur in 2003, especially considering extremely low results that recently occurred (-$87.95 in Sept.). This should have motivated producers to put considerable energy into exploring and implementing possible risk management options in order to help protect against these large potential operating cash flow losses.

5.5.2 20% CFaR Results

The results of the estimated 20% CFaR measures follow the same general pattern as the estimated 5% CFaR results (Table 5.18 and Figure 5.6). Initially in the first quarter, the 20% CFaR starts off negative, and continue to decline as time increases. However, the results begin to improve (become less negative) by the annual time horizon, with positive results of $76250 occurring at the 2-year horizon (Table 5.18). Also similar to the 5% results, the 20% CFaR results per market hog sold improved over every time horizon (Table 5.18), reiterating that the CFaR model is continually forecasting fewer negative operating cash flows.

[23] Toma & Bouma used a $55 non-feed cost per hog in their analysis, which is close to the $51.10 used in this research (30.37 for non-feed variable costs and $20.73 for operating interest, investment, and other fixed costs)

It is important to note that the patterns seen in the CFaR results are attributed to the stochastic price components of the model. The stochastic production components are independent of time and therefore will not produce any patterns or trends in the results over time. This will be further discussed below in section 5.5.4.

A 20% CFaR level was chosen for evaluation because it will analyze potential losses to operating cash flows that are more likely to occur (a 1 in 5 chance) when compared to the 5% measure (1 in 20 chance). As previously mentioned, it is suspected that this measure may be of more interest to agricultural managers than the 5% CFaR when being used to help make everyday business and planning decisions as the 5% CFaR losses may be too extreme for regular planning and decision making. Using the 6-month time horizon again as an example, the 1000 sow operation has 20% CFaR level of about -$139,400 (Table 5.18). Thus, there is a 1 in 5 chance that the operations may experience a loss to cash flow of -$139,400 or below. Thus, even at the 20% CFaR level the potential loss to operating cash flow is large, which should signal to management that potential risk management strategies should be implemented in order to help reduce the downside risk to operating cash flow. This is especially true if this potential loss is more than management can accept.

If the 20% CFaR is violated for the 6-Month period, such that CF<-$139,400, then the expected value of CFaR predicted by the model is -$224,531 (Table 5.20). This is substantially more than the 20% CFaR measure. Thus, the producer should expect a loss to cash flow significantly lower than the predicted 20% CFaR measure if the CFaR measure is violated.

Like the 5% CFaR measure the 20% CFaR measure is still anticipating large losses to operating cash flows, especially for the first year of analysis (2003). Using the quarterly 20% CFaR results as an example, the 1000 sow operation has a 20% chance that the losses to their cash flow will be -$96,329 or below. Per hog marketed[24], this equates to an operating cash flow loss of about a -$18.22. With the subtraction of another $20.74 for operating loan interest, investment, and other fixed costs (MAFRI[a]), the total expected loss per hog marketed at the 20% CFaR level is -$38.96, which is very close to the average loss of -$41.65 actually experienced by Alberta producers around this time

[24] Based on the expected number of hogs that will be sold in the CFaR model (5286) over the first quarter.

(Toma & Bouma Management Consultants 2003). This level of loss is lower than the \$48.85 loss per hog at the 5% level, but this level of loss is 4 times more likely to occur. Thus, the potential downside risk to operating cash flow is substantial over the first quarter of 2003, again indicating to management that perhaps the use of some form of risk management should be pursued.

5.5.3 Probability of Cash Flows < 0

The estimated results for CF<0 exhibit a different pattern than both the estimated 5% and 20% CFaR results. The probability of CF<0 for the first quarter is 72.68% (Table 5.18), indicating a very high chance that operating cash flows will be negative. However, as the length of the time horizons increase, the probability of CF<0 steadily decreases (Figure 5.6). For the 2-year time horizon, the probability of CF<0 is only 16.45% (Table 5.18).

Producers may prefer to use a CFaR measure such as CF<0, or perhaps another fixed value of interest such as debt obligations. Choosing a fixed value instead allows producers to evaluate the level of risk corresponding to a specific cash flow value that is of economic interest. The CF<0 measure reports a significant risk that the 1000 sow operation will have a negative operating cash flow for the first half of 2003, with the semi-annual time horizon results indicating a probability of about 56% that CF<0. Thus, the operation has over a 1 in 2 chance that there will be insufficient cash to meet their operating cash flow requirements, let alone other cash requirements such as those from operating loan interest, investments, and other fixed costs. Thus, based on the high probability of obtaining negative operating cash flows over the year, the CF<0 CFaR measure also indicates that the operation would likely want to participate in some sort of risk management strategy in order to lower the probability of negative operating cash flows. If the 56% CF<0 probability is exceeded, the expected loss to operating cash flows over 6-months would be about –\$127,700 (Table 5.20).

5.5.4 Overall CFaR Results

Looking at all of the CFaR results in Figure 5.6, a pattern in the cash flow distributions over time can be intuitively determined. As mentioned above, the 5% CFaR, which is near the very tail end of the cash flow distributions, continues to decline until the last reported time horizon of 2-years. The 20% CFaR results, which occur further away from the tail of the distribution, initially decline, but begin to improve by the annual time horizon. Finally, the CF<0 results, which occur furthest from the lower tail of the CF distributions (at least in this research), continually improve over the entire 2-years of analysis. Considering all of this information, it can be determined that over time, the lower tails of the non-cumulative quarterly cash flow distributions are slow to change. However, as time increases, more and more of the forecasted cash flows move right and shift towards the positive end of the distribution. This is shown graphically by comparing the distributions of the non-cumulative cash flows for quarters 1-3 and quarter 8 (Figure 5.7). The distribution's lower tails for the first three quarters stay about the same. The central point and the right tail continue to shift right as time increases, showing that more and more cash flow forecasts are improving each quarter. By quarter 8 the entire cash flow has shifted to the right (positive), including the lower tail. Thus, from this pattern we can see why the patterns in the 5%, 20%, and CF<0 occur, as cash flows associated with higher probabilities will improve the quickest initially, with low probability cash flows slower to change.

This pattern in the individual quarterly distributions, and the pattern of the CFaR results, is due to the mean reversion model and the low 2002 hog prices and high 2002 barley prices used to start the AR(n) forecasting models. As time increases, the price forecasts want to revert back towards the more favorable average prices (Table 5.1) and away from the poor price levels starting the forecasting models (Table 5.19).

We would expect the opposite results to occur if better than average prices were used to start the AR(n) models. It is also expected that the non-cumulative cash flow distributions will widen around a central point if mean prices were used to start the model. Testing the model using mean[25] and better than average prices[26] shows these hypothesis to hold (Figures 5.8 and 5.9).

Table 5.21 indicates that when mean prices are used to start the CFaR model, the 5% CFaR values initially decline a small amount and then increases, while the 20% CFaR value constantly increases over the time horizons. However, the CFaR values per market

[25] The mean prices used to start the AR(n) models are conditional means based on the AR(n) models with no random shocks. By removing the random shocks and forecasting the AR(n) models over several years, the models eventually converge to their mean prices, and these are the prices used.
[26] Better than average prices are feed prices that are lower than their mean values, and hog prices that are above their mean values.

hog sold remain fairly constant (Table 5.21). When better than average starting prices are used (Table 5.22), the 5% CFaR and 20% CFaR both increase over time, however, per market hog sold, both continually decrease as the better than average prices used to start the model are not anticipated to continue.

When comparing the non-cumulative quarter 8 cash flow distributions generated from using various starting prices (Figures 5.7-5.9), they appear to be very similar, as the lower and upper tails of the distributions have very similar values. Thus, one might expect when using the different starting values, the 2-year time horizon CFaR results values may begin to converge. However, because the CFaR results are cumulative cash flows, the impact of the positive results obtained during the initial quarters (or negative when 2002 prices are used to start the model) carry through the entire analysis, influencing even the last time horizon analyzed.

5.6 Backtesting Results

The LR and Z-tests are used to evaluate if the CFaR model is performing accurately. These two tests are evaluated using both quarterly and monthly time horizons, and the results are shown in Tables 5.23 and 5.24 respectively. Monthly tests are used as the minimum test horizon as this is the smallest time horizon forecasted in the CFaR model. Quarterly tests are used as the maximum test horizon as time horizons longer than this would provide too few backtesting data points. In total, 37 out of sample quarterly time periods and 111 out of sample monthly time periods are used to perform the two tests, and are obtained using observed out of sample data for the period of Oct. 1993 to Dec. 2002. More test points are not used because enough data have to be held back to estimate representative AR(n) parameters and because all available columns in the CFaR backtesting spreadsheet were used[27].

The LR and Z-stat test are calculated by comparing the CFaR results to cash flows produced by using subsequent out of sample data. This is achieved by estimating the AR(n) forecasting model parameters on an annual basis up until the subsequent data period used for testing. The data used to estimate the AR(n) parameters are then updated annually, and the parameters re-estimated for the next year's test period. For example;

[27] The spreadsheets in the student version of @RISK 4.5 are limited in size to 256 columns.

the AR(n) parameters used for producing the 1996 CFaR backtesting result are estimated using the price data from Jan 1979 to Dec. 1995; actual prices from Oct.-Dec1995 are used to generate the Jan.-Mar. 1996 CFaR results; actual prices from Jan.-Mar. 1996 are used to generate Apr.-Jun. 1996 CFaR results; actual prices from Apr.-Jun. 1996 are used to generate Jul.-Sep. 1996 CFaR results; and actual prices from Jul-Sep. 1996 are used to generate Oct.-Dec. 1996 CFaR results. These CFaR results are then compared to subsequent cash flows that are produced when the actual observed prices from 1996 are entered into the CFaR model. This one backtesting period produces 4 quarterly backtesting points or 12 monthly backtesting points. The AR(n) parameters are then re-estimated using the data from Jan. 1979 to Dec. 1996 in order to produce 1997 CFaR results. The 1997 CFaR results are then compared to subsequent cash flow results obtained form using the 1997 observed price data, producing another 4 quarterly or 12 monthly test points (N from equations [4.20] and [4.21]). The AR(n) forecasting parameters are updated in this manner using data from the periods of 1992 to 2001 so that the CFaR results can be compared to the subsequent out of sample results from 1993 to 2002. Following this procedure, the number of realized violations (X described in equations [4.20] and [4.21]) that occur at specific stated probability levels can be determined by counting the number of times the subsequent cash flow values exceed (violate) the simulated CFaR values.

5.6.1 Quarterly Backtesting

Comparing the percent of observed quarterly violations (X/N) to the expected percent of violations (stated probability), the model is shown to underestimate the downside potential of cash flow risk as the observed percent of violations is higher than the stated probability levels (Table 5.23). This is especially true for lower stated probability levels, indicating that a stronger bias to underestimate risk at these lower levels. However, using only 37 monthly data points (N as described in Equation [4.20]), a slight change in observed value of X (described in Equation [4.20]) can cause a large change in the observed percent of violations (X/N), and no strong conclusions can be made regarding the models overall accuracy. The only conclusion that can be made for certain is that the model is underestimating the downside risk to cash flow when compared to the 37 historical data points. However this is to be expected, as the underestimation of downside risk at low stated probability levels is a common problem with VaR. This underestimation problem is consistent with the VaR models tested by Manfredo and Leuthold (2001), as all 15 models tested underestimated the downside risk to the cattle margin at the 1%, 5%, and 10% levels when using 564 weekly data points (N). The most suitable model tested by Manfredo and Leuthold (2001) that can be compared to the Monte Carlo simulation model used in this research is the historical simulation model, as this is the only full valuation or non-parametric method Manfredo et Leuthold (2001) tested. However, the results of their historical simulation model are not necessarily transferable and consistent to this research's application of VaR as the underlying models are different. When tested at the 1%, 5%, and 10%, levels, Manfredo and Leuthold (2001) found that the historical simulation method produced well calibrated results (Table 5.25). The non-parametric methods based on RiskMetrics-97 and several other models also performed well, with the GHIST-VaR model and several others performing less accurate[28] (Table 5.25).

Because only 37 quarterly test points are obtainable from the test period used (Oct. 1993 to Dec. 2002), the power of the statistical tests are low. However, these results are still presented as they provide a statistical measure of how well the CFaR model performs for the shortest time horizon analyzed in our analysis. As shown on Table 5.23, the LR test fails to reject the null hypothesis that the stated CFaR probability is equal to the realized probability (Ho: $\delta=\delta^*$), as all LR-stat test statistics are below the critical 5% chi-square value of 3.84. The failure of the LR-stat test to reject the null indicates that the realized CFaR model results are not significantly different than the stated probabilities used for testing. Thus, violations of the CFaR model occur at probabilities similar to those tested (1%-50%). Keeping in mind the low statistical power of the test due to the data restrictions, we can consider the CFaR model to perform adequately. For example, at the 5% coverage level we would expect the model's quarterly CFaR results to be violated roughly 5 out of every 100 times.

The Z-stat test also fails to reject the null (Ho: $\delta=\delta^*$) for all stated probability levels tested (1%-50%), as all of the Z-test results were between the critical 5% Z-stat

[28] For a full description of the RiskMetrics-97 and GHIST-VaR estimation methods see Manfredo et al. 2001. The RiskMetrics-97 is calculated using RiskMetrics volatilities and correlations using a λ=.97. GHIST-VaR is calculated using GARCH-t volatilities and historical average correlations.

values of +/-1.96 (Table 5.23). Because the Z-test fails to reject the null, the model is not significantly over or underestimating downside risk. Again, because of the limited amount of backtesting data available, consideration must be given with regards to the low statistical power of the test.

5.6.2 Monthly Backtesting

In order to increase the number of backtesting observations, the LR and Z-stat are performed on a monthly basis. Again, by comparing the percent of observed violations (X/N) the expected percent of violations (stated probability), the model is shown to underestimate the downside risk potential of cash flow as the observed percent of violations that occur monthly are higher than the stated probability levels (Table 5.24). Similar to the quarterly backtest results, the monthly results indicate a stronger bias at lower stated probability levels. However, this bias steadily improves as the stated probability level increases. By the 20% stated probability level the percent of observed violations is only 1.3% different.

The LR and Z-stat are now tested at monthly time horizons in order to improve the statistical power of the tests, as 111 subsequent test points are available. As shown in Table 5.24, the LR test statistic at the stated probabilities of 3% and 4% are greater than the critical chi-square statistic of 3.84, indicating that the CFaR model results are significantly different than the stated probability test levels of 3% and 4%. The LR test statistics at all other probability levels are less than the critical chi-square stat, indicating that the CFaR model results are not statistically different than the stated probability test levels.

The Z-test produces significant bias values for the 1-5% stated probability levels as the Z-stat exceeds the critical Z-test level of +1.96. All of these results are significantly positive, indicating that the CFaR model is significantly underestimating the downside risk at each of the corresponding stated probability levels. This means that at the 1-5% stated probability levels, the CFaR model is generally not anticipating large enough losses to operating cash flows as more violations (X) occur than is statistically acceptable. Thus, it is expected that the true 1-5% CFaR values are lower than those predicted by the model in this research.

5.6.3 Overall Backtesting Results

Based on the observed violations for monthly and quarterly results, and the monthly Z-test results, the CFaR model potentially underestimates the downside risk to cash flow at lower stated probability levels. This bias is largest at low stated probability levels, which is indicated by both the significant monthly Z-tests results at the 1-5% stated probability levels.

However, the backtesting results are considered adequate with regards to validating the CFaR models performance. First, as mentioned previously in Chapter 4 (section 4.2.5), it is expected that the use of a low probability test level (e.g. 5%) would not be as informative to producers. Second, at low probability levels there are very few historical observations that can be used and compared to the CFaR results in the backtesting procedure, making it difficult to determine if the results are simply due to chance or if in fact the model is truly bias. Third, although the statistical power of the LR and Z-stat are considered low, they generally support that the model is performing adequately. The majority of the monthly LR tests fail to reject the null, with only two occurring at low probability levels (null only rejected at 3% and 4% stated probability levels). The monthly LR tests also only reject the null at low probability levels (null is rejected from 1%-5%). Fourth, as previously mentioned, the underestimation of downside risk is a typical problem in VaR models, which is why Odening and Hinrichs (2002) explored the use of Extreme Value Theorem in their research. Considering these factors, but understanding that a potential bias to underestimate the downside risk to cash flow exists, the CFaR model is considered to adequately represent the downside risk to the cash flow for this research, especially for the tested stated probability of 20%.

Although a direct comparison can not be made, the backtesting result of the Manfredo and Leuthold (2001) Historical Simulation model at the 10% stated probability level is very similar to the Monte Carlo simulation model of this research. When performing monthly backtesting, the percent of observed violations at the 10% stated probability level is 12.51% (Table5.24), which is similar to the 12.23% (Table 5.25) observed violations of Manfredo and Leuthold (2001) at the 10% level. The results of Manfredo and Leuthold (2001) at the 1% and 5% test levels are not similar to the results of this research.

Finally, consideration must be given regarding the quarterly time horizons used for backtesting. Because the longest time horizon used to test the CFaR model's performance is quarterly, the assumption is made that because the model performs adequately over this length of time, it will also perform adequately over the longer time horizons used in this research. This assumption is made as the longer time horizons used in this research are simply cumulative quarterly results.

5.7 Square Root Rule Comparisons

As indicated in Chapter 3, section 3.6.1, the square root rule can be used to analyze VaR results over longer time horizons. This is based on the three assumptions that; the structure or weighting of the portfolio must remain the same over the course of time analyzed, returns are normally distributed, and returns are identically and independently distributed [i.i.d.] (Odening and Hinrichs 2002). Odening and Hinrichs (2002, p.1) also note that "little is known about its [square root rule] properties if returns are not independently distributed (for instance if they follow a GARCH process or a mean reverting process)". Thus, the quarterly CFaR results of this research are extended to longer time horizons using the square root rule in order to determine how it performs with regards to this application of CFaR.

The application of the square root rule is used in a similar manner as that used by Odening and Hinrichs (2002) [$VaR(h) = VaR(1)\sqrt{h}$], such that $VaR(1) \approx \mathrm{CFaR}_{1,p}$ where: 1 = the CFaR results for Quarter 1 and p = the corresponding CFaR probability level (5% and 20%). The $\mathrm{CFaR}_{1,p}$ results can then be extended for longer time horizons by using the square root rule $\sqrt{t}$ where t = time in quarters.

$$CFaR_{t,p} = CFaR_{1,p}\sqrt{t} \qquad [5.1]$$

The extended CFaR results obtained when using the square root rule are then compared to the longer time horizon CFaR results estimated by the Monte Carlo simulation model (Table 5.26). When comparing the results at the 5% probability level, the square root results underestimates the downside risks to operating cash flow for shorter time horizons and overestimates the downside risk for the 2-year horizon. This finding is consistent with Odening and Hinrichs (2001) findings when using low probability levels. Comparing results at the 20% level, the square root rule results are similar to the CFaR results when extending the quarterly CFaR results to semi-annual. But when using the square root rule to extend the quarterly CFaR results to the tri-quarterly to 2-year horizons, the square root rule increasingly overestimates the potential downside risk to operating cash flow (Table 5.26). Thus, for the application of CFaR used in this research, the square root rule cannot be used to extend shorter term CFaR results over longer time horizons as the square root results are inconsistent with the simulated CFaR results. Thus, when using the CFaR model for long time horizons, the entire length of the time horizon must be simulated.

The inability of the square root rule to perform accurately in this research is likely due to two of the three required assumptions being violated. First, because the CFaR model is based on both mean reverting price forecasts and cumulative cash flows, the i.i.d. property is unlikely to hold as the CFaR results are dependent on both previous prices and previous CFaR results. Secondly, the distribution of the simulated operating cash flows for quarter one is closer to a lognormal distribution than a normal distribution.

5.8 Impact of Production Risk on the CFaR Results

Previous applications of VaR agriculture, such as that done by Manfredo and Leuthold (2001) to the cattle industry and Odening and Hinrichs (2002) to the hog industry, have not included the impact of production risks. This is likely due to both of the above papers using and testing the Variance-Covariance (V-C) method.

Also, as indicated by the survey results performed by Patrick et al. (2000), the performance variability of hogs, or the production risk, is only ranked number 7 by producers (Table 4.2), indicating that the impact of production risk may not be substantial. However, as mentioned previously in Chapter 4 (Section 4.2.3), Alberta industry personnel identified production as an important source of risk, therefore it was included in the CFaR model of this research.

In order to determine how much the production risk contributed to the downside risk to operating cash flow, the CFaR model was re-run, this time removing all stochastic production variable behavior and simulating the model with the production variables held at the expected values. This produced CFaR results with no production risk for the 1000 sow farrow to finish operation, which are then be compared to the original reported CFaR results (Table 5.18) that were generated with production risks included.

The comparison of the CFaR results with and without production risks are given in Table 5.27. It can be determined that there is less downside risk to operating cash flow when production risks are not included in the model, as both the 5% and 20% CFaR levels over all time horizons are lower when production risks are stochastic. However, is the potential loss to operating cash flows caused by production risks important, and is it worth identifying and including the production risks into the CFaR model? For example, the 5% and 20% CFaR for quarterly results are $5,000 lower when production risks are included. Although $5,000 may not seem like a substantial amount considering the 1000 sow operation size, it may still make a considerable difference between the operation being able to make all of their quarterly operating cash flow commitments or not. Thus, the research concludes that including production risks into the CFaR model is important as it allows the operation to gain a better understanding of the potential downside risk to operating cash flow.

5.9 Chapter Summary

This chapter discussed the results of the calculations and tests that were performed in order to develop and test the Cash Flow at Risk model. This began by first determining that the price data fulfilled the stationary requirement, followed by the development and estimation of the Random Walk, AR(n), and Vector AR(n) forecasting models. Before the best price forecasting method was determined, the optimal lag structures for the AR(n) and Vector AR(n) models were determined. All the forecasting models were then tested against 2003 data, and it was determined that the AR(n) forecasting model produced the best forecast using the MSE, MAPE, and BIAS measures. Next, the parameters and distributions of the stochastic production variables were estimated. These were accomplished using several different data sources and were applied to the final CFaR results through the use of two separate simulation stages.

Finally, both the stochastic production and price components were combined with the non-stochastic components in the Monte Carlo simulation model to produce the CFaR results. The CFaR results were measured for the 5% and 20% level, as well as the probability of CF<0. Examining the various CFaR results identified that potential losses to operating cash flow over 2003 and 2004 have a high probability of occurring and may be quite large. Also, by calculating the expected loss for each specific CFaR measure, it was determined that if the value produced by the CFaR measure is violated, the expected loss to operating cash flow will be substantially larger than the estimated CFaR value.

Although there can be significant data restrictions regarding the backtesting of longer CFaR horizons, we were able to test both quarterly and monthly horizons using the LR and Z-stat tests. The quarterly results produced no significant results, deeming the CFaR model statistically acceptable at all stated probability levels tested. But because there are only 37 data test points, these results have low statistical power. To improve the statistical power of the results, monthly backtesting was performed, increasing the number of data test points to 111. Because of the increased number of backtesting data points, these tests are statistically stronger and can be given more confidence.

The overall conclusion can be made that the model performs adequately for purpose of estimating the potential loss to operating cash flows in this research, recognizing that a slight bias of underestimating the true downside risk to operating cash flow may exist. Based on the monthly backtesting results, once the coverage level was 5% or greater, the performance of the model was not statistically different than the number of times the CFaR values would have been violated during the 111 historical months tested.

However, when using the model to identify risk, certain cautions must be taken. First, as identified by the Z-test, the model will most likely underestimate the downside risk facing operating cash flow when measured at low coverage levels. Thus, it is important for individuals using the model to be aware of this, as the true downside risk facing the operation may be lower than the CFaR estimation. Second, as identified by the Expected Loss calculations in Table 5.20, if the CFaR value is exceeded or violated, the expected loss to operating cash flow will be much larger than estimated CFaR values. In this case, the operation using the model must be aware that the loss to operating cash flow will likely exceed the CFaR value substantially once the loss to operating cash flow exceeds the value estimated by the CFaR model.

5.10 Chapter 5 Tables

Table 5.1 Descriptive Statistics and Unconditional Correlations of Historical Data for Period of Jan. 1979 to Dec. 2002

	Hogs ($/kg @ 100 index)	Barley ($/tonne)	Canola Meal ($/tonne)	Corn ($/tonne)
Mean	1.47	114.98	213.55	172.12
Standard Error	0.0159	1.65	1.92	1.78
Median	1.46	113.71	209.00	167.00
Mode	1.34	97.03	198.00	168.00
Standard Deviatior	0.27	27.84	32.55	30.22
Sample Variance	0.0726	775.02	1059.31	913.53
Minimum	0.60	58.55	140.00	105.10
Maximum	2.13	197.00	323.00	323.00
Count	288.00	288.00	288.00	288.00
Correlation	**Hogs**	**Barley**	**Canola Meal**	**Corn**
Hogs	1.000			
Barley	-0.010	1.000		
Canola Meal	0.264	0.315	1.000	
Corn	0.196	0.652	0.387	1.000

Table 5.2 Dickey-Fuller and Phillips-Perron Unit Root Tests (10%) for the Hogs, Barley, Canola Meal, and Corn Data (1979-2002)

	Hogs	Barley	Canola Meal	Corn
CONSTANT, NO TREND				
Dickey-Fuller A(1)=0 T-TEST	-4.88	-2.67	-3.57	-3.40
Phillips-Perron A(1)=0 T-TEST	-4.71	**-2.45**	-4.32	-4.85
CONSTANT, TREND				
Dickey-Fuller A(1)=0 T-TEST	-5.05	-3.20	-3.57	-3.46
Phillips-Perron A(1)=0 T-TEST	-4.77	**-2.65**	-4.33	-4.91

Note: - 10% critical levels for "No Trend" and "Trend" are -2.57 and -3.13 respectively for both ht Dickey-Fuller and Philleps Perron tests
- Bold underlined values indicate failure to reject the null hypothesis of unit roots

Table 5.3 Error Standard Deviations for Random Walk Models

	Standard Deviation
Hogs	0.1074
Barley	0.0628
Canola Meal	0.0766
Corn	0.0962

Table 5.4 **Min, Mean, Max, and Average Variance Results for the Various Price Forecasting Methods (10,000 Simulations) and the Historical Data**

Forecasting Models	Min	Mean	Max	Variance
Hogs ($/kg at 100 index)				
Historical Data Results	0.601	1.468	2.130	0.0726
Random Walk	0.065	1.357	12.157	0.3695
AR Model	0.653	1.429	3.130	0.0651
Vector AR Model (1 Lag)	0.666	1.493	3.312	0.0726
Vector AR Model (2 Lag)	0.654	1.459	3.263	0.0675
Vector AR Model (3 Lag)	0.647	1.452	3.371	0.0696
Vector AR Model (4 Lag)	0.661	1.479	3.212	0.0739
Barley ($/tonne)				
Historical Data Results	58.55	114.98	197.00	775.02
Random Walk	34.47	198.17	857.61	1814.25
AR Model	50.80	137.67	289.93	669.71
Vector AR Model (1 Lag)	50.19	150.57	394.20	981.28
Vector AR Model (2 Lag)	44.95	136.94	362.90	994.25
Vector AR Model (3 Lag)	48.47	147.08	373.08	943.26
Vector AR Model (4 Lag)	47.06	148.27	371.46	967.64
Canola Meal ($/tonne)				
Historical Data Results	140.00	213.55	323.00	1059.31
Random Walk	26.84	260.40	2238.29	7314.87
AR Model	116.30	216.68	377.08	829.02
Vector AR Model (1 Lag)	115.90	221.08	399.07	895.52
Vector AR Model (2 Lag)	114.03	213.81	383.48	838.21
Vector AR Model (3 Lag)	112.17	217.38	387.77	822.04
Vector AR Model (4 Lag)	113.38	218.76	389.14	838.76
Corn ($/tonne)				
Historical Data Results	105.10	172.12	323.00	913.53
Random Walk	11.75	218.41	2356.28	7900.72
AR Model	88.32	176.11	331.02	600.54
Vector AR Model (1 Lag)	91.26	193.40	407.46	804.16
Vector AR Model (2 Lag)	87.68	181.60	367.77	705.02
Vector AR Model (3 Lag)	91.24	186.33	369.68	721.84
Vector AR Model (4 Lag)	92.46	188.30	374.07	719.25

Note: - AR(n) models were evaluated using optimal lag structures identified by the AIC tests (Table 5.5)

Table 5.5 **AR(n) Lag Specification Test Results for Hogs, Barley, Canola Meal and Corn Using AIC, SC, Coefficient Significant Tests, and Adjusted R^2 Values**

	Lag(g)	AIC	SC	Significant Coefficient t-tests ($\Phi_{t-g} \neq 0$ where g=lags)	Adjusted R^2
Hogs	1	-4.521	**-4.508**	1	0.7151
	2	-4.512	-4.486	1	0.7146
	3	**-4.526**	-4.488	**1,2,3**	**0.7206**
	4	-4.518	-4.466	1,2,3	0.7201
	5	-4.508	-4.444	1,2,3	0.7195
	6	-4.503	-4.426	1,2,3	0.7201
Barley	1	-5.530	-5.517	1	0.9307
	2	-5.607	**-5.582**	1,2	0.9363
	3	**-5.612**	-5.573	**1,2,3**	0.937
	4	-5.602	-5.551	1,2	0.9368
	5	-5.592	-5.527	1,2	0.9366
	6	-5.610	-5.532	1,2,5,6	**0.9382**
Canola Meal	1	**-5.179**	**-5.166**	**1**	0.7595
	2	-5.172	-5.146	1	0.7595
	3	-5.170	-5.131	1	0.7608
	4	-5.164	-5.112	1	**0.761**
	5	-5.154	-5.089	1	0.7603
	6	-5.143	-5.066	1	0.7595
Corn	1	-4.744	-4.731	1	0.6726
	2	**-4.800**	**-4.774**	**1,2**	0.6925
	3	-4.791	-4.752	1,2	0.6921
	4	-4.781	-4.729	1,2	0.6911
	5	-4.794	-4.730	1,2,5	0.6974
	6	-4.794	-4.716	1,2,5	**0.6994**

Note: - Bold underlined values indicates optimal lag structure for each test
- Coefficient t-test were tested at a 5% critical level

Table 5.6 LM-Stat and Box-Pierce-Ljung Tests for Error Autocorrelation in Hog, Barley, Canola Meal, and Corn AR(n) Models

	Hogs		Barley		Canola Meal		Corn		X^2_p Critical
LAG (p)	LM-STAT	B-P-L	LM-STAT	B-P-L	LM-STAT	B-P-L	LM-STAT	B-P-L	Value (5%)
1	0.70	0.01	0.21	0.00	0.90	0.63	1.02	0.07	3.84
2	0.65	0.02	0.68	0.05	1.25	1.95	0.68	0.37	5.99
3	0.48	0.18	0.31	0.13	1.70	4.55	1.36	1.97	7.81
4	0.90	0.77	0.99	1.01	0.63	4.91	1.59	4.19	9.49
5	1.00	1.52	2.20	5.43	0.22	4.95	2.31	9.17	11.07
6	0.71	1.93	1.77	8.28	1.31	6.56	1.01	10.12	12.59
7	0.54	2.17	0.97	9.17	0.56	6.86	0.35	10.24	14.07
8	1.13	3.30	1.38	10.93	0.10	6.87	0.02	10.24	15.51
9	0.83	3.91	3.65	**23.25**	0.87	7.59	0.38	10.38	16.92
10	2.44	9.34	0.92	**24.00**	1.54	9.95	0.24	10.44	18.31
11	1.35	10.98	2.27	**28.57**	1.24	11.51	0.83	11.14	19.68
12	4.83	**31.91**	2.26	**33.29**	0.81	12.18	0.36	11.27	21.03
13	2.77	**38.26**	1.95	**36.91**	1.06	13.31	0.45	11.48	22.36
14	0.34	**38.35**	2.63	**43.42**	0.05	13.32	0.74	12.04	23.68
15	1.73	**40.85**	0.95	**44.25**	0.37	13.45	0.56	12.36	25.00
16	0.88	**41.54**	0.51	**44.49**	0.35	13.58	0.45	12.57	26.30
17	2.44	**46.81**	0.44	**44.67**	1.63	16.31	3.11	22.54	27.59
18	1.39	**48.54**	1.16	**45.99**	0.39	16.47	0.72	23.06	28.87
19	1.44	**50.40**	1.09	**47.15**	1.22	18.00	0.34	23.18	30.14
20	1.00	**51.30**	1.73	**50.11**	0.32	18.10	0.86	23.96	31.41
21	0.82	**51.91**	2.65	**56.97**	1.51	20.48	1.60	26.67	32.67
22	2.04	**55.66**	1.71	**59.79**	0.83	21.19	0.58	27.02	33.92
23	2.00	**59.22**	1.05	**60.84**	0.92	22.07	0.69	27.53	35.17

Note:
- The X^2_p critical values at a 5% significance level are used to compare the B-P-L stat where p=number of lags
- The critical value for the LM stat is a X^2_1 at a 5% level of significance (3.84)
- Bold underlined values indicate the null hypothesis of no error autocorrelation is rejected

Table 5.7 Correlations and Standard Deviations of AR(n) System Estimation Error Terms for Hogs, Barley, Canola Meal, and Corn

	Hogs	Barley	Canola Meal	Corn
Hogs	**0.1021**			
Barley	-0.0263	**0.0596**		
Canola Meal	0.0836	0.1546	**0.0745**	
Corn	0.0281	0.2414	0.1955	**0.0892**

Note: - The standard deviations are the bold underlined values while the regular text are the correlation coefficients

Table 5.8 **Seemingly Unrelated Regression Parameter Estimates for the Hog, Barley, Canola Meal, and Corn AR(n) Models**

	Constant (α)	Φ_{t-1}	Φ_{t-2}	Φ_{t-3}
Hog	0.0620	0.8050	0.1617	-0.1396
Barley	0.2243	1.2096	-0.35922	0.10277
Corn	0.76421	0.85734		
Canola Meal	0.70742	0.59117	0.27131	
Note: - Parameters for AR(n) modols (equation [4.7])				

Table 5.9 **Vector AR(n) Lag Specification Test Results**

	AIC	SC
VAR(1)	-20.1856	**-19.9779**
VAR(2)	-20.2804	-19.8650
VAR(3)	**-20.2894**	-19.6666
VAR(4)	-20.2286	-19.3900
VAR(5)	-20.1696	-19.1311
VAR(6)	-20.1267	-18.8800
- Bold underlined values indicates optimal lag structure for each test		

Table 5.10 Vector AR(n) Coefficient Estimates for Model Structures Ranging from 1-4 Lags

	Vector AR(n) Coefficients																
Model Lag Structures	Const.	HG1	HG2	HG3	HG4	BLY1	BLY2	BLY3	BLY4	CM1	CM2	CM3	CM4	CRN1	CRN2	CRN3	CRN4
Hogs (L1)	-0.3266	0.8364	-----	-----	-----	0.0091	-----	-----	-----	0.0337	-----	-----	-----	0.0316	-----	-----	-----
Hogs (L2)	-0.3007	0.7984	0.0475	-----	-----	0.0172	-0.0053	-----	-----	0.0590	-0.0331	-----	-----	0.0283	0.0031	-----	-----
Hogs (L3)	-0.2998	0.8053	0.1709	-0.1524	-----	0.0069	0.0951	-0.1119	-----	0.0392	0.0550	-0.0802	-----	0.0019	-0.0335	0.0969	-----
Hogs (L4)	-0.1727	0.8127	0.1581	-0.2055	0.0692	-0.0217	0.1258	-0.2595	0.1635	0.0489	0.0781	0.0745	-0.2104	0.0168	-0.0216	0.1456	-0.0936
Barley (L1)	-0.0565	-0.0686	-----	-----	-----	0.9574	-----	-----	-----	0.0425	-----	-----	-----	0.0113	-----	-----	-----
Barley (L2)	0.0629	-0.0435	-0.0079	-----	-----	1.1983	-0.2468	-----	-----	0.0224	0.0077	-----	-----	0.0419	-0.0369	-----	-----
Barley (L3)	-0.0041	-0.0464	-0.0679	0.0651	-----	1.2376	-0.4289	0.1523	-----	0.0455	0.0077	-0.0191	-----	0.0415	-0.0549	0.0183	-----
Barley (L4)	-0.0307	-0.0392	-0.0737	0.0459	0.0191	1.2285	-0.4081	0.1012	0.0420	0.0372	0.0156	-0.0585	0.0469	0.0440	-0.0485	0.0172	-0.0122
Canola (L1)	0.7170	0.0169	-----	-----	-----	0.0162	-----	-----	-----	0.8669	-----	-----	-----	-0.0168	-----	-----	-----
Canola (L2)	0.7202	0.0802	-0.0640	-----	-----	0.2034	-0.2012	-----	-----	0.7854	0.0868	-----	-----	-0.0172	0.0070	-----	-----
Canola (L3)	0.6590	0.0842	-0.0278	-0.0556	-----	0.2174	-0.3600	0.1511	-----	0.7755	-0.0042	0.1257	-----	0.0308	0.0360	-0.0954	-----
Canola (L4)	0.6700	0.0883	-0.0343	-0.0921	0.0444	0.1995	-0.3337	0.0973	0.0493	0.7829	0.0032	0.1677	-0.0630	0.0383	0.0290	-0.0978	0.0022
Corn (L1)	0.6921	0.0117	-----	-----	-----	0.1298	-----	-----	-----	0.0733	-----	-----	-----	0.6688	-----	-----	-----
Corn (L2)	0.6079	-0.0136	0.0397	-----	-----	0.4151	-0.3291	-----	-----	0.1502	-0.1152	-----	-----	0.4881	0.2760	-----	-----
Corn (L3)	0.5968	-0.0106	0.0791	-0.0504	-----	0.4093	-0.3181	-0.0089	-----	0.1381	-0.1428	0.0465	-----	0.4991	0.2819	-0.0178	-----
Corn (L4)	0.5801	-0.0060	0.0730	-0.0820	0.0353	0.3896	-0.2812	-0.0922	0.0693	0.1406	-0.1327	0.0681	-0.0359	0.5062	0.2770	-0.0267	0.0087

Where: - HG=hog, BLY=barley, CM=Canola Meal, and CRN=Corn

- L1, L2, L3, and L4 are the number of lags used in the Vector AR(n) model, and the

Table 5.11 Vector AR(n) Model Error Standard Deviations For Model Structures Ranging from 1-4 Lags

Model Lag Structures	Hogs	Barley	Canola meal	Corn
Vector AR(1)	0.1033	0.0613	0.0746	0.0892
Vector AR(2)	0.1032	0.0591	0.0731	0.0844
Vector AR(3)	0.1014	0.0580	0.0717	0.0842
Vector AR(4)	0.0995	0.0578	0.0714	0.0840

Table 5.12 Vector AR(n) Model Error Correlation Coefficients For Model Structures Ranging from 1-4 Lags

Model Lag Structures	Bar-Can	Bar-Corn	Can-Corn
Vector AR(1)	0.1977	0.2453	0.1818
Vector AR(2)	0.1660	0.2367	0.1749
Vector AR(3)	0.1676	0.2508	0.1699
Vector AR(4)	0.1687	0.2503	0.1655

Table 5.13 Average MSE Test Results and Relative Rankings for 10,000 Simulations of the Various Price Forecasting Models Using 2003 Monthly Forecasts and 2003 Out of Sample Observed Monthly Prices

	Price Series	Rand. Walk	AR(n)	VAR(1)	VAR(2)	VAR(3)	VAR(4)
MSE	Hogs	0.219	0.118	0.143	0.129	0.129	0.134
	Barley	4509.181	1428.449	2927.911	2018.230	2509.162	2689.009
	Canola meal	5532.593	2044.600	2274.483	1977.724	2211.130	2266.859
	Corn	4565.722	1074.749	2732.898	1572.022	1783.587	1858.300
Rank	Hog Rank	6	1	5	2	3	4
	Bar Rank	6	1	5	2	3	4
	Can Rank	6	2	5	1	3	4
	Corn Rank	6	1	5	2	3	4
	Average Rank	6	1.25	5	1.75	3	4
	Note: - the best performing model is ranked 1, with the worst performing model Ranked 6						

Table 5.14 Average MAPE Test Results and Relative Rankings for 10,000 Simulations of the Various Price Forecasting Models Using 2003 Monthly Forecasts and 2003 Out of Sample Observed Monthly Prices

	Price Series	Rand. Walk	AR(n)	VAR(1)	VAR(2)	VAR(3)	VAR(4)
MAPE	Hogs	0.223	0.165	0.181	0.172	0.172	0.174
	Barley	0.304	0.164	0.244	0.193	0.221	0.231
	Canola meal	0.214	0.138	0.146	0.136	0.145	0.147
	Corn	0.225	0.118	0.195	0.142	0.152	0.156
Rank	Hog Rank	6	1	5	2	3	4
	Bar Rank	6	1	5	2	3	4
	Can Rank	6	2	4	1	3	5
	Corn Rank	6	1	5	2	3	4
	Average Rank	6	1.25	4.75	1.75	3	4.25
	Note: - the best performing model is ranked 1, with the worst performing model Ranked 6						

Table 5.15 Average BIAS Test Results and Relative Rankings for 10,000 Simulations of the Various Price Forecasting Models Using 2003 Monthly Forecasts and 2003 Out of Sample Observed Monthly Prices

	Price Series	Rand. Walk	AR(n)	VAR(1)	VAR(2)	VAR(3)	VAR(4)
BIAS	Hogs	-0.127	0.059	0.142	0.105	0.097	0.093
BIAS	Barley	52.852	19.216	41.621	26.280	34.717	37.520
BIAS	Canola meal	27.472	5.663	10.978	2.265	9.643	8.625
BIAS	Corn	28.252	9.351	40.717	21.919	25.598	26.926
Rank	Hog Rank	1	2	6	5	4	3
Rank	Bar Rank	6	1	5	2	3	4
Rank	Can Rank	6	2	5	1	4	3
Rank	Corn Rank	5	1	6	2	3	4
	Average Rank	4.5	1.5	5.5	2.5	3.5	3.5

Note: - the best performing model is ranked 1, with the worst performing model Ranked 6

Table 5.16 Triangular Distribution Parameters for % Sows Culled and % Sows that Die per Year

Production Factor	Low	Expected	High
% of Sows that Die per Year	2.00%	4.98%	6.90%
% of Sows Culled per Year	30.30%	42.81%	53.20%

Note: - Results based off statistics from 19 Alberta Producers obtained directly from PigCHAMP data base

Table 5.17 Triangular Distribution Parameters for Death Loss of Growers and Finishers

Production Factor	Low	Expected	High
Death to grower	0.40%	1.74%	5.50%
Death to finishers	0.80%	2.50%	6.00%

Note: - Results based off 1999 PigCHAMP statistic summaries obtained from the Bacon Bits Vol. X, No 10, Oct 2001

Table 5.18 Cash Flow at Risk Results for Year Starting Jan. 2003 when Using Oct. to Dec. 2002 Prices to Start the AR(n) Price Forecasting Models

Time Horizon	5% CFaR	5% CFaR per Market Hog Sold	20% CFaR	20% CFaR per Market Hog Sold	Prob CF< 0
First Quarter	-$150,086.00	-$28.39	-$96,329.00	-$18.22	72.68%
Semi-Annual	-$263,886.00	-$24.96	-$139,407.00	-$13.19	54.57%
Tri-Quarterly	-$335,985.00	-$21.19	-$150,191.00	-$9.47	43.86%
1Year	-$370,921.00	-$17.54	-$125,001.00	-$5.91	35.24%
1.5 years	-$397,270.00	-$12.53	-$6,751.00	-$0.21	23.51%
Two Years	-$319,111.00	-$7.55	$141,367.00	$3.34	16.45%

Note: - 5% and 20% CFaR per hog marketed based on the expected number of 5286 hogs marketed per quarter

Table 5.19 Historical Prices From Sept. to Dec. 2002 That are Used to Start AR(n) and Vector AR(n) Forecasting Models

Price Series	Sept. 2002	Oct. 2002	Nov. 2002	Dec. 2002
Hogs ($/Kg)	$0.94	$1.27	$1.07	$1.17
Barley ($/Tonne)	$196.50	$188.75	$197.00	$187.25
Camola Meal ($/Tonn	$251.00	$222.00	$236.00	$234.50
Corn ($/Tonne)	$215.00	$210.00	$198.50	$192.00

Table 5.20 Expected Loss to Cash Flow if Estimated CFaR Value from Table 5.18 Exceeded (Violated)

Time Horizon	5% CFaR	20% CFaR	Prob CF< 0
First Quarter	-$171,043.64	-$132,369.15	-$72,383.05
Semi-Annual	-$311,448.90	-$224,530.60	-$127,677.87
Tri-Quarterly	-$421,735.57	-$282,186.99	-$170,329.92
1Year	-$486,704.74	-$304,075.18	-$201,792.33
1.5 years	-$560,917.35	-$290,720.47	-$251,733.44
Two Years	-$577,613.14	-$226,166.37	-$283,852.33

Table 5.21 Cash Flow at Risk Results When Using AR(n) Conditional Mean Prices to Start the AR(n) Price Forecasting Models

Time Horizon	5% CFaR	5% CFaR per Market Hog Sold	20% CFaR	20% CFaR per Market Hog Sold
Quarterly	$151,126.20	$28.59	$218,253.40	$41.29
Semi-Annual	$228,222.20	$21.59	$367,492.00	$34.76
Tri-quarterly	$282,807.30	$17.83	$485,579.90	$30.62
Annual	$340,770.90	$16.12	$602,522.10	$28.50
1.5-year	$449,007.40	$14.16	$840,093.80	$26.49
2-year	$599,834.90	$14.18	$1,063,308.00	$25.14
Note: - 5% and 20% CFaR per hog marketed based on the expected number of 5286 hogs marketed per quarter				

Table 5.22 Cash Flow at Risk Results When Using Better Than Average Prices to Start the AR(n) Price Forecasting Models

Time Horizon	5% CFaR	5% CFaR per Market Hog Sold	20% CFaR	20% CFaR per Market Hog Sold
Quarterly	$13,654.35	$2.58	$74,577.13	$14.11
Semi-Annual	$10,100.26	$0.96	$140,464.80	$13.29
Tri-quarterly	$9,545.99	$0.60	$202,975.30	$12.80
Annual	$28,202.11	$1.33	$280,936.90	$13.29
1.5-year	$79,526.41	$2.51	$470,231.20	$14.83
2-year	$200,204.70	$4.73	$661,813.80	$15.65
Note: - 5% and 20% CFaR per hog marketed based on the expected number of 5286 hogs marketed per quarter				

Table 5.23 Quarterly LR-Test and Z-Test Statistic Results of CFaR Model when Compared to Out of Sample Subsequent Operating Cash Flows (Sept. 1994 to Dec. 2002)

Stated Probabilty	X	N	X/N	LR	Z Test
1%	1.04	37	2.80%	0.81	1.10
2%	1.48	37	4.00%	0.59	0.87
3%	1.94	37	5.25%	0.53	0.80
4%	2.22	37	5.99%	0.33	0.62
5%	2.92	37	7.89%	0.56	0.81
6%	3.89	37	10.53%	1.11	1.16
7%	4.82	37	13.01%	1.67	1.43
8%	5.66	37	15.29%	2.15	1.63
9%	6.31	37	17.06%	2.38	1.71
10%	6.76	37	18.27%	2.32	1.68
15%	7.59	37	20.52%	0.81	0.94
20%	8.96	37	24.21%	0.39	0.64
25%	10.08	37	27.24%	0.10	0.31
30%	10.88	37	29.41%	0.01	-0.08
35%	12.37	37	33.43%	0.04	-0.20
40%	13.99	37	37.82%	0.07	-0.27
45%	15.70	37	42.43%	0.10	-0.31
50%	16.99	37	45.91%	0.25	-0.50

Where:
- X = the average number of simulation violations
- N = the number of out of sample observations
- Bold underlined values reject the null that the realized CFaR probability equals the stated probability
- Critical X^2 = 3.84 @ 5% and the z=+/- 1.96 @ 5%

Table 5.24 Monthly LR-Test and Z-Test Statistic Results of CFaR Model when Compared to Out of Sample Subsequent Operating Cash Flows (Sept. 1994 to Dec. 2002)

Stated Probabilty	X	N	X/N	LR	Z Test
1%	3.53	111	3.18%	3.38	**<u>2.31</u>**
2%	5.35	111	4.82%	3.25	**<u>2.12</u>**
3%	7.73	111	6.96%	**<u>4.40</u>**	**<u>2.45</u>**
4%	9.39	111	8.46%	**<u>4.40</u>**	**<u>2.40</u>**
5%	10.19	111	9.18%	3.31	**<u>2.02</u>**
6%	10.74	111	9.67%	2.26	1.63
7%	11.29	111	10.17%	1.51	1.31
8%	12.00	111	10.82%	1.09	1.09
9%	12.90	111	11.62%	0.86	0.96
10%	13.89	111	12.51%	0.73	0.88
15%	19.48	111	17.55%	0.54	0.75
20%	23.65	111	21.30%	0.12	0.34
25%	27.95	111	25.18%	0.00	0.04
30%	32.88	111	29.62%	0.01	-0.09
35%	38.02	111	34.25%	0.03	-0.17
40%	43.03	111	38.77%	0.07	-0.27
45%	47.23	111	42.55%	0.27	-0.52
50%	50.73	111	45.70%	0.82	-0.91

Where:
- X = the average number of simulation violations
- N = the number of out of sample observations
- Bold underlined values reject the null that the realized CFaR probability equals the stated probability
- Critical X^2 = 3.84 @ 5% and the z=+/- 1.96 @ 5%

Table 5.25 Backtesting Results Found by Manfredo and Leuthold (2001) for Various VaR Models

VaR Method	X/N			LR-Stat			Z-test Stat		
Stated Proability Level	1%	5%	10%	1%	5%	10%	1%	5%	10%
Historical Simulation	1.77	6.38	12.23	2.768	2.096	2.941	1.845	1.507	1.769
RiskMetric97-VaR	1.06	5.67	10.99	0.023	0.518	0.6	0.152	0.734	0.786
GHIST-VaR	4.08	10.28	15.43	**30.48**	**25.74**	**16.1**	**7.347**	**5.757**	**4.295**

Where: - X = the average number of model violations
- N = the number of out of sample observations
- Bold underlined values reject the null that the realized VaR probability equals the stated probability
- Critical X^2 = 3.84 @ 5% and the z=+/- 1.96 @ 5%

(Source: Manfredo and Leuthold 2001)

Table 5.26 CFaR Simulation Results for the Various Time Horizons vs. Results Produced Using the Square Root Rule

Time Horizon	5% CFaR Model Results	Square Root Results (5%)	20% CFaR Model Results	Square Root Results (20%)
Quarterly	-$150,086.00	-----------	-$96,329.00	-----------
Semi-Annual	-$263,886.00	-$212,253.66	-$139,407.00	-$136,229.78
Tri-quarterly	-$335,985.00	-$259,956.58	-$150,191.00	-$166,846.72
Annual	-$370,921.00	-$300,172.00	-$125,001.00	-$192,658.00
1.5-year	-$397,270.00	-$367,634.12	-$6,751.00	-$235,956.90
2-year	-$319,111.00	-$424,507.31	$141,367.00	-$272,459.56

Table 5.27 The Downside Risk to Operating Cash Flows Attributable to the Inclusion of Production Risk Into the CFaR Model

Time Horizon	5% CFaR With Production Risk	5% CFaR Without Production Risk	5% CFaR That is Attributable to Production Risk	20% CFaR With Production Risk	20% CFaR Without Production Risk	20% CFaR That is Attributable to Production Risk
Quarter	-$150,086.00	-$144,748.00	-$5,338.00	-$96,329.00	-$91,152.07	-$5,176.93
semi	-$263,886.00	-$254,838.30	-$9,047.70	-$139,407.00	-$133,470.70	-$5,936.30
Tri	-$335,985.00	-$334,019.60	-$1,965.40	-$150,191.00	-$134,923.60	-$15,267.40
Ann	-$370,921.00	-$357,394.30	-$13,526.70	-$125,001.00	-$104,681.90	-$20,319.10
1.5-year	-$397,270.00	-$355,419.60	-$41,850.40	-$6,751.00	$17,482.10	-$24,233.10
2-year	-$319,111.00	-$272,871.30	-$46,239.70	$141,367.00	$182,751.80	-$41,384.80

Note: - The grey shaded columns are calculated by subtracting the 5% (20%) CFaR without production risk from the 5% (20%) CFaR with production risk

5.11 Chapter 5 Figures

Figure 5.1 Triangular Distribution Best Fit Results for Litters/Sow/Year

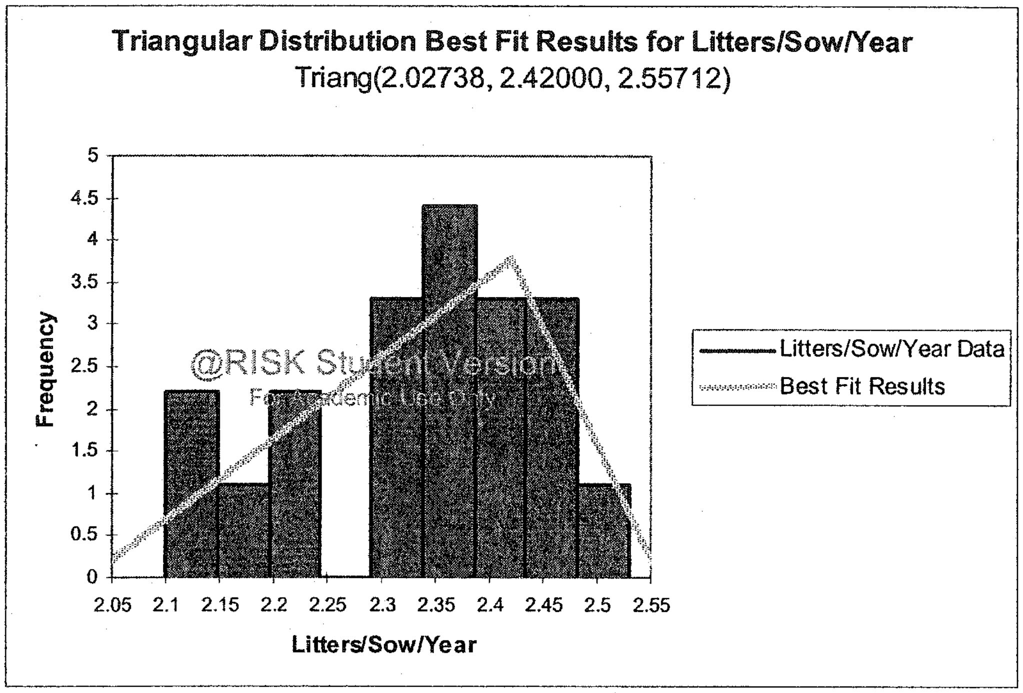


Figure 5.2 Logistic Distribution Best Fit Results for Piglets Weaned/Sow/Litter

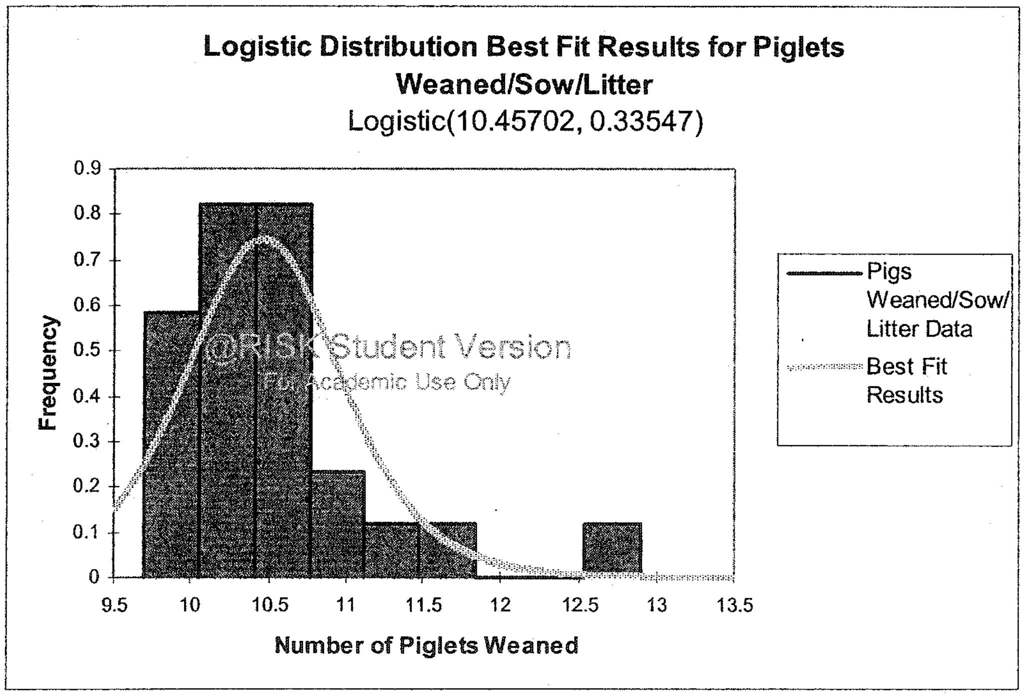


Figure 5.3 Lognormal Distribution Best Fit Results for Piglets/Month

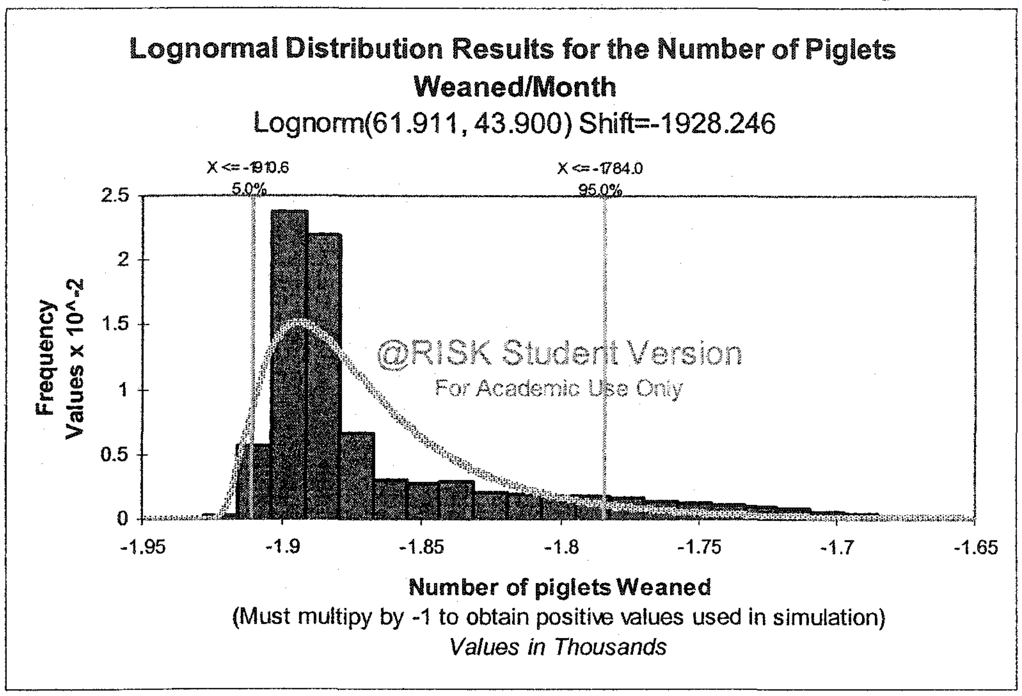


Figure 5.4 Binomial Distribution Best Fit Results for Sows Culled per Month

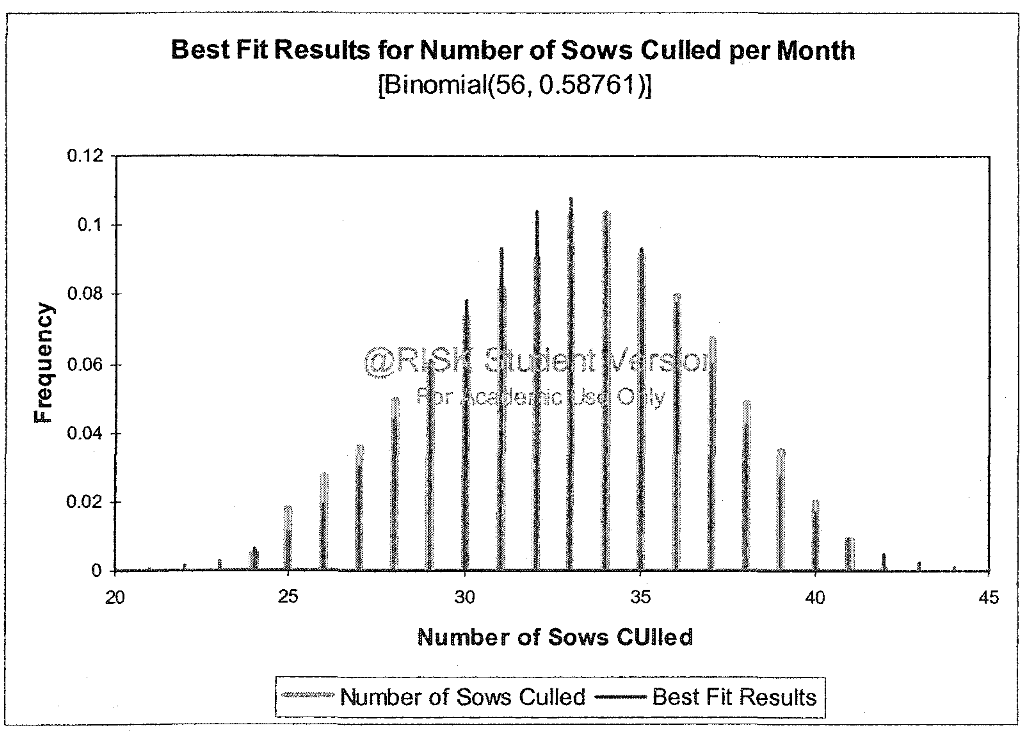


Figure 5.5 Binomial Distribution Best Fit Results for Sows That Die/Month

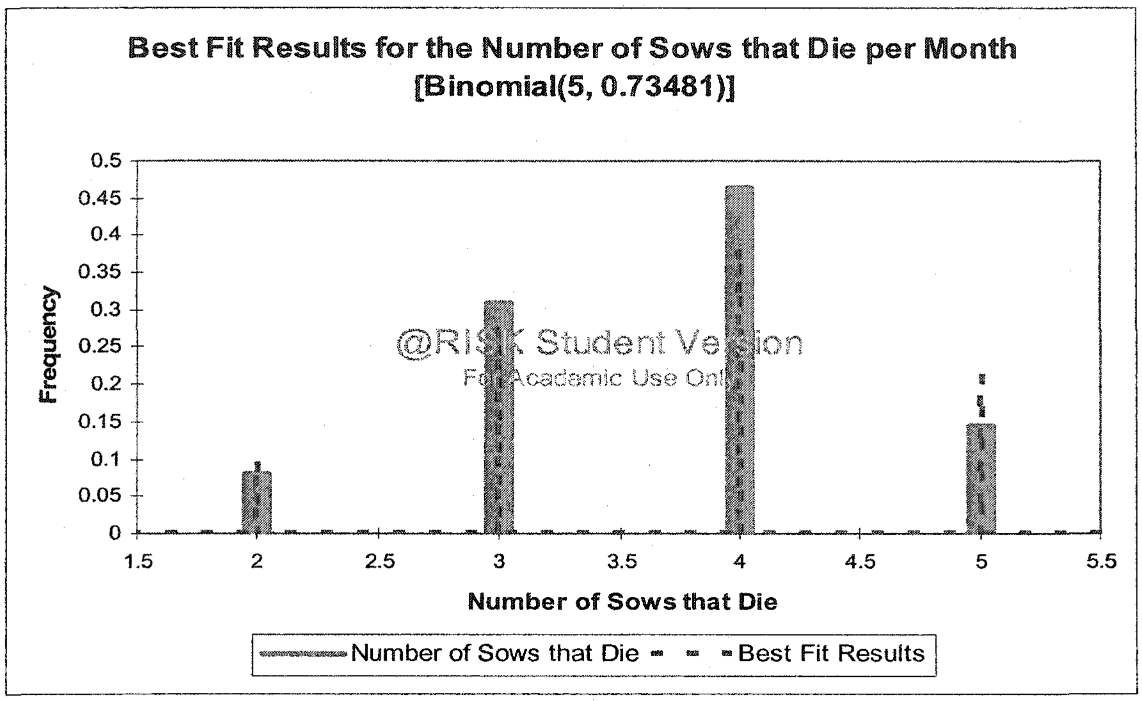


Figure 5.6 Cash Flow at Risk Results for Year Starting Jan. 2003 when Using Oct. to Dec. 2002 Prices to Start the AR(n) Price Forecasting Models

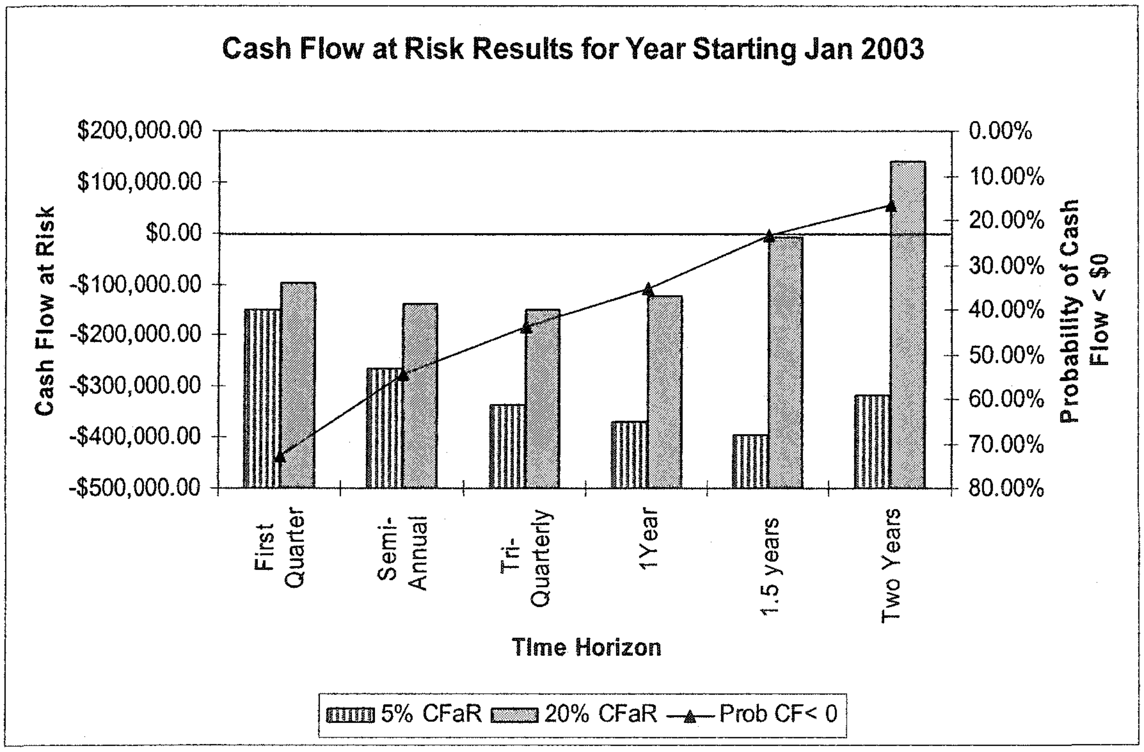


Figure 5.7 Distributions of Non-cumulative Cash Flows for Quarter1,2, 3 and 8 When Using 2002 Prices to Start the CFaR Model

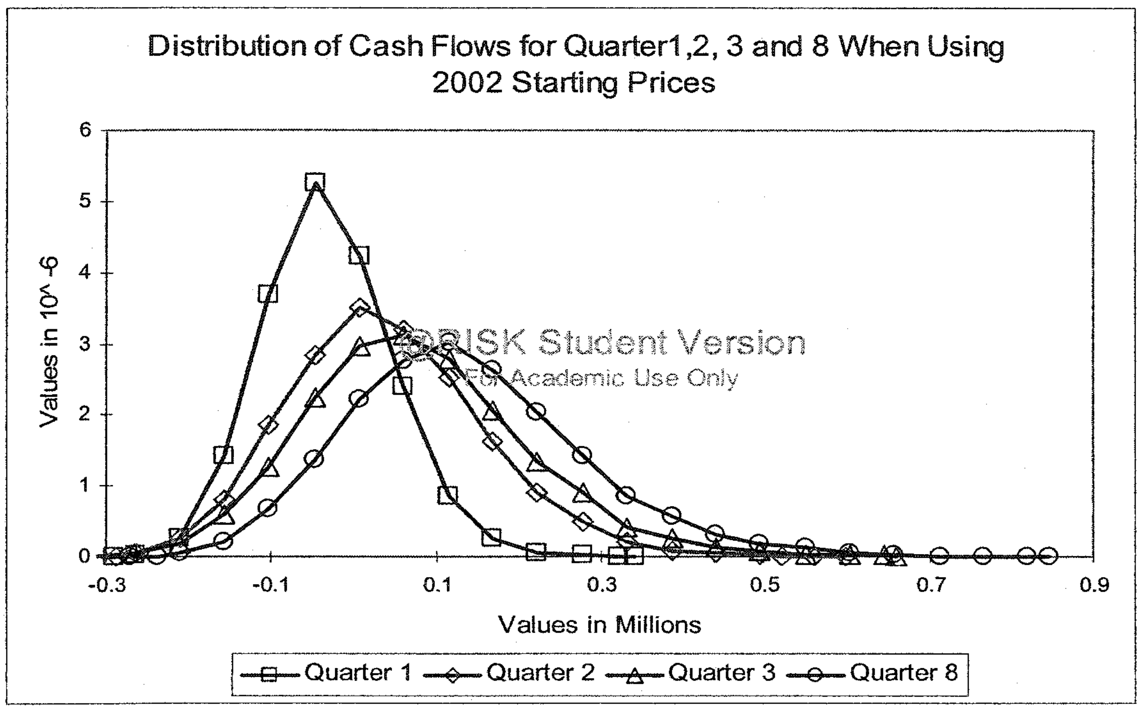


Figure 5.8 Distributions of Non-cumulative Cash Flows for Quarter1,2, 3 and 8 When Using AR(n) Model Conditional Mean Prices to Start the CFaR Model

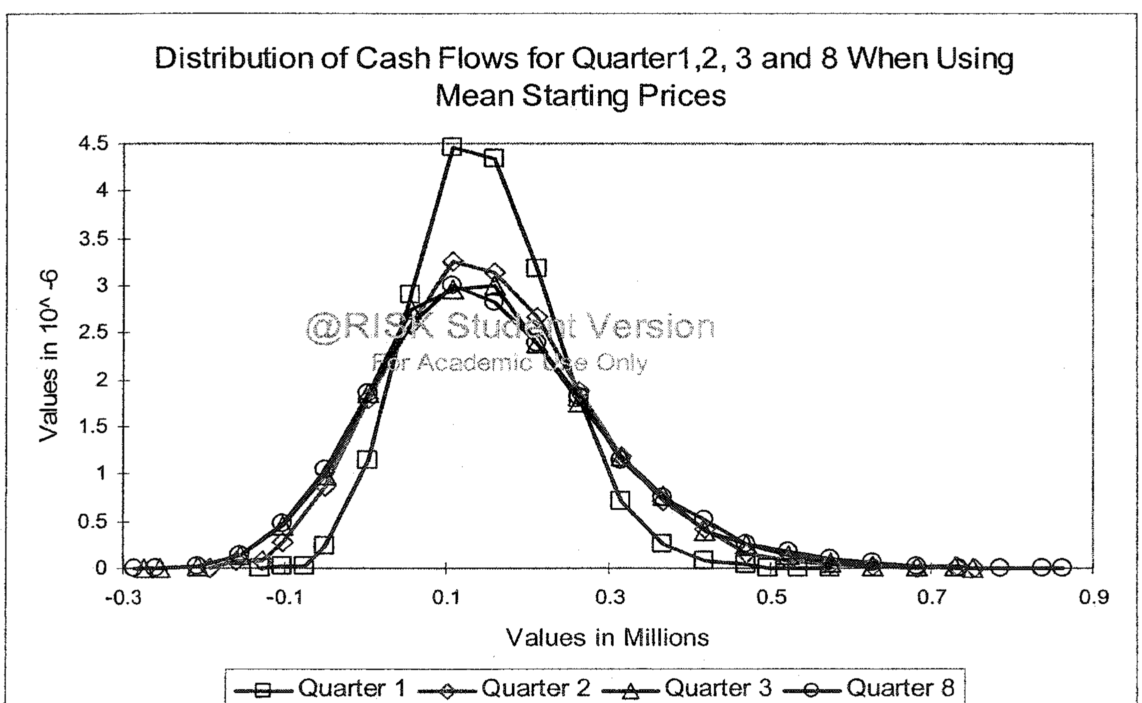
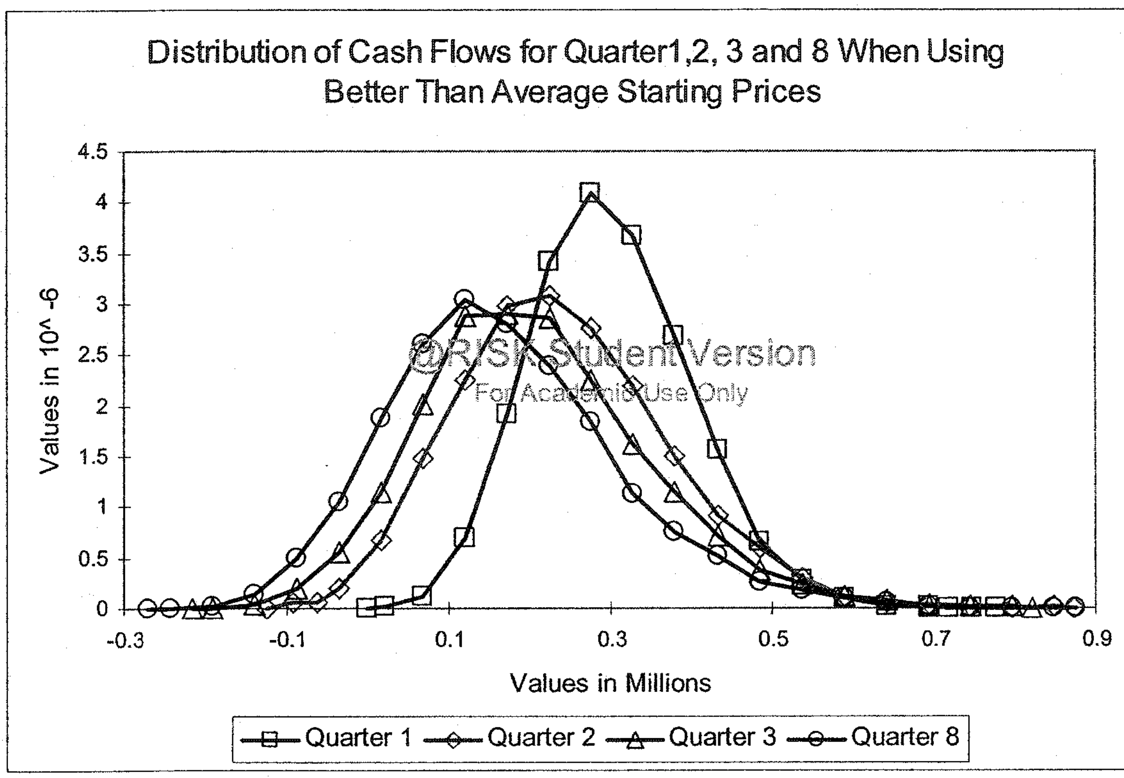


Figure 5.9 Distributions of Non-cumulative Cash Flows for Quarter1,2, 3 and 8 When Using Better Than Average Prices to Start the CFaR Model



CHAPTER 6: Evaluation of Risk Management Strategies

This chapter will first explain the various risk management strategies that were evaluated using the CFaR model. Next, the CFaR results obtained from including various risk management strategies into the Monte Carlo simulation model are described and discussed, along with the relative ranking of their performance. The ranking results obtained by this research when using both the CFaR measure are then compared to the rankings of alternative risk management decision criteria. Finally, the ranking results of the various decision criteria results used in this research are compared to those found in other research.

6.1 Risk Management Strategies

Various risk management strategies are evaluated using the CFaR model; however, the strategies evaluated only address market risks. Specifically, barley and hog price risks are addressed, as barley is the major input price risk and hogs are the major output price risk. In total, eight different risk management strategies are evaluated, including a base case, three hog price risk management strategies, a barley price risk management strategy, as well as each of the three hog price strategies combined with the barley strategy. Due to the 1000 sow operation's southern Alberta location, the risk management strategies evaluated are intended to reflect options that are or have potentially been available to Alberta producers. Each risk management strategy is explained next.

6.1.1 Base Case (BC)

The base case (BC) strategy assumes that the 1000 sow operation purchases and sells all inputs and outputs at current market (simulated) prices. This strategy is consistent with the results reported in Chapter 5 (Table 5.18). Using the CFaR model, the base case strategy is compared to the other risk management strategies in order to determine if, and by how much the use of the strategies will lower the downside risk to operating cash flow.

6.1.2 Fixed Price Window Contract (FPW)

A window contract is generally a long-term contract where the producer and packer share the price differential above or below the fixed floor and ceiling price

(Lawrence 2000). However, the contract used in this research assumes that there is no sharing in the price differential, where the floor and ceiling prices are the minimum and maximum obtainable prices. The floor and ceiling prices are based off the prices given for the Rocky Mountain Pork fixed window contract (www.rockymountainpork.com) held with the Olymel processing plant in Red Deer Alberta for the year 2000. Because of a lack of any other available fixed hog price window contract information for Alberta, the 2000 floor and ceiling prices of $1.25/kg and $1.65/kg (100 index) are used. This type of contract was available to Alberta producers around the year of 2000, and could be locked in for up to 10-15 years. Thus, this analysis assumes that the 1000 sow operation would have entered the fixed price window (FPW) contract in 2000 for at least a 5-year term. All market hogs sold (100%) by operation over the 2 years of the simulation analysis are priced using the fixed window price contract.

6.1.3 Cost Based Window Contract (CBW)

The cost based window (CBW) contract is similar to the fixed price window contract in that it also has a floor and ceiling price, however, the prices determining the window change according to the cost of feed. Lawrence (1999) specifically states that this type of contract is intended to help with producer's cash flows, and not necessarily guarantee a profit. If this is true, this contract should perform well regarding the CFaR evaluations due to the model's cash flow focus.

This contract is also based off of a contract option that was available through Rocky Mountain Pork. However, for confidentiality reasons, the specifics of how the window is determined could not be disclosed, as this is a unique contract to Rocky Mountain Pork. Thus, the derivation of the cost based window prices used in this research are determined using the ad hoc calculation described below, and are not actually calculated according to the contract offered by Rocky Mountain Pork. The CBW contract used in this research is only intended to represent a cost based contract, as it was a potential contract available to Alberta producers. The floor price is first calculated according to current feed prices, upon which a $0.40/Kg is added in order to derive the ceiling price (same $0.40/Kg window spread used in the fixed price window). The price floor is calculated as:

$$\text{PriceFloor} = \max[(((((0.8*\widetilde{P}^{b} + 0.2*\widetilde{P}^{cm})*\phi)^{\psi} + \alpha) - 1.25)*\delta) + (((0.8*\widetilde{P}^{b} + 0.2*\widetilde{P}^{cm})*\phi)^{\psi} + \alpha)), (((0.8*\widetilde{P}^{b} + 0.2*\widetilde{P}^{cm})*\phi)^{\varphi} + \alpha)] \quad [6.1]$$

where $\widetilde{P}^{b}$ is the simulated price of barley, $\widetilde{P}^{cm}$ is the simulated price of canola meal, ϕ is the coefficient (0.0095) that adjusts the weighted average feed price to \$/Kg hog price, δ is the coefficient (0.5) that adjusts the price floor price when the price floor is above the \$1.25/Kg level, ψ is the exponent coefficient (0.45) that smoothes the variation of the hog price transformations, and α is a constant (0.152) used to adjust the smoothed hog floor price upwards. The 80% barley and 20% canola meal weightings are the same as the energy and protein feed weights identified by Lawrence (1996) for cost based pricing.

Using historical feed price data, the average floor price calculated by the ad hoc cost based method is about \$1.25/Kg, which was purposely generated in order to be consistent with the floor price of the fixed price window contract. Again, due to a lack of current contract information, this contract is based off of 2000 information, with the assumption that the producer locked into the contract in 2000 for 5 or more years. Under this contract, all market hogs sold over the simulation's two year time horizon are priced using the CBW contract prices.

6.1.4 Western Hog Exchange Forward Prices (WHE)

The Western Hog Exchange[29] prices used are the monthly forward prices for 2003 that were available as of Dec 30th, 2002. These are the actual forward prices that could have been used by Alberta producers for the year of 2003 (Table 6.1). In this strategy, roughly 70% of the market hogs sold each month are priced using the WHE forward prices, with the remaining 30% priced using the simulated monthly cash prices. The 70% level was chosen based on a statistic reported by Lawrence (2000), who indicated that larger American producers have 75% or more of their production under a marketing contract. Because the operation in this research is about 40% smaller than those discussed by Lawrence (2000), a more conservative 70% level is used, as this percentage level is more tolerant to fluctuations in production that a smaller firm may experience.

[29] The Western Hog Exchange is a non-profit marketing organization developed in Dec, 1996 to provide marketing options for Alberta hog producers after the dismantling of the single desk selling system. (www.westernhogexchange.com)

6.1.5 Fixed Price Barley Contract (FB)

Due to a lack of actual available barley contracts, a hypothetical fixed barley price (FB) contract is used. This contract is design based on recommendations from the *Cooperative Contracts* article from Market Master (2002), which states that a long-term mutually beneficial contract should be negotiated between the barley and hog producer. Thus, to be mutually beneficial, the historical mean barley price of roughly $114/tonne (Table 5.1) is used as the base. Half of the annual storage costs of $13.68 (AAFRD 2002) and half of the $4.90/tonne 40km trucking cost (SAFRR – Trucking Costs) are then added to the mean price to produce a mutually beneficial fixed price of $131.10/tonne delivered on site. Roughly 70% of barley is purchased using this contract, with the remaining 30% purchased at the simulated monthly cash price.

6.1.6 Combined Hog and Barley Price Risk Management Strategies

The last three risk management strategies evaluated are based on a combination of each of the three hog price strategies and the fixed barley price. The combination strategies are; the Fixed Price Window contract and Fixed Barley (FPW+FB), the Cost Based Window and Fixed Barley (CBW+FB), and the Western Hog Exchange forward prices and Fixed Barley (WHE+FB). The individual risk management strategy specifics are the same as described above.

6.2 CFaR Evaluation of Risk Management Strategies

The various risk management strategies are evaluated using the estimated CFaR results for each specific probability level (5%, 20%, and prob. CF > 0) and for the same time horizons previously analyzed in Chapter 5. The strategies are then ranked from 1 to 8 for each of the CFaR probability levels tested, where 1 is given for the highest CFaR value and 8 for the lowest. These results are reported in Tables 6.2-6.7. Due to the large number of results, the CFaR values will be discussed in two generalized sections; quarterly to annual time horizons, and the 1.5 year to 2 year time horizons.

6.2.1 Quarterly to Annual CFaR Risk Management Results

In general, the ranking results of the risk management strategies between the estimated 5%, 20%, and CF<0 measures for the quarterly to annual time horizons are very similar (Tables 6.2-6.5). The overall average risk management rankings of the

CFaR results are shown in Table 6.8, and are calculated by taking an average of the CFaR rankings for each specific risk management strategy across the quarterly to annual time horizons. With the exception of the quarterly time horizon, the CFaR rankings of risk management strategies are consistent across both the different CFaR measures (5%, 20%, CF<0) and time horizons.

On average, the risk management strategy that improves the downside risk to operating cash flow the most is the WHE+FB strategy, as it received an average rank of 1.33 across the 4 time horizon periods. The second, third, and fourth ranked strategies are the CBW+FB, the WHE, and the CBW as they received an average rank of 1.58, 3.50, and 3.67 respectively. Thus, the risk management strategies WHE and CBW perform best individually, but are further improved with the addition of the FB strategy. Over the same four time horizons, each CFaR measure ranked the base case number 8 (Tables 6.2 to 6.5), indicating that the use of cash prices (BC) consistently had the greatest downside risk potential for operating cash flows.

The CBW+FB and the WHE+FB generated the best average rank (Table 6.8), but by how much better were the actual CFaR results improved upon when compared to the BC CFaR results? Due to the large quantity of output data, the use of the 20% CFaR measure for the annual time horizon will be used as an example. Looking at Table 6.5, the base case (BC) 20% CFaR results of -$125,000 are considerably improved upon when the WHE+FB and the CBW+FB risk management strategies are implemented, as their 20% CFaR results are $391,129 and $280,691 respectively. Thus, the potential downside risk to operating cash flow would be greatly reduced in comparison to the BC strategy if the manager of the 1000 sow operation was to implement either the WHE+FB or the CBW+FB strategy. Also, even though the WHE+FB and the CBW+FB seem to be close alternatives regarding their respective rankings of 1 and 2 for the annual 20% CFaR, the WHE+FB is shown to be considerably better when using the actual 20% CFaR values as the WHE+FB 20% CFaR is over $110,000 higher than the CBW+FB 20% CFaR value. This shows the intuitive, yet simple reporting ability of the CFaR measure as it allows the decision maker to see the differences between strategies in dollar terms.

6.2.2 1.5 and 2-year CFaR Risk Management Results

The 1.5-year and the 2-year time horizon results also share similarities, however, the ranking of these risk management strategies exhibit more noticeable differences across both the different CFaR measures and time horizons. Overall, the number 1 ranked risk management strategy for the 1.5-year and 2-year CFaR time horizons is the CBW+FB, as indicated by the average rank results for these two time horizons (Table 6.8). The only exception to this ranking is the 1.5 year 20% CFaR, which ranks WHE+FB number 1 and the CBW+FB number 2. The BC strategy was ranked the lowest (number 8) by every CFaR measure and across both the 1.5 and 2-year time horizons.

The simple and intuitive information provided by the CFaR measure is useful for distinguishing the best strategy to management. For example, using the 1.5-year horizon, with the 20% CFaR as the management's objective, the number 1 ranked strategy is the WHE+FB with a 20% CFaR of $493,240, and the number 2 strategy is the CBW+FB with a 20% CFaR of $479,234. The difference between the 20% CFaR CBW+FB and WHE+FB values is small (approximately $14,000). However, if management also looked at the other CFaR values (Table 6.6), they would be able to determine that the CF<0 CBW+FB is actually slightly better than the CF<0 WHE+FB measure (only 0.26% better), and is substantially better when using the 5% CFaR measure (about $85,000 better). Thus, management may want to sacrifice the WHE+FB $14,000 improvement gained when using the 20% CFaR measure, and instead implement the CBW+FB strategy for an improvement of $85,000 to the 5% CFaR.

6.2.3 Overall CFaR Risk Management Results

As shown above, the estimated CFaR results can be used to rank the performance of various risk management strategies. In general, the ranking of the CFaR strategies tend to be very consistent across the various CFaR levels of measurement (5%, 20%, and prob. CF > 0). This consistency can be further shown using Spearman's Rank correlation analysis[30], which indicates that the correlations between the various CFaR rankings (5%,

[30] Spearman's Rank correlation is used to test the correlation relationships between rankings as it is more meaningful because it does not require the relationship to be linear (Bhattacharyya and Johnson 1977). The significance of all the spearman rank correlations in Table 6.9 were tested at the 5% level and were all found to reject the null hypothesis of independence.

20%, and prob. CF > 0) over all time horizons are all very positive (Table 6.9). The Spearman Rank correlations between the 5% CFaR to 20% CFaR, 5% CFaR to CF<0, and 20% CFaR to CF<0 are 0.9766, 0.9739, and 0.9375 respectively.

The ranking results also tend to be consistent over various time horizons, although some differences begin to occur when comparing shorter to longer time horizons. This identifies that certain strategies, such as the number 1 ranked CBW+FB for the two year time horizon (Table 6.7), may be more effective at managing the downside risk to operating cash flow in the long run. However, in this research the possibility exists to outperform this strategy in the short-run, as shown by the number 1 rank of WHE+FB for the time horizons of semi-annual, tri-quarterly, and annual (Table 6.3-6.5). Ultimately the choice would be up to the manager of the 1000 sow operation as the time frame chosen should reflect the managements planning horizon and objectives.

Despite the ability of the CFaR to rank strategies, it is important to consider the actual values of the CFaR results, as this information will help to distinguish how much better one strategy is over the other in dollar terms. This is a very important aspect regarding the use of CFaR, as it provides decision making information that is understandable to management. Most managers understand the value of a dollar with regards to their operation's performance. Thus, it is recommended that the ranking procedure be used to identify the top few risk management strategies. After the strategies are ranked, careful consideration and substantial decision weight should then be given to the actual CFaR values as this will provide more intuitive decision making information, enabling managers to make better risk management decisions.

Overall, the implementation of risk management strategies by the 1000 sow operation has a large potential to reduce the downside loss to operating cash flows. This reduced cash flow risk is apparent when comparing the various risk management strategies from each time horizons to their respective base case scenarios (Tables 6.2-6.7). Each contract considerably improves the CFaR results when compared to the base case CFaR measure. Also, hog price contracts greatly outperform the potential risk reduction obtained when only using the barley contract. Thus, the conclusion can be made that hog prices have the greatest impact on operating cash flows over the time periods analyzed in this research (2003-2004).

It is important to mention that these contracts may not necessarily receive the same rankings if used in other years. The performance of each contract is time specific and depends on factors such as the current prices at the time of analysis (starting prices of the AR(n) models), as well as changes to contract specifics. For example, WHE forward prices are quoted daily; making WHE based risk management strategies very dependent on the forward prices quoted at the time when the CFaR model is performed. Thus, the CFaR risk management strategy rankings obtained above are relevant strictly for the time frame used in this research (2003-2004). To analyze other periods of time, the prices and contract specifics would have to be updated and implemented into the CFaR model.

6.3 Comparison of CFaR Ranks to Alternative Risk Management Decision Criteria Ranks

Because VaR is criticized as being "Safety First", and because of the unlikely chance that the expected utility consistent conditions of CFaR (stated in Chapter 3.5.1) will hold, the CFaR ranking results are compared to the ranking results of decision criteria more consistent with expected utility maximization. Because both the CFaR and alternative decision criterion have different assumed underlying expected utility restrictions, they may not necessarily produce similar ranking results of the risk management strategies. The comparison between the CFaR and the various decision criteria are made using the same risk management strategies used above.

6.3.1 First Order Stochastic Dominance (FSD) Comparative Results

First Order Stochastic Dominance may fail to identify a dominant (efficient) strategy, as several of the most dominant strategies may be determined to be indifferent. In general, the stochastic dominance criterion "lacks discriminatory power and the efficient sets tend to be large" (Gloy and Baker 2001, p. 41). As described in section 3.4.3, the cumulative distribution that lies furthest to the right, without crossing any other distributions, is dominant. In Figure 6.1, the dominant strategy for the quarterly results can be identified as the CBW+FB as it lies furthest to the right and does not cross any of the other distributions. However, choosing the next dominant strategy is not possible as the second furthest to the right (WHE+FB) crosses several other distributions, making the distributions indifferent.

In fact, a dominant strategy can only be identified for the quarterly time horizon results using this method as the distributions in all the other time horizons are indifferent. For example, the cumulative distributions for the 1.5-year time horizon all cross at least one other distribution (Figure 6.2). Although simple, this risk management decision criteria produces hard to interpret results, and is ineffective for the purpose of ranking the dominant or most efficient risk management strategies used in this research.

In order to improve the ability of the FSD to choose smaller efficient sets (or to rank risk management strategies), an assumption that the decision maker can borrow or lend at the risk free rate can be introduced when FSD is used to analyze potential returns. This is called stochastic dominance with a risk free asset (FSDRA), and was performed by both Gloy and Baker (2001) and Manfredo et al. (2003) for evaluating potential returns (%) when using various risk management strategies. Essentially, all this is doing is evaluating the cumulative distributions at a fixed point, where the fixed point is chosen based on economic value (e.g. risk free rate when evaluating returns). However, this process is similar to VaR results when the VaR is analyzed at a fixed point (Gloy and Baker 2001). Thus, this is essentially the same process performed by this research when evaluating the CFaR at CF < 0, where the break even point of zero is chosen as the fixed point of analysis due to the economic implications breaking even has when managing cash flow (See Figure 6.2 for an example of fixed point analysis at CF=O). Thus, we can expect the CFaR CF < 0 results to perform consistently to the FSDRA performed by Gloy and Baker (2001) and Manfredo (2003) to rank risk management strategies.

A comparison of the CF<0 measure and the other CFaR measures (5% and 20%) was already performed using the correlation analysis in section 6.2.3, and found the CF<0 to be very consistent with the rankings of the 5% CFaR and 20% CFaR due to the high and positive Spearman Rank correlations (Table 6.9). The Spearman Rank correlation analysis will also be used below to compare the CF<0 rankings to the Sharpe ratio and Coefficient of Variation rankings.

6.3.2 E-V Efficiency Comparative Results

The use of E-V space can be used to identify the most efficient set of risk management strategies within a mean-variance framework. The E-V results of the various risk management strategies for all 6 time horizons analyzed in this study are reported in Figures 6.3 to 6.8. The efficient sets for each time horizon are also displayed in Table 6.10.

As mentioned in section 3.4.1, the E-V framework will often fail to identify one specific strategy as the most efficient and instead identifies an efficient set. This is the case for the quarterly, 1.5-year, and 2-year time horizon E-V results, where both the CBW+FB and WHE+FB strategies are identified to be in the efficient set. Based on this analysis, the most efficient risk management strategy can not be determined for these time horizons. However, for the semi-annual, tri-quarterly, and annual results, the WHE+FB is the only risk management strategy comprising the efficient set, identifying it as the most efficient risk management strategy for these specific time horizons.

In general, the risk management strategy(s) identified by the E-V space analysis are consistent with the top ranks of the CFaR risk management strategy analysis. When comparing the CFaR ranking results for the various time horizons (Table 6.2-6.7) to the E-V efficient sets (Table 6.10), all E-V efficient sets are comprised of either the number 1 ranked CFaR strategy, or the number 1 and number 2 ranked CFaR strategies. The only exception is the 2-year time horizon, as the CFaR ranks CBW+FB and CBW as number 1 and 2 respectively, while the E-V efficient set is comprised of the CBW+FB and the WHE+FB strategies. Despite this one small discrepancy, the CFaR rankings of this research are considered consistent with E-V efficiency analysis.

6.3.3 Coefficient of Variation and Sharpe Ratio Rankings

The coefficient of variation and Sharpe ratio are similar; however, they are both used to rank the risk management strategies listed above. The coefficient of variation is simple to calculate, and derived by dividing standard deviation of the operating cash flows (or returns) by the expected operating cash flows (or returns (R)) [$\sigma_{CF}/E(CF)$ *or* $\sigma_R/E(R)$]. This unit-less measure, which considers both risk and return, can then be used to compare the efficiency of multiple risk management strategies. The ranking results of the coefficient of variation are reported in Tables 6.2 to 6.7, and are discussed below.

The Sharpe ratio, as described in section 3.4.4, is very similar to the coefficient of variation, except that returns are evaluated against the risk free rate of return. Because the Sharpe ratio must be calculated using returns, the operating cash flow values produced by this research have to be converted into returns in order to calculate the Sharpe ratio for the 1000 sow firm.

In general, returns can be calculated as (similar to Cleary and Jones (2000)):

$$R_{Ft} = \frac{(V_t - V_{t-1}) + CF_t}{V_{t-1}} \qquad [6.2]$$

where R_{Ft} is the return on the fund in period t, V_t is the value of the asset in time t, CF_t is the cash flow generated by the asset V over the time horizon t, and V_{t-1} is the starting value of the asset. Due to the lack of accounting information for the firm modeled in this research, V_t and V_{t-1} are held constant over time and are based on the $4819.79/sow capital cost provided by Manitoba Agriculture (MAFRI[b]). The CF_t are equal to the cumulative stochastic cash flows corresponding to each specific time horizon evaluated. The R_{Bt} (benchmark return from Equation [3.4]) used is the risk free rate of return of 2.77%, which is the average 2002 yield on the 6-month Canada Treasury Bill (www.bankofcanada.ca). Using the above information, the Sharpe ratios are calculated (according to Equations [3.1] and [3.2]) and ranked for the 6 different time horizons (Tables 6.2 - 6.7).

Comparing the results from Tables 6.2 - 6.7, the Sharpe ratio and coefficient of variation ranking results look almost identical. This is further confirmed by the Spearman rank correlation analysis in Table 6.9, which indicates that the ranks of these two measures have a correlation of 0.9844. This is the highest correlation reported in Table 6.9.

The rankings produced by the Sharpe ratio and coefficient of variation each have the same highly positive Spearman rank correlation relationship with the 5% CFaR and 20% CFaR measure rankings (0.9804 and 0.9609 respectively). The Spearman correlation rankings between the Sharpe ratio and CF<0 CFaR and between the coefficient of variation and CF<0 (Table 6.9) are only slightly different from each other (0.9635 and 0.9564 respectively). Overall, the results of this study determine the 5%, 20% and CF<0 CFaR risk management strategy rankings perform consistently with the Sharpe ratio and coefficient of variation rankings. However, it is important to note that the similarities between rankings may not be as strongly related during different time periods when results are calculated using different contract specifics and different starting prices.

6.3.4 Comparison of Ranking Results with Literature

Gloy and Baker (2001) and Manfredo et al. (2003) also compare the VaR rankings of various risk management strategies to the rankings provided by mean-variance (risk and return) measures. Gloy and Baker (2001) test and compare the ranking ability of a 10% VaR, the Sharpe Ratio, and FSDRA (considered consistent with the CF<0 CFaR measure of this study) when applied to a simulated crop/hog farm model. Upon testing, they too found their CFaR, Sharpe Ratio, and FSDRA risk management rankings to be highly correlated, with the lowest correlation found to be 0.96 (FSDRA to 10% VAR) and the other two found to be 0.99. These high correlations are consistent with the Spearman Rank correlation results obtained in this research (Table 6.9).

Gloy and Baker (2001) also compare their 10% VaR measure to the utility maximization decision criteria of certainty equivalent. Their results suggest that if individuals are not risk-averse and do not have access to financial leverage, then the 10% VaR measure was not very consistent with utility maximization. However, when individuals were strongly risk-averse, and when they had access to financial leverage, the 10% VaR and FSDRA ranking results were strongly correlated with utility maximization (0.84 and 0.95 respectively). Considering this information, the hypothesis can be made that the various CFaR measures in this research should be fairly consistent with the utility maximization of Alberta hog producers, assuming that the model produced in this research is consistent with their VaR results. This hypothesis is based on; first, producers are considered risk-averse (Hardaker 1997); and second, as mentioned in Chapter 2, hog producers debt levels are increasing, indicating access to financial leverage. However, testing would need to be performed in order to confirm this hypothesis.

Manfredo et al (2003) also evaluated the ability of different risk measures, and used a 5% VaR, the Sharpe ratio, and the FSDRA to compare the rankings of risk management strategies for various sizes of agricultural cooperative firms. Their findings are also consistent with those found in this research, in that the rankings of the FSDRA measure tended to perform quite consistently with the Sharpe. However, they found the 5% VaR measure to generally produce slightly different rankings when compared to the

Sharpe ratio and FSDRA rankings. Despite the slightly different rankings, the top two rankings of the 5% VaR were always consistent with the top two rankings of the Sharpe ratio, indicating that the %5 VaR still performed consistently when ranking the top couple of strategies.

6.4 Chapter Summary

This chapter first defined the type of risk management strategies that are evaluated by the CFaR model. The CFaR results of the risk management strategies are then reported and ranked. The WHE+FB strategy was found to generally outperform the rest of the strategies for the first year of analysis, while the CBW+BC strategy outperformed the rest for the 2nd year of analysis. Although rankings were used to show which strategies performed best, the actual CFaR values were shown to provide intuitive decision making information, beyond the information obtained from the rankings. The actual CFaR values also showed that the downside risk to operating cash flow could be greatly reduced through the adoption of risk management strategies.

Comparing the ranking ability of the various CFaR measure (5%, 20%, and CF<0) found them to provide consistent results between each other across the various time horizons tested. The ranking results of the various CFaR measures were then tested against alternative mean-variance (risk and return) type risk measure rankings. Generally, the CFaR rankings were found to perform very similar to the mean-variance efficient strategies. However, because the CFaR values are reported in dollar terms, this research anticipates that the use of the actual CFaR measures would provide better risk management decision making information than the ranking results of the alternative risk management decision criteria.

Despite the potential risk reduction ability of the various strategies used in this research, there are two important points that must be mentioned. First, there are often costs associated with risk management strategies. These costs may be incurred from implementing the strategy itself, or the costs might be a reduced upside potential of financial returns. In this research, the reduced upside potential of operating cash flow can be seen in the Figure 6.2, as the upper tail of the risk management strategy distributions are generally to the left of the base case. However, VaR literature generally ignores reporting the impact risk management strategies may have on the upside potential of returns, as the VaR measure focuses on loss. Thus, this research also does not report the impact of the risk management strategies have on the upside potential of operating cash flows. Secondly, the successes of the risk management strategies in reducing operating cash flow risk are very dependent on the contract specifics and the specific time period of this research (Jan. 2003 – Dec. 2004). Using different contract specifics or different time periods would likely change the strategies' ability to reduce the downside risk to operating cash flow, their relative rankings, and potentially change the consistency of ranks between the CFaR measures and the alternative decision criteria.

6.5 Chapter 6 Tables

Table 6.1 Western Hog Exchange Forward Prices for 2003 at Dec. 2002

Month	WHE Forward Prices
Jan-03	1.308
Feb-03	1.446
Mar-03	1.462
Apr-03	1.515
May-03	1.701
Jun-03	1.688
Jul-03	1.624
Aug-03	1.601
Sep-03	1.507
Oct-03	1.403
Nov-03	1.32
Dec-03	1.361

Table 6.2 Quarterly CFaR, Sharpe Ratio, and Coefficient of Variation Rankings of Risk Management Strategies Starting Jan. 2003

Risk Management Strategy	5% CFaR	5% CFaR Rank	20% CFaR	20% CFaR Rank	CFaR < 0	CFaR < 0 Rank	Sharpe Ratio	Coefficient of Variation Ranking
BC	-150086	8	-96329	8	67.78%	8	8	8
CBW	3444	3	17226	3	3.27%	3	3	3
FPW	-55066	6	-32212	6	55.02%	7	7	6
WHE	-23713	5	1333	5	18.97%	5	5	5
FB	-110402	7	-59193	7	50.02%	6	6	7
CBW+FB	43963	1	55349	1	0.01%	1	1	1
FPB+FB	-8187	4	6955	4	11.20%	4	4	4
WHE+FB	21165	2	41042	2	0.61%	2	2	2

Where: - the best performing strategy is ranked 1, with the worst performing strategy Ranked 8
BC=Base Case (Spot Prices) CBW=Feed Cost Based Hog Price Window Contract
FB=Fixed Barley Price Contract FPW=Fixed Hog Price Window Contract

Table 6.3 Semi-Annual CFaR, Sharpe Ratio, and Coefficient of Variation Rankings of Risk Management Strategies Starting Jan. 2003

Risk Management Strategy	5% CFaR	5% CFaR Rank	20% CFaR	20% CFaR Rank	CFaR < 0	CFaR < 0 Rank	Sharpe Ratio	Coefficient of Variation Ranking
BC	-263886	8	-139407	8	50.14%	8	8	8
CBW	25448	4	54743	4	0.95%	4	4	4
FPW	-84506	6	-28965	6	32.23%	6	7	6
WHE	56634	3	112137	3	0.67%	3	2	2
FB	-188849	7	-72737	7	35.77%	7	6	7
CBW+FB	100555	2	123477	2	0.00%	1	3	3
FPB+FB	3862	5	39284	5	3.99%	5	5	5
WHE+FB	142501	1	186049	1	0.00%	1	1	1

Where: - the best performing strategy is ranked 1, with the worst performing strategy Ranked 8
BC=Base Case (Spot Prices) CBW=Feed Cost Based Hog Price Window Contract
FB=Fixed Barley Price Contract FPW=Fixed Hog Price Window Contract

Table 6.4 Tri-Quarterly CFaR, Sharpe Ratio, and Coefficient of Variation Rankings of Risk Management Strategies Starting Jan. 2003

Risk Management Strategy	5% CFaR	5% CFaR Rank	20% CFaR	20% CFaR Rank	CFaR < 0	CFaR < 0 Rank	Sharpe Ratio	Coefficient of Variation Ranking
BC	-335985	8	-150191	8	40.16%	8	8	8
CBW	51033	4	104064	4	0.61%	4	4	4
FPW	-99367	6	-1813	6	20.43%	6	6	6
WHE	128798	3	217350	2	0.25%	3	2	2
FB	-234879	7	-57557	7	27.36%	7	7	7
CBW+FB	158220	2	196093	3	0.00%	1	3	3
FPB+FB	26041	5	86925	5	2.06%	5	5	5
WHE+FB	255874	1	320017	1	0.00%	1	1	1

Where: - the best performing strategy is ranked 1, with the worst performing strategy Ranked 8
BC=Base Case (Spot Prices) CBW=Feed Cost Based Hog Price Window Contract
FB=Fixed Barley Price Contract FPW=Fixed Hog Price Window Contract

Table 6.5 Annual CFaR, Sharpe Ratio, and Coefficient of Variation Rankings of Risk Management Strategies Starting Jan. 2003

Risk Management Strategy	5% CFaR	5% CFaR Rank	20% CFaR	20% CFaR Rank	CFaR < 0	CFaR < 0 Rank	Sharpe Ratio	Coefficient of Variation Ranking
BC	-370921	8	-125001	8	31.47%	8	8	8
CBW	92720	4	169235	4	0.25%	3	4	4
FPW	-87057	6	47045	6	13.21%	6	6	6
WHE	144554	3	264301	3	0.40%	4	3	2
FB	-248738	7	-13529	7	21.05%	7	7	7
CBW+FB	222006	2	280691	2	0.00%	1	2	3
FPB+FB	63073	5	157073	5	0.94%	5	5	5
WHE+FB	304376	1	391129	1	0.01%	2	1	1

Where: - the best performing strategy is ranked 1, with the worst performing strategy Ranked 8
BC=Base Case (Spot Prices) CBW=Feed Cost Based Hog Price Window Contract
FB=Fixed Barley Price Contract FPW=Fixed Hog Price Window Contract

Table 6.6 1.5-Year CFaR, Sharpe Ratio, and Coefficient of Variation Rankings of Risk Management Strategies Starting Jan. 2003

Risk Management Strategy	5% CFaR	5% CFaR Rank	20% CFaR	20% CFaR Rank	CFaR < 0	CFaR < 0 Rank	Sharpe Ratio	Coefficient of Variation Ranking
BC	-397270	8	-6751	8	20.43%	8	8	8
CBW	198242	3	339896	4	0.09%	2	3	3
FPW	-30675	6	193883	6	6.28%	6	6	6
WHE	87180	5	346736	3	2.66%	5	5	5
FB	-218973	7	131811	7	13.06%	7	7	7
CBW+FB	365730	1	479234	2	0.00%	1	1	1
FPB+FB	162975	4	337414	5	0.29%	4	4	4
WHE+FB	278462	2	493240	1	0.26%	3	2	2

Where: - the best performing strategy is ranked 1, with the worst performing strategy Ranked 8
BC=Base Case (Spot Prices) CBW=Feed Cost Based Hog Price Window Contract
FB=Fixed Barley Price Contract FPW=Fixed Hog Price Window Contract

Table 6.7 2-Year CFaR, Sharpe Ratio, and Coefficient of Variation Rankings of Risk Management Strategies Starting Jan. 2003

Risk Management Strategy	5% CFaR	5% CFaR Ranking	20% CFaR	20% CFaR Ranking	CFaR < 0	CFaR < 0 Ranking	Sharpe Ratio Ranking	Coefficient of Variation Ranking
BC	-319111	8	141367	8	14.13%	8	8	8
CBW	338682	2	547373	3	0.04%	2	2	2
FPW	83607	6	380228	6	2.88%	5	6	5
WHE	108446	5	464584	5	3.07%	6	5	6
FB	-137461	7	298932	7	8.37%	7	7	7
CBW+FB	525702	1	699857	1	0.00%	1	1	1
FPB+FB	305642	4	538176	4	0.09%	3	3	3
WHE+FB	314742	3	629336	2	0.73%	4	4	4

Where: - the best perfoming strategie is ranked 1, with the worst performing strategy ranked 8
BC=Base Case (Spot Prices) CBW=Feed Cost Based Hog Price Window Contract
FB=Fixed Barley Price Contract FPW=Fixed Hog Price Window Contract

Table 6.8 Average Ranks of All Quarterly to Annual CFaR Ranks and All 1.5-Year and 2-Year CFaR Ranks

Risk Management Strategy	Average CFaR Result Ranks for the Time Horizons of Quarterly to Annual	Average CFaR Result Ranks for the Time Horizons of 1.5-Years and 2-Years
BC	8.00	8.00
CBW	3.67	2.67
FPW	6.08	5.83
WHE	3.50	4.83
FB	6.92	7.00
CBW+FB	1.58	1.17
FPB+FB	4.75	4.00
WHE+FB	1.33	2.50

Note: - Where 1 is the best strategy and 8 is the worst

Table 6.9 Spearman Rank Correlation Analysis of Decision Criteria Rankings for all Time Horizons Analyzed

	5% CFaR	20% CFaR	CFaR < 0	Sharpe Ratio	Coefficient of Variation
5% CFaR	1				
20% CFaR	0.9766	1			
CFaR < 0	0.9739	0.9375	1		
Sharpe Ratio	0.9804	0.9609	0.9635	1	
Coefficient of Variation	0.9804	0.9609	0.9564	0.9844	1

Table 6.10 E-V Analysis Efficient Sets

Time Horizon	E-V Efficient Set
Quarterly	CBW+FB, WHE+FB
Semi-Annual	WHE+FB
Tri-Quarterly	WHE+FB
Annual	WHE+FB
1.5-Years	CBW+FB, WHE+FB
2-Years	CBW+FB, WHE+FB

6.6 Chapter 6 Figures

Figure 6.1 Cumulative Distributions of Quarter 1 Operating Cash Flows Starting in Jan. 2003

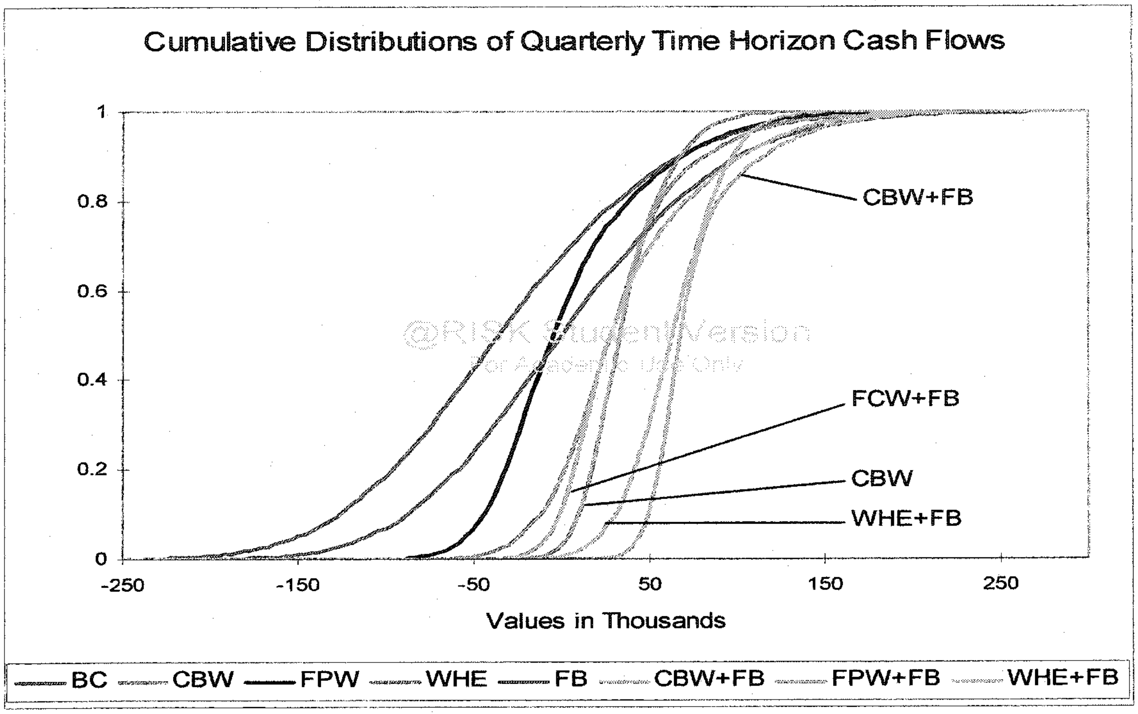


Figure 6.2 Cumulative Distributions of 1.5-Year Time Horizon Operating Cash Flows Starting in Jan. 2003

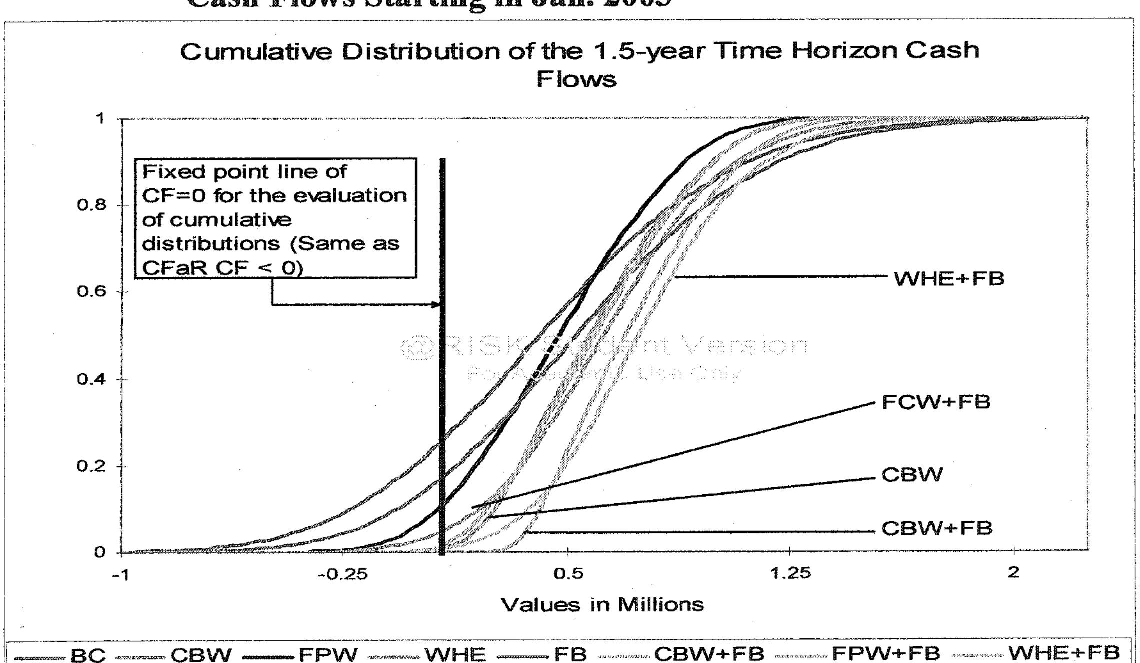


Figure 6.3 E-V Analysis of Quarter 1 Operating Cash Flows Starting Jan. 2003

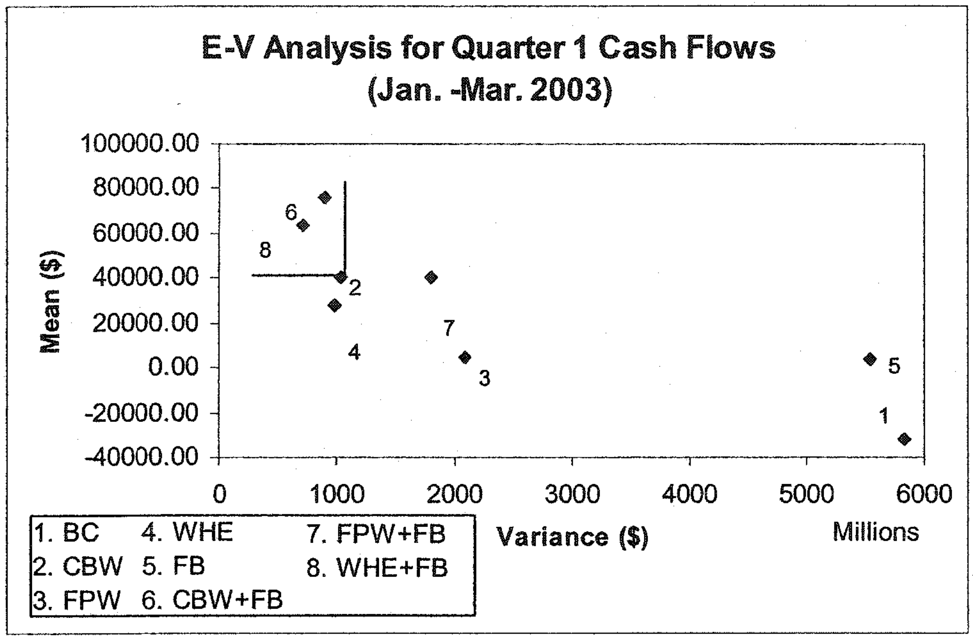


Figure 6.4 E-V Analysis of Semi-Annual Operating Cash Flows Starting Jan. 2003

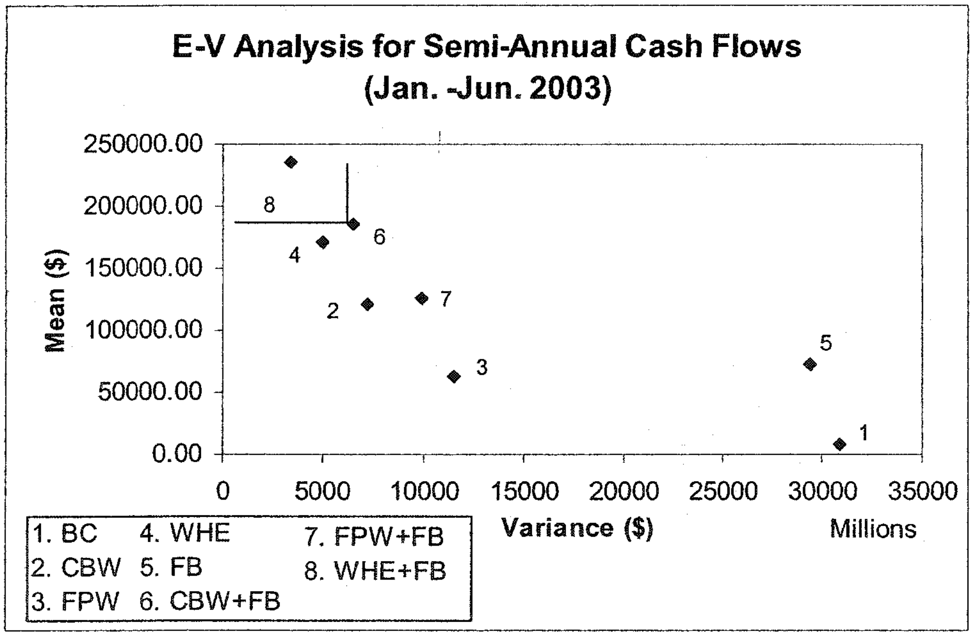


Figure 6.5 E-V Analysis of Tri-Quarterly Operating Cash Flows Starting Jan. 2003

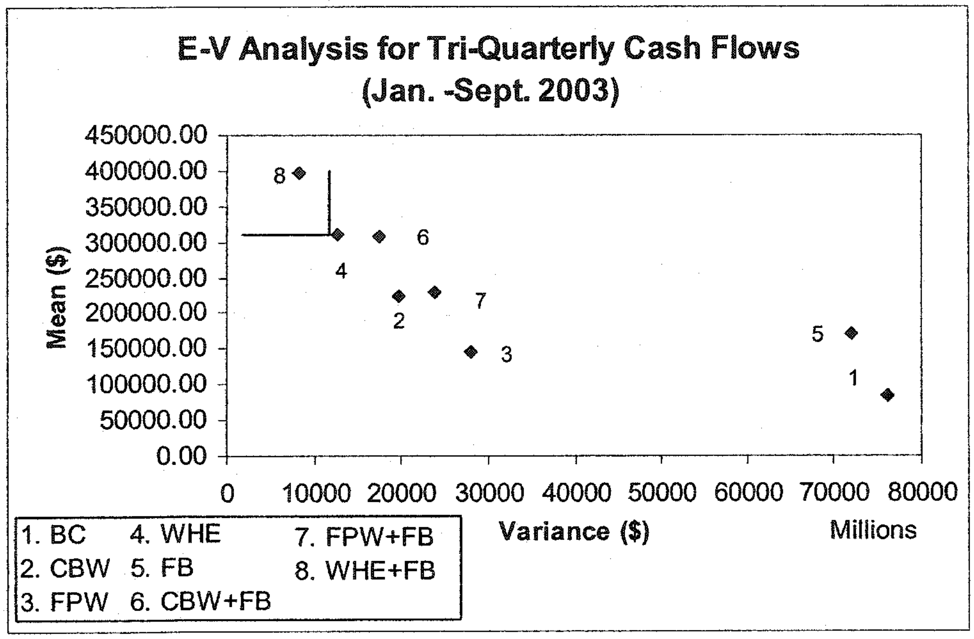


Figure 6.6 E-V Analysis of Annual Operating Cash Flows Starting Jan. 2003

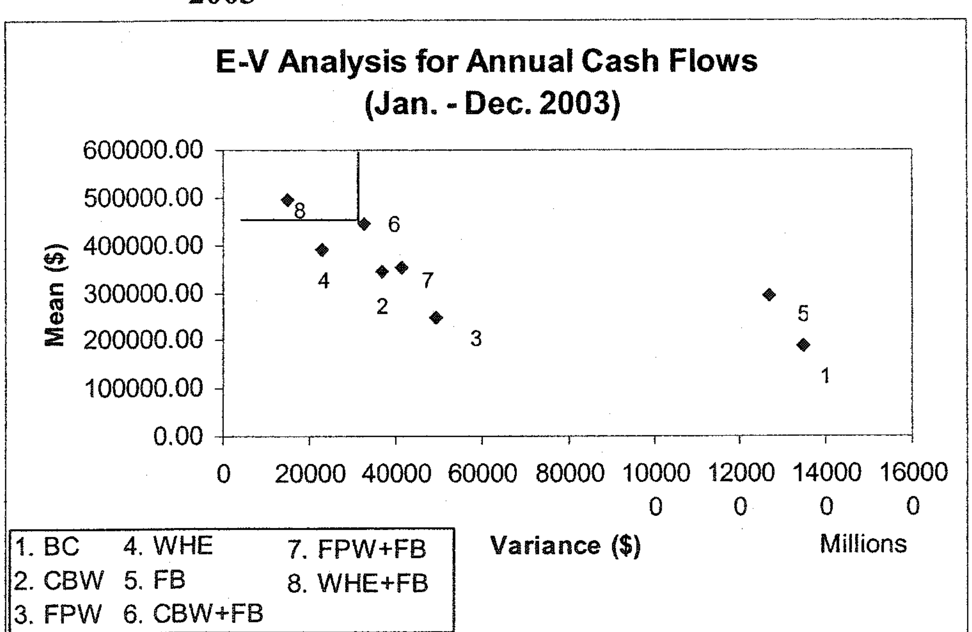


Figure 6.7 E-V Analysis of 1.5-Year Operating Cash Flows Starting Jan. 2003

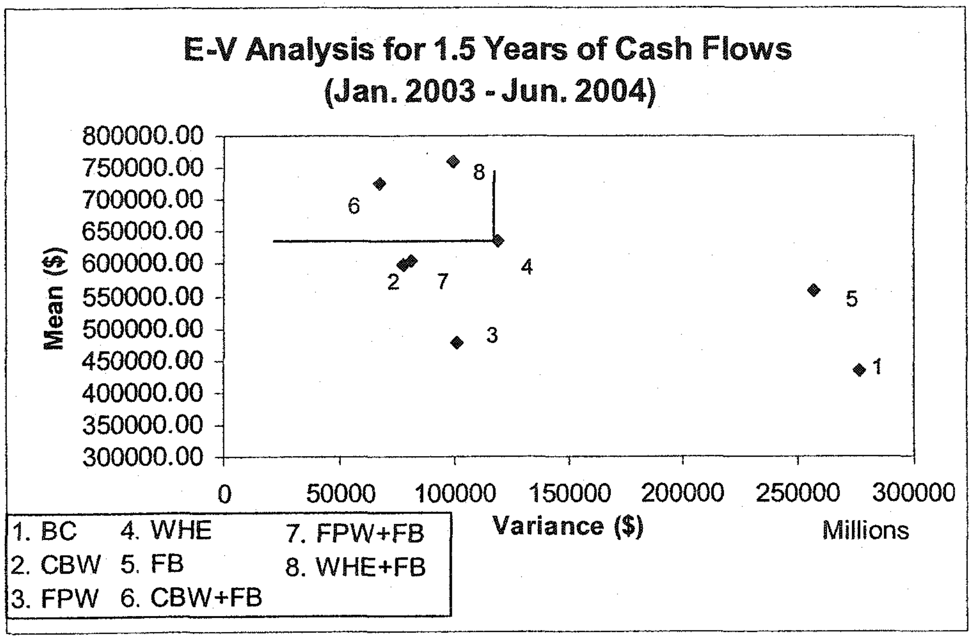
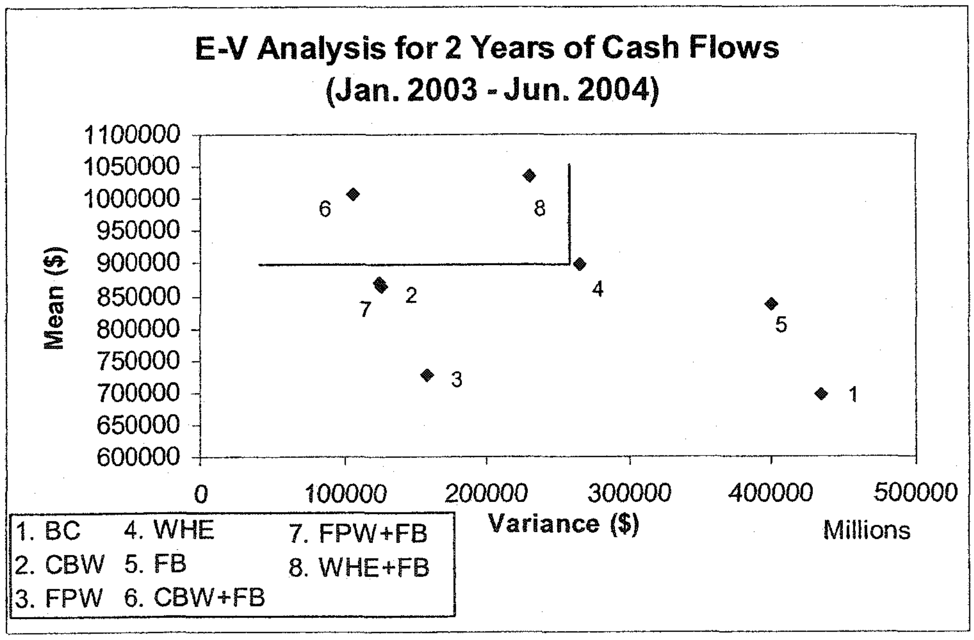


Figure 6.8 E-V Analysis of 2-Year Operating Cash Flows Starting Jan. 2003



CHAPTER 7: Conclusions, Risk Management Implications to Management, and Further Research Suggestions

The Alberta hog industry has become larger and more industrialized over the last couple of decades, resulting in changes to both the size of their risk exposures and the methods that can be used to manage them. In order to provide a new alternative for operations to measure and manage their risks, the application of Cash Flow at Risk (CFaR) was applied to the Alberta hog industry. The objective of the research was to develop a method for applying CFaR to the hog production industry, and determine whether it provided a useful and effective tool for managers to identify, measure, and manage their risk exposures.

7.1 Data, Forecasting Model, and CFaR Model Conclusions

The application of CFaR to the hog production industry was accomplished using Monte Carlo simulation. After identifying both the stochastic and non-stochastic components of the model, several key steps had to be performed and conclusions made in order to estimate and test the final CFaR measure.

7.1.1 Price Data and Price Forecasting Model Conclusions

The log transformed time series price data used in the research were found to be stationary for all variables. This indicated that the data were in the proper form to proceed with the estimation of the forecasting models using regression analysis. The stationarity property of the time series data also indicated that the prices series used in the CFaR model may follow a mean reversion pattern, indicating that the use of mean reverting price forecasting models, such as the AR(n) and Vector AR(n), may reasonably represent the behavior of the commodity prices used in the research.

Several statistical tests (AIC, SC, R2, and Coefficient t-tests) were used to identify the most appropriate lag structures for the AR(n) and Vector AR(n) forecasting models. The AR(n) model was found using the MSE, MAPE, and BAIS measures, to provide the best forecasting results when compared to the subsequent year (2003) of out of sample monthly price data. Thus, the conclusion was made that the AR(n) model would provide the best representation of price risk in this application of CFaR to the hog production industry.

7.1.2 Production Simulation Conclusions

In total, six different production risks were simulated in the CFaR model. The production risks are independent of each other, and are represented in the model using different distributions. The distributions were determined using either the @Risk best fit results of actual Alberta production data, or basic statistics obtained from actual production data. The production components were then represented in the CFaR model through a two stage simulation. The two stage simulation simplified the construction of the final CFaR model and converted continuous annual statistics used in stage one into discrete monthly statistics for use in stage 2 (actual CFaR model). Through the use of the two simulation stages, the CFaR measure accounted for the potential operating cash flow impacts caused by the various production risks.

7.1.3 CFaR Model Conclusions

Using the 2002 Oct. to Dec. monthly prices as the starting point of the AR(n) forecasting models (Table 5.19), the 5%, 20%, and CF<0 CFaR results were estimated for time horizons spanning over 2003, and 2003 to 2004. The CFaR measures at the 5%, 20%, and at the CF<0 levels anticipated large potential losses to operating cash flow and a high probability of obtaining negative cash flows. These large anticipated losses at the 5% and 20% levels were greatest for the first year of the analysis, but both showed improvement in operating cash flows by the end of the 2-year time horizon. The CF<0 measure showed improvement over all time horizons analyzed.

5% CFaR

Chapter 4 (4.2.5) indicated that the 5% CFaR measure could be used to identify a level of liquid capital that could be held in order to protect against operating cash flow losses. This research instead finds that the use of the 5% CFaR measure in this respect may not provide pork producers as much value as it does for the financial industry. The 5% CFaR measures (Table 5.18) report potentially large losses to operating cash flows over 2003 to 2004, indicating that a very large amount of liquid capital would have to be held (or accessible) by the 1000 sow operation. However, the 5% CFaR measures reported (Table 5.18) are only for cash flows from operating activities. Thus, even more liquid capital than indicated by the 5% CFaR measure would be needed in order to cover other cash needs, such as investing, debt servicing, and other fixed costs. If these other cash flow requirements are not met, the operation may still face bankruptcy as the liquid capital reserve does not adequately cover all cash flow needs necessary to remain solvent. This research instead recommends using the 5% CFaR measure as an indicator of the potential extreme downside risks to operating cash flows, identifying to management just how low operating cash flows might become. If the 5% CFaR is larger than the operation can handle, or more than what management is comfortable with, the operation would be better off considering the use of other risk management options instead of maintaining a level of liquid capital equal to the 5% CFaR.

20% CFaR

As indicated in Chapter 4 (4.2.5), it is anticipated that the 20% CFaR measure is more likely be used by operations when evaluating cash flows at risk. This is because the 20% CFaR measures the potential downside losses to operating cash flows that may occur more often (1 in 5 chance). Using the 20% CFaR, producers could determine if the downside risk to operating cash flow is tolerable, or if the use of risk management strategies should be implemented in order to reduce the identified downside risk. After completing the 20% CFaR analysis, the research results provide no reasons why the 20% CFaR measure could not be used in this manner.

CF < 0 CFaR

The measure of CF<0 is chosen because it measures the probability of producers achieving a fixed operating cash flow value such as meeting all of their operating cash flow commitments. As previously mentioned, the research anticipates this type of measure will likely be of most interest to producers as it enables them to determine the probability of achieving a level of operating cash flow which has economic implications regarding to the performance of their firm. Similar to the 20% CFaR, the analysis of the basic CF<0 measure provided no reasons for objecting the use of the CFaR measure in this respect.

Using this measure, the 1000 sow operation would have been able to determine that there is a very high probability that negative operating cash flows will occur in the future. Again, using the quarterly results as an example, there is a about a 67% chance of obtaining a negative operating cash flow over the first quarter of 2003. If management had this information at the end of 2002, considerable effort could have been made to implement risk management strategies in order to improve the probability of obtaining a positive operating cash flows.

Despite the anticipated interest producers may have in evaluating a fixed cash flow value, such as CF<0, this research recommends to also consider the information provided by measure such as the 20% CFaR. The reasoning behind this recommendation is that the CF<0 CFaR measures are reported in a percentage form. Although this indicates the probability of the producer's goal being met, it fails to identify the potential downside loss to cash flow that the operation faces. By using the combination of both the CF<0 measure, and a measure such as the 20% CFaR measure, the producer can identify both the probability of reaching an economic target value, as well as the potential downside loss to operating cash flow measured in dollars. Again, the ability of CFaR to provide results in dollar terms is one of the reasons why it is considered simple, yet intuitive, as producers will generally understand the impact a dollar of cash flow has on their operation. Thus, in order to allow producers to make full use of the available CFaR results, the research recommends using a combination of both a fixed value CFaR measure (such as CF<0) and a probability based (%) CFaR measure.

7.1.4 Backtesting Conclusions

Comparing the observed percent of model violations to the percent that was expected identified that there still may be some bias in the model to underestimate risk for probability levels higher than the 5% level, even though these results were not statistically significant The LR and Z-test backtesting procedures were performed for monthly and quarterly time horizons. Both the LR and Z-test quarterly results indicated that the CFaR model performs adequately as both tests failed to reject their respective nulls at all coverage levels. However, the quarterly results are low in power due to the use of only 37 backtesting data points. In order to improve on the test measures, monthly periods were used for backtesting. This provided a total of 111 backtesting data points. The LR test found the realized CFaR results to be different than the 3% and 4% stated probability test levels. The Z-test found that the CFaR model underestimated the potential downside risk to operating cash flows at the 1-5% stated probability levels.

Thus, results from the 5% to the 50% stated probability test levels are considered adequate. However, when using the CFaR measures at lower stated probability levels, the results should be taken conservatively as the Z-test results identified CFaR measure at the 5% level and lower to underestimate the potential downside risk to operating cash flow. However, any bias that exists by the 20% CFaR measure appears to be negligible, and the 20% CFaR measure used in this research is considered to adequately estimate the downside risk to operating cash flow without any considerable bias.

The limited backtesting data points undoubtedly restrict the statistical power of the LR and Z-tests, a common problem when attempting to backtest the application of VaR (CFaR in this case) to longer time horizons (Jorion 2001). However, the conclusion of this research is that the monthly Z-tests and LR test results provide adequate backtesting results regarding the performance of the CFaR model. The shorter CFaR time horizons (quarterly to annual) are taken with more confidence as these time horizons are closer to the time horizon used when backtesting. The performance of the longer 1.5 and 2-year time horizons are still considered by this research to adequately measure the potential downside risk to cash flow, however, these are taken with slightly less confidence. This is due to quarterly backtesting time horizon being less representative of these longer-time horizons, as well as the decreased accuracy which plagues any long-term forecasts. If the time horizons were extended beyond the two-year time horizon analyzed by this research, the CFaR model may not provide as useful results.

7.2 Risk Management CFaR Conclusions

A total of 8 different risk management strategies were analyzed, including a spot cash price only strategy (base case), and strategies addressing both hog and barley price risk. The ability of these strategies to reduce risk were then ranked using the three different estimated CFaR measures (5%, 20%, and CF<0), as well as several other alternative decision criteria.

The comparison of the CFaR ranking results indicates very few differences across both the different CFaR measures (5%, 20%, and CF<0), and across the various time horizons. A strong relationship between the various CFaR measure rankings was found, as indicated by the high Spearman Rank in correlations (Table 6.9). More specifically, the rankings between the quarterly to annual horizons analyzed were most alike, with the 1.5 and 2-year ranks sharing more similarities (Tables 6.2 to 6.7).

For the time horizons of quarterly to annual, the combination of the Western Hog Exchange forward prices and the Fixed Price Barley contract (WHE+FB) received the best overall average rank of 1 (Table 6.8), with the combination of the Cost Based Window contract and the Fixed Price Barley contract (CBW+FB) receiving the number 2 rank. This indicates that the combination of both hog and barley risk management strategies provided the most downside risk protection to operating cash flow. The only exception to this ranking over the four time horizons is the first quarter results, which instead ranked the CWB+FB number one and the WHE+FB number 2. The overall average ranking results obtained for the 1.5-year to 2-year time horizons (Table 6.8) are the opposite of the overall average quarterly to annual time horizon ranks, as the CBW+FB was ranked number one, with a the WHE+FB receiving the number 2 rank.

Out of all the CFaR measures used in this research, the CF<0 provided the least informative information. This is again due to the reasons stated in 7.1.3 under the "CF<0 CFaR" section, but is also due to the very low probability levels that were produced. For example, the CF<0 for the annual time horizon produced probability levels of 0%, 0.01%, 0.25%, and 0.4%. The differences between these levels is small, indicating that none of the strategies are extremely better than one another with regards to obtaining CF<0. However, the small CF<0 probabilities reported by this research are due to the success of some of the risk management strategies and their ability to greatly reduce the probability of CF<0. It is expected that more useful probabilities would have been reported if a higher fixed cash flow value was chosen for the analysis, such as CF<$50,000.

Due to the results reported by Manfredo et al. (2003) and Gloy and Baker (2001), it was expected that the CFaR rankings would generally perform similar to the rankings of alternative mean-variance decision criteria. After comparing the CFaR ranking results of this research to E-V space, Sharpe ratio, and coefficient of variation rankings, these same conclusions were reached. The top ranked risk management strategies from the CFaR analysis were consistent to the E-V space efficient sets, and the Spearman Rank correlations between the CFaR ranks and the Sharpe ratio ranks, and the CFaR ranks and coefficient of variation ranks were all high and positive (Table 6.9). First order stochastic dominance (FSD), which is not considered a mean-variance decision criteria, was generally not able to rank the different management strategies.

Considering the consistency of the CFaR rankings when compared to the mean-variance measure ranks, this research finds the CFaR measures to be better than the alternative decision criteria that were tested when used to rank between risk management strategies in hog production. The reason why the CFaR is considered better is due to the added information provided by the actual CFaR results. Because the CFaR measure is reported using actual dollars, producers can make a decision based on a unit that can be interpreted economically. This allows producers to see how much better one risk management strategy is in comparison to another in dollar terms. For measures such as the Sharpe ratio and the coefficient of variation, the value reported is a unit-less number which can only be used to distinguish between strategies, providing no economic information. Thus, this research considers the CFaR measures better for making risk management decisions than the more traditional mean-variance alternatives, due to the intuitive yet simple decision making information it provides.

7.3 Risk Management Strategy Implications for Management

Overall, the best individual risk reduction strategies over the time horizons analyzed in this research were those that addressed hog price risk. This indicates that hog prices were a larger source of risk to operating cash flows in comparison to barley prices, at least during the time periods of this analysis (2003 to 2004). The WHE was the best performing hog price strategy over the first year of the analysis (2003), and the CBW was the best over the second year (2004). The success of the WHE strategy over the first year was due to the high quoted WHE forward prices (Table 6.1), as well as the fact that forward prices completely remove the variability of price for about 70% of the hogs marketed under this strategy. The reduction in the overall average ranking of WHE based strategies over the longer time horizons is no surprise, due to the implementation of WHE forward prices for only 1 year. Because cash prices are used for the last year of the WHE strategy, the longer horizon cooperating ash flows are subjected to risks associated with using spot cash prices.

The success of the CBW based strategies in the very first quarter is due to the high observed 2002 feed prices (Table 5.19) used at the start of the analysis. These high feed prices generate a hog floor price high enough to compensate for the high feed costs, while at the same time protect against low hog prices. Essentially, the CBW contract is successful over the long-term because this contract addresses hog, barley, and canola meal price risk all in one. Although the price floor has no relation to the changing cash price of hogs, due to its derivation from feed prices, it ensures that feed costs are covered, protects against extremely low hog prices, and still allows producers to receive the benefit of hog price rallies until the ceiling price is reached. From a producer's perspective, obtaining a long term contract such as this is ideal if only one strategy is to be used, as the producer is essentially passing on the majority of their feed price, as well as their hog price risks to the party at the other end of the contract.

Although the CFaR rankings indicate which strategies perform best, it is still recommended that management use the actual CFaR measures when making risk management decisions. The reasoning behind this recommendation is similar to that made above in section 7.1.3 under the "*CF<0 CFaR*" section. Although the rankings provide a relative performance measure, they fail to provide intuitive information. By looking at the actual CFaR measure, the decision maker can determine how much better one risk management strategy performs over the other using dollar values, allowing for more informative decision making.

7.4 Model Limitations and Further Research Suggestions

7.4.1 Price Forecasting Models

The AR(n) price forecasting models used were found both by this study, and the study by Gjolberg and Bengtsson (1997), to successfully forecast hog prices. However, the AR(n) models used are relatively simple in comparison to other time series forecasting models (e.g. GARCH and ARIMA), and did not include factors such as seasonality or the hog price cycle. Although the overall results of the CFaR model are considered accurate, the use of alternative forecasting models may further increase the performance of the CFaR model, especially when used over longer time horizons or at low CFaR probability levels. This would specifically be useful for analyzing 5 year plus time horizons in order to analyze the risk management ability of long-term contracts offered, such as those previously offered by Rocky Mountain Pork (sections 6.1.2 and 6.1.3).

7.4.2 Production Data and Assumptions

The production factors included in the CFaR model are derived using actual historical production data, statistics based on historical data, and general production assumptions. The stochastic production variables derived from data are from either the 24 weeks of production data from a single hog operation, or the aggregated data from 19 different operations. Although the data were enough to develop adequate estimates of the production risks, increased data would likely provide observations outside the range used in this research. These added observations would then generate a more robust representation of the specific factors.

Several production assumptions were made due to insufficient data. These assumptions are held constant throughout the model, and include factors such as the average price index achieved, average carcass weight, and production technology. Changing these factors to stochastic and estimating them based a specific operation's data would further improve the CFaR model, making it more representative of what an actual operation might experience. Thus, further research could avoid the production assumptions used in this CFaR model and instead estimate them using actual data. However, because production risk comprises only a small portion of the total risk to operating cash flows, as was shown by this research, it is anticipated that the overall improvement, if any, would likely be small.

Finally, no catastrophic production risks were included in the model, such as those resulting from a serious disease infection. The introduction of disease could have large impact regarding the potential risk to operating cash flow, as some diseases require depopulation in order for them to be eliminated. Including this type of catastrophic risk into the model would be considered more of a stress test or scenario analysis. Thus, further research could analyze the impact various diseases may have on operating cash flows.

7.4.3 Risk Management Strategies

The risk management strategies used in this research are all based on forward prices or contract prices. WHE forward prices are generally available, however, long term contracts, such as the type once offered by Rocky Mountain Pork, are scarce in Alberta. However, an alternative price risk management strategy is the use of futures and option markets. Thus, further research should include the use of futures and option based risk management strategies into the CFaR analysis.

7.4.4 Other Suggestions

This research compared the CFaR results to the First Order Stochastic Dominance and mean-variance decision criteria. Further CFaR comparisons could be made using Second or Third order Stochastic Dominance, as well as how the CFaR measure performs relative to measures that include utility theory.

Also, more research could be performed on determining the appropriate measure for reporting the CFaR values, such as the most appropriate probability or fixed value level. This would require feedback from producers regarding what type of measure that would provide the best information. The feedback may vary depending on operation specifics, such as operation type, size, and debt structure.

7.4.5 Overall Model Suggestions

Overall, the CFaR model was determined to adequately estimate the potential downside risk to operating cash flows for the 1000 sow farrow to finish operation. Over the analyzed time periods of 2003 to 2004, the CFaR model identified potentially large losses to operating cash flows. By including various risk management strategies into the CFaR model, the model was shown to effectively evaluate and rank each strategy's risk reduction performance, and provided intuitive information that could be used by management. However, continued research addressing the above suggestions could further advance the usability and performance of the CFaR model. Ideally, further research would lead to a model that was more flexible, one that could address a multitude of operation specific risks, new risk management strategies, and longer time horizons. The end goal would be to produce an available model for the hog industry that was flexible enough to be used by many Alberta hog producers.

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