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Stochastic Tests on Live Cattle Steer Basis Composite Forecasts

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STOCHASTIC TESTS ON LIVE CATTLE STEER

BASIS COMPOSITE FORECASTS

by

Elliott James Dennis

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ABSTRACT

Stochastic Tests on Live Cattle Steer Basis Composite Forecasts

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Utah State University, 2014

Major Professor: Dr. DeeVon Bailey
Department: Applied Economics

The behavior of basis and the current methods to derive accurate live cattle basis forecasts were examined. The current literature on basis using econometric estimation with an emphasis on composite forecasts in particular was discussed. Mechanical weights of the composite weights were derived using a nonlinear approach. This was supported by a stochastic dominance and efficiency analysis. Considerable support was found for the use of composite basis forecasts in the live cattle industry. Further research should be conducted in the feeder cattle market.

(237 pages)

PUBLIC ABSTRCT

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Since the seminal papers of Bates and Granger in 1969, a superfluous amount of information has been published on combining singular forecasts. Materialized evidence has habitually demonstrated that combining the forecasts will produce the best model. Moreover, while it is possible that a best singular model could outperform a composite model, using multiple models provides the advantage of risk diversification. It has also been shown to produce a lower forecasting error. The question to whether to combine has been replaced with what amount of emphasis should be placed on each forecast.

Researchers are aspired to derive optimal weights that would produce the lowest forecasting errors. An equal composite of the mean square error, by the covariance, and the best previous model, among others, have been suggested. Other academicians have suggested the use of mechanical derived weights through the use of computer programs. These weights have shown robust results.

Once the composite and singular forecasts have been estimated, a systematic approach to evaluate the singular forecasts is needed. Forecasting errors, such as the root

mean square error and mean absolute percentage error, are the most common criteria for elimination in both agriculture and other sectors. Although a valid mean of selection, different forecasting errors can produce a different ordinal ranking of the forecasts; thus, producing inconclusive results. These findings have promoted the inspection for other suitable candidates for forecast evaluation. At the forefront of this pursuit is stochastic dominance and stochastic efficiency.

Stochastic dominance and stochastic efficiency have traditionally been used as a way to rank wealth or returns from a group of alternatives. They have been principally used in the finance and money sector as a way to evaluate investment strategies. Holt and Brandt in 1985 proposed using stochastic dominance to select between different hedging strategies. Their results suggest that stochastic dominance has the opportunity to feasibly be used in selecting the most accurate forecast.

This thesis had three objectives: 1) To determine whether live cattle basis forecasting error could be reduced in comparison to singular models when using composite forecasts 2) To determine whether stochastic dominance and stochastic efficiency could be used to systematically select the most accurate forecasts 3) To determine whether currently reported forecasting error measures might lead to inaccurate conclusions in which forecast was correct. The objectives were evaluated using two primary markets, Utah and Western Kansas, and two secondary markets, Texas and Nebraska. The data for live cattle slaughter steer basis was taken and subsequently computed from the Livestock Marketing Information Center, Chicago Mercantile Exchange, and United States Department of Agriculture from 2004 to 2012.

Seven singular were initially used and adapted from the current academic literature. After the models were evaluated using forecasting error, stochastic dominance and stochastic efficiency, seven composite models were created. For each separate composite model, a different weighting scheme was applied. The “optimal” composite weight, in particular, was estimated using GAMS whose objective function was to select the forecast combination that would reduce the variance-covariance between the singular forecasting models. The composite models were likewise systematically evaluated using forecasting error, stochastic dominance and stochastic efficiency.

The results indicate that forecasting error can be reduced in all four markets, on the average by using an optimal weighting scheme. Optimal weighting schemes can also outperform the benchmark equal weights. Moreover, a combination of fast reaction time series and market condition, supply and demand, forecasts provide the better model. Stochastic dominance and stochastic efficiency provided confirmatory results and selected the efficient set of the forecasts over a range of risk. It likewise indicated that forecasting error may provide a point estimate rather than a range of error. Suggestions for their application and implementation into extension outlook forecasts and industry application are suggested.

DEDICATION

This thesis is dedicated to Dr. DeeVon Bailey. Only through him have I been able to come this far in my education. From the friendly office meetings to stirring intellectual debates, his thoughts and experiences provided me with a solid ground to begin a fruitful career in applied economics. Likewise, it was through his lectures on price analysis that the ideas presented in this paper were formed. No one could ask for a greater beginning.

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The ideas that have been generated herein have largely been the product of countless conversations with professors, professionals and fellow students. As such, it has become difficult to ascertain which ideas, if any, can be solely claimed by myself, although I would like to acknowledge Dr. DeeVon Bailey – notably, for creating a suitable environment where my ideas could bud and research could be conducted.

Mention should also be given to the members on my committee who helped provided quintessential advice which subsequently, blossomed these ideas. I also need to publicly thank my wife, Tiffany, for her patience and forbearance through the laborious process of working and supporting me all while being pregnant and giving birth to our first daughter, Audrey.

Elliott J. Dennis

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CHAPTER 1

INTRODUCTION

"Basis" is generally defined as the difference between local cash and the Chicago-based future's price. Because basis information is essential to hedging decisions, crop and cattle producers are generally interested in the basis for an explicit time and location for a given commodity. Accordingly, basis was defined in this study as:[1]

(1) $\text{Basis}_{l,c,t} = \text{Cash price}_{\,l,c,t} - \text{Futures price}_{l,c,t}$

where 'l' refers to the l^{th} geographical location, 'c' refers to the c^{th} commodity with its corresponding grade/quality and 't' refers to the t^{th} time period (Dhuyvetter 1997). As a result, cash prices and futures prices are both linked to an exact location, grade/quality, and time. For example, the December Live Cattle (LCZ)[2] contract traded on the Chicago Mercantile Exchange (CME) in Chicago, Illinois, with contract specifications of 55% Choice, 45% Select, Yield Grade 3 live steers (CME Group 2014), represents an exact time, location, and commodity grade.

Producers strive to accurately forecast basis for a given commodity, time, and location in order to make informed marketing decisions about current and future commodity prices. As such, accurate knowledge of basis becomes a significant factor in making informed marketing decisions that directly contribute to determining the profitability of an agribusiness enterprise. The Chicago Board of Trade (1990)[3] further illustrated this point by noting:

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[1] Some literature defines basis as Basis = Futures – Cash with the difference being in the sign of the coefficient.
[2] It should be noted that Live Cattle (LC) is sometimes referred to in the literature as fed cattle. This paper makes no distinction between the two but uses these terms interchangeably.
[3] CBOT merged with CME Group in 2007 and is now known as CME/CBOT. At the time of the quoted publication, CBOT was a singular exchange mainly dealing with grains (as quoted in Hatchett, Bronsen, and Anderson 2010).

> without a knowledge of the usual basis and basis patterns for [a] particular commodity, it is impossible to make fully informed decisions, for example, whether to accept or reject a given price…….and when and how to turn an [atypical] basis situation into a possible profit opportunity. (p. 23)

Thus, the current and historical basis should help form future price expectations of producers. Likewise, it may support current marketing decisions assuring ongoing profitability.

Within the last 50 years, it has been commonly accepted, albeit unsuspectingly, that when basis is forecasted, it is produced using a pooled singular forecast.[4] Inspection of the data in Utah and current basis models suggest that a singular forecast model may not always reflect the most accurate forecast available. Because the basis is derived as the difference between two prices (Leuthold and Peterson 1983), a single forecast model may not accurately reflect all pertinent information (Bates and Granger 1969). The use of a singular model assumes that all relevant/pertinent market information has been included in the model. Hence, the use of an additional forecast (outside of the singular model) would not be seen as pragmatic because it assumes there was in fact additional, relevant information that was omitted from the original forecast. In short, under the guise of being pragmatic and time sensitive, multiple forecasts are generated, pretested, and ultimately, the forecast that produces the lowest forecasting error is used.

When multiple singular basis forecasts are combined,[5] using a simple arithmetic mean is seen as an inexpensive alternative to capture any additional information that might have otherwise been missed when only a singular forecast model was used (Park

[4] A pooled forecast is defined as a forecast that combines all relevant, current and readily available information.
[5] The phrases “composite forecast” and “combined forecast” are used interchangeably within the literature and in this paper

and Tomek 1988). While combining forecasts is considered a valid method for potentially improving forecast performance, doing so assumes some of the following conditions: 1) “bracketing” occurred in which one forecast is higher and the other is lower than the actual price (i.e. surrounds the actual price) (Larrick and Soll 2006); 2) the forecasts have encompassed new information (Newbold and Harvey 1993); 3) the standard deviations are not equal to each other and their correlations are not equal to one (Timmerman 2006). If one or more of these conditions holds, then it implies that the combined error of the pooled forecasts will be lower than the forecast error produced by a singular model.

The purpose of this study is to reconsider the feasibility of combining basis forecasts from alternative forecast models. Specifically, this study applies stochastic dominance and stochastic efficiency tests to determine relative composite basis forecast accuracy. In 1985, Holt and Brandt explored a related idea with a simple average econometric-ARIMA model for cash and futures hog prices. Using five additional models and eight forecasting horizons, they looked at risk preference and forecasting/hedging error measures.

Of all of these potential forecasting combinations, the simple composite average performed best or second best in all cases as determined by stochastic dominance. Holt and Brandt’s results were promising, but based on review, no follow-up studies to the Holt and Brandt study have used stochastic dominance for composite forecasting models for agricultural basis.

Likewise, using stochastic efficiency in composite cattle basis forecasting has not been attempted. This study also holds as its purpose to mechanically derive composite weights for the forecasts using a nonlinear programming formulation that minimizes the combined forecast variance. Relying on the variance-covariance of the individual forecasts, Timmerman (2006) affirms that the gains from diversification will *only* be zero if:

1) σ_1 or σ_2 are equal to zero
2) $\sigma_1 = \sigma_2$ and $\rho_{1,2} = 1$
3) $\rho_{1,2} = \sigma_1/\sigma_2$

where σ is the standard deviation and ρ is the correlation. Many people have attempted to use the above information to derive weights for each forecast. Some of these methods have included equal weights, odds-matrix, and the inverse of the error. Bunn (1988) suggested that decision makers would be better served by mechanically weighting the forecasts. This study builds on this idea and strives to derive mechanical weights that can be used in a composite forecasting scheme.

To determine the accuracy of singular or composite forecasting models of agricultural commodity prices, various methods have been used. For example, the mean absolute error (MAE) and root mean square (RMSE) are frequently used (Dhuyvetter et al. 2008; Hatchett, Bronsen, and Anderson 2010), as well as various econometric variations of these two measures (Dhuyvetter 1997; Kastens, Jones, and Schroeder 1998). One of the major conclusions of this study is that while MAE and RMSE are commonly used, they do not offer an accurate level of comparison across studies, and that by using a different forecasting error, different conclusions can be determined.

This study reports forecast combinations from seven singular historical and statistically-proven basis forecasts methods from peer-reviewed journals. These models are then applied to forecasting Friday live cattle (LC) prices in Utah and Western Kansas. This study is organized in five chapters, this being Chapter 1. Chapter 2 examines the purpose of the hypothesis that combining forecasts leads to reductions in forecast errors for agricultural price forecasts. A series of principles and methods for testing that hypothesis are discussed and how they can specifically impact producers. Chapter 2 continues with a review of the literature about combining basis forecasts for agricultural commodities with an emphasis on cattle. Chapter 3 uses the principles and forecasts suggested and discussed in Chapter 2 and discusses the data and methodology used to combine and test composite basis forecasts. Particular interest is given in Chapter 3 to the stochastic dominance and stochastic efficiency approach. Chapter 4 displays the results in a series of tables and figures explaining how they relate to the current literature. Lastly, Chapter 5 looks at the previous sections, draws conclusions, and explains applications to business practices.

CHAPTER 2

REVIEW OF THE LITERATURE

The purpose of this study is to reconsider the feasibility of combining basis forecasts from singular forecast models. Specifically, it applies stochastic dominance and stochastic efficiency tests to determine which composite forecast is most accurate over a range of risk. This paper also strives to derive weights that should be given to singular forecasts using a nonlinear programming formulation that minimizes the combined forecast variance-covariance.

If forecast variance-covariance can be reduced while simultaneously reducing forecast error, cattle producers in Utah and Western Kansas could be more profitable if they use that information. This chapter presents a review on the examination of the hypothesis that combining forecasts leads to reductions in forecast errors for agricultural price forecasts. A series of principles and methods for testing that hypothesis are discussed and how they can specifically impact producers. The chapter continues with a review of the literature about combining basis forecasts for agricultural commodities with an emphasis on cattle. A case is made for why composite models should be used for live cattle in Utah and Western Kansas.

Current Consensus on Composite Forecasting

More than 40 years have passed since the seminal Bates and Granger (1969) and Reid (1968) papers. These papers proposed, and subsequently proved, that a reduction in forecasting error could be gained through combining forecasts. Since that time, considerable amount of literature has accumulated in regard to combining forecasts in both the business and agricultural economics application.[6]

Using a combination of different forecasts has been used in a variety of areas such as accounting (Ashton 1985), corporate earnings (Cragg and Malkiel 1968), meteorology (Kaplan, Skogstad, and Girshick 1950), sports (Winkler 1971), political risk (Bunn and Mustafaoglu 1978), and livestock prices (Bessler and Brandt 1981). Clemen (1989, p. 559) in summarizing the overabundance of composite forecast studies, said, “The results have been virtually unanimous: combing multiple forecasts leads to increased forecast accuracy….in many cases one can make dramatic performance improvements by simply averaging the forecasts.”

Since then, similar comprehensive studies on combining forecasts have been carried out (Clemen 1989; Diebold and Lopez 1996; Makridakis and Hibon 2000; Newbold and Harvey 2002; Stock and Watson 2001; Stock and Watson 2004; Timmerman 2006). All of these studies have concluded that, “The accuracy of the combination of various methods outperforms [a singular forecast], on average” (Makridakis and Hibon 2000, p. 458).

While researchers have concluded that combining forecasts is valid, there are still some who disagree with such evidence (Yang 2006). They and others claim that estimation errors are distorted when dealing with non-stationary data. If this claim is true, then the weights placed on certain forecasts would be distorted over different time periods and the results associated with combining forecasts ruled invalid. Timmerman (2006) explains and simultaneously refutes these arguments by explaining that it is not

[6] Although, it should be noted that psychology was the first recorded science to introduce the concept of using multiple forecasts to generate a superior single forecast (Gordon, 1924).

necessarily whether or not combination schemes should be used, but whether companies should spend the time searching for a single best forecast.

With the growth in access to increasingly inexpensive and user-friendly computer applications and forecasting programs, numerous forecasts are now widely available to producers and economists. While virtually free of charge, each forecast carries with it a corresponding amount of information, bias, and error. "Since all discarded forecasts nearly always contain some useful independent information" (Bates and Granger 1969 p. 451), how this influx of free data and forecasts can be combined, particularly in agriculture, should be examined. Before exploring the use of composite models in agriculture, consideration must be given to "the underlying assumptions [which] are associated with combining." (Winkler 1989, p. 607) The following explains these assumptions and follows the formulation and mathematics of Timmerman (2006, pp. 13-24) in his paper *Forecast Combinations*.

Theory of Combining

Assume two individual unbiased forecasts (F_1 , F_2) with respective errors $e_1 = Y - \hat{Y}_1$ and $e_2 = Y - \hat{Y}_2$. Further, assume that the covariance between $e_1$and e_2 is $e_1 \sim (0, \sigma_1^2)$,$e_2 \sim (0, \sigma_2^2)$ and where $\sigma_1^2 = var(e_1), \sigma_2^2 = var\ (e_2), \sigma_{1,2} = \rho_{1,2}\sigma_1\sigma_2$ with $\rho_{1,2}$ is the correlation of the two forecasts. Further suppose that the combination of the weights will sum to one (i.e. 100%) with the weights on the first (F_1) and second forecasts (F_2) defined as $(w, 1-w)$. Thus, the forecast error (e^c), which results from the combination of the two forecasts is:

(2) $e^c = (w)e_1 + (1-w)e_2$

and its respective variance-covariance of

(3) $\sigma_c^2(w) = w^2\sigma_1^2 + (1-w)^2\sigma_2^2 + 2w(1-w)\sigma_{1,2}$

To solve for the first order condition and obtain the optimal weight based on the variance-covariance, the derivative with respect to w is taken (p 14); and we obtain:

(4) $w^* = \frac{\sigma_2^2 - \sigma_{1,2}}{\sigma_1^2 + \sigma_2^2 - 2\sigma_{1,2}}$

(5) $1 - w^* = \frac{\sigma_2^2 - \sigma_{1,2}}{\sigma_1^2 + \sigma_2^2 - 2\sigma_{1,2}}$

where w* becomes the optimal weight for F_1 and 1-w* becomes the optimal weight for F_2. In order to derive the expected squared loss that is subsequently associated with the derived optimal weights, w^* is substituted into equation (3) to obtain:

(6) $\sigma_c^2(w^*) = \frac{\sigma_1^2\sigma_2^2(1-\rho_{1,2}^2)}{\sigma_1^2\sigma_2^2 - 2\rho_{1,2}\sigma_1\sigma_2}$

Based on equation (6), Timmerman (2006), quoting Bunn (1985), stated an important conclusion about the gains from diversifying risk with more than one forecast. He affirms that the gains from diversification will *only* be zero if the following condition are met (p 15):

1) σ_1 or σ_2 are equal to zero
2) $\sigma_1 = \sigma_2$ and $\rho_{1,2} = 1$
3) $\rho_{1,2} = \sigma_1/\sigma_2$

In accordance with that conclusion, knowing a specific point is not as important in determining the gains from diversification as knowing the variance-covariance. Hence, knowing the mean square error or other forecasting error method (i.e., point) is subservient to the variance-covariance matrix (i.e. standard deviation) of a singular or composite forecast.

A Hedge Against Structural Change and Breaks

One of the main complaints levied against composite forecasts is they tend to not perform well when time variations are built into the forecasts, either through discounting the past or placing varying weights based on time. Winkler (1989) addressed this argument stating, “In many situations there is no such thing as a ‘true’ model for forecasting purposes. The world around us is continually changing, with new uncertainties replacing old ones” (p. 606).

Stock and Watson (2004) lent validity to this claim by showing that while in certain cases they underperform, composite forecasts tend to be more stable over time, particularly under structural breaks and model insecurity[7] conditions. Within agriculture, this is of great concern for producers who often need to forecast nine months in advance to make planting decisions, thus exposing themselves to the possibility of structural breaks and modifications in market demand.[8] Summarizing the findings from Aiolfi and Timmerman (2004) in Timmerman (2006, pp. 24-25), they find that equal weights provide a broad range of support for structural breaks in the data and forecast model instability. Many studies in stock and bond growth, interest rates and exchange rates concentrating on composite forecasts have confirmed Timmerman’s assumptions (2006). Likewise, their results have been replicated for agricultural commodity forecasts for cash and futures markets. Composite models that have followed a similar formulation claim that simple averages tend to perform best when structural shocks occur, thus reducing

[7] Model insecurity is uncertainty in regards to which forecast will perform the most accurate over a given period of time.
[8] For an in-depth discussion on the mathematics behind structural breaks and how composite forecasts perform under the prescribed conditions, see Timmerman (2006, pp. 24-25).

model insecurity. Thus, recursively updating the weights can also be used as a way to lower risk and future model insecurity.

Marriage of Forecasts: The Eternal Dilemma

With the benefits of composite forecasting apparent, businesses, including farmers, are faced with questions such as, “Are the marginal gains of finding a composite model worth it?” or “Should a simple attempt to find a singular forecast that works well be pursued?”

These empirical questions were tested by Larrick and Soll (2006) at the INSEAD School of Business in Paris. They found statistical evidence that MBA students, arguably some of the brightest future business leaders, thought that taking an average of two forecasts would result in only average/sub-par performance. Consequently, Larrick and Soll concluded that the benefits of combining were not intuitively obvious to the students. If the students were unwilling to try combining forecasts even in an experiment, then they would be even less likely to do so in the workforce.

In his comparable study, Hogarth (2012) found that participants statistically chose more complex models instead of their simple alternatives to solve a problem. His results suggested that combining seemed too simple to participants and that participants, when provided the option, would never combine forecasting models.

Lastly, Dalrymple (1987) surveyed firms regarding how many forecasts they used. He found that 40% of firms used combining techniques, although he suggests that these combining techniques may be more of an informal manner. Perhaps this is because by generating multiple forecasts, from possibly different forecasters, a particular forecast developer is silently admitting to his/her inability to create an “ideal forecast.” Clemen

(1989, p. 566) affirms that, “Trying evermore combining models seems to add insult to injury as the more complicated combinations do not generally perform that well.”

It is important to remember that one of the overall objectives of combining forecasts is to obtain new information about the data set. When adding forecasts cease to add new information, forecast error will also cease to decrease. New information is typically added through the inclusion of subsequent explanatory variables; thus, as alluded to in the introductory paragraphs, had the forecaster thought that a certain variable was relevant to the initial overall question, it would have been included in the primary forecast. A possible explanation to this dilemma could be a lack of access to full data sets or proprietary information.

The simple question of whether to combine forecasts or not cannot be easily answered. Many business leaders, as indicated above, tend to mistakenly believe a singular forecast exists and, by identifying that forecast, they can reduce costs or increase profits. In a related study, Soll and Larrick (2009) found that when people are given advice, they systematically sort through the advice and choose one piece they deem as most accurate. This consequently leads to reduced forecast accuracy. These ideas are supported by a quote from Makridakis and Winkler (1983, p. 990):

> When a single method is used, the risk of not choosing the best method can be very serious. The risk diminishes rapidly when more methods are considered and their forecasts are averaged. In other words, the choice of the best method or methods becomes less important when averaging.

In summary, the question of whether to combine is more psychological than economical. On one hand, evidence suggests a need to increase combination schemes. On the other, it is not socially accepted or logical to do so. Yet when examined through the lens of the risky sector of agriculture, the data and previous findings urge producers and farmers to find ways to combine data and/or forecasts.

The Art of Choosing Forecasts: A Methodological Approach

Once the choice has been made to combine forecasts, particular attention should be given to the forecasts that are to be included in the “final” composite model. Some critics of composite forecasting have claimed that composite models underperform the best selected model because the models chosen are intermixed with poor models (Aiolfi and Timmerman 2006). This criticism can be avoided by prescreening the forecasts based on economic theory, different methods and data, current consensus, and practicality. Likewise, this criticism can likely be overcome by using a combination technique that systematically gathers the best information and discards the rest.

Theories have been developed about properties that would allow one to screen individual forecasts, and these properties are often well-known to econometricians. All these properties endeavor to show that certain predictive measures can be used to determine whether or not a forecast represents a “true” value. Methods to screen forecasts have included using the Swartz’s Information Criteria (SIC), Akaike Information Criteria (AIC), Bayesian Information Criteria, R^2, and a variety of error measures (MSE, RMSE, etc.). The most common of these being the SIC and error measures, which is possibly due to their familiarity and relative performance.

Once the candidate models have been evaluated for their individual performance, tests are generally conducted on whether or not the chosen forecasts "encompasses" each other (Diebold and Lopez, 1993) – thus accounting for all the additional and relevant information. This idea, although introduced many years before, became noticeably popular with the publication of Chong and Hendry (1986) and Fair and Shiller (1989; 1990). Fair and Shiller (1990) noted that although an individual forecast could have a high R^2 it may not necessitate inclusion because all relevant information was already accounted for in other forecasts. This finding suggests that it may be more relevant to combine/pooled data sets to create a super model that would perform well rather than to combine separate forecasts. While this has been proposed in the academic literature as "ideal," constraints such as time, money, and model complexity may prompt an easier response – simply combine individual forecasts.

Weights

Once the choice has been made to combine a given set of forecasts, particular consideration should be given to the weight (e.g. emphasis) given to each forecast. The gains previously proposed for combining forecasts are based upon one critical assumption – a simple arithmetic mean or simple average (equal weights to each forecast with the sum of the weights being unity). This implies that each forecast is given an equal explanatory proportion in the composite model. A simple mean is considered, by default, as the benchmark against which to compare other composite forecast performances due to their resilience in forecasting literature. Although popular, others question whether using a simple composite average is the most efficient. If equal weights are not efficient, then which weights are more efficient?

Forecasters often claim that a simple arithmetic mean performs the best, on average. Palm and Zellner (1992, p. 699) summarize the advantages that are unique to using equal weighted forecasts as follows:

1) Its weights are known and do not have to be estimated, an important advantage if there is little evidence on the performance of individual forecasts or if the parameters of the model generating the forecasts are time-varying;
2) In many situations a simple average of forecasts will achieve a substantial reduction in variance and bias through averaging out individual bias;
3) It will often dominate, in terms of MSE, forecasts based on optimal weighting if proper account is taken of the effect of sampling errors and model uncertainty on the estimates of the weights.

As aforementioned, one approach to combining is to minimize the expected forecast error variance (i.e. MSE, RMSE, etc.). Timmerman (2006, p. 17) thus suggests minimizing the forecast error variance. To do so, let's once again follow Timmerman and superimpose the constraint that the weights (ω) of the forecasts sum to one.[9]

(7) $\min \omega' \sum_e \omega$

(8) $s.t. \omega' \iota = 1$

Imposing this constraint subsequently ensures an unbiased element within the model. Hence, Timmerman (2006) concludes that "Equal weights are optimal in situations with an arbitrary number of forecasts when the individual forecast errors have

[9] It could also be said "so that they sum to 100%" implying that there it is constrained by 100%

the same variance and identical pair-wise correlations" (p. 18). In short, one needs to observe the forecast error variance before combining can be viewed as effective or not. Moreover, if there are situations with an arbitrary number of forecasts and the individual errors do not have the same variance and identical pair-wise correlations, then equal weights may not be the optimal solution.

Other Weighting Methods

It is purported that using equal weights are the most reliable in reducing overall forecast error. These claims have not inhibited researchers from striving to obtain the "optimal weights" as encouraged by Bates and Granger (1969). Some academics have found that simple averages do not perform well under certain conditions.

This has often caused a heated debate about how much weight should be placed on each forecast. This is in part because forecasts have relatively little value to business minds unless they help improve on the decision-making process, thus adding value for managers. The value of weighting is often determined by whether or not the weighted forecasts results in a lowering of the forecast error. Hence, if there are weights that can help improve the decision-making process, then weights should be used. This has caused others to propose alternative weighting methods. These have generally centered on the idea of whether alternative weights outperform a simple average. Some researchers have published elaborate weighting combination schemes involving weights that vary with time, horizon, and performance. Others remain true to a simple arithmetic mean. Some see benefits from both. The current consensus on composite weighting generally focuses on the latter (likely some benefits to both approaches).

While many value the importance of using simple averages for composite forecasting, often using it as a bench mark, researchers continue to search for the optimal weights to use. Makridakis and Winkler (1983) found that weights inversely proportional to the sum of squared errors performed well. A more common system relies on weights derived from the inverse of the MSE as shown by Stock and Watson (2001). Other weighting systems have included a MSE composite (Colino et al. 2012), regression weights (Manfredo, Leuthold, and Irwin 2001), regression weights summed to one, time varying with covariance (Granger and Newbold 1973), time varying with regression (Diebold and Pauly 1987), optimal linear (Bates and Granger 1969), covariance (Mehta et al. 2000), and outperformance (McIntosh and Bessler 1988). Further, more elaborate combination schemes include the best-previous model (Brandt and Bessler 1981), recursively updated (Yang 2004), relative performance (Makridakis and Winkler 1983), rank-based (Wright and Satchell 2003), spread combinations (Aiolfi and Timmerman 2004) and odds-ratio (Min and Zellner 1993). Clemen (1989) suggested using mechanical weights.[10] To our knowledge, no work has been done on a mechanical weighting scheme.

The aforementioned combination schemes, based on the different studies cited, have varied in their relative performance. The variation in successful methods may have come as a result of different data sets, time periods, and/or the sector being studied. While many more weighting systems have been proposed and empirically tested, those listed above represent the prominent weighting systems proposed and empirically tested in the academic forecasting literature.

[10] Mechanical weights can be thought of as weights use computer programs to test an infinite number of weighting combinations before returning the ideal weight given to each forecast. As explained later in this thesis, this is accomplished by using mathematical programming.

In the agricultural composite forecast literature, a narrow number of studies have focused on different weighting systems as most opt to use simple, and arguably more practical, weighting systems. These have included the best previous result (Brandt and Bessler 1981), simple averages (Harris and Leuthold 1985), Bayesian composite (McIntosh and Bessler 1988), restricted ordinary least squares (McIntosh and Bessler 1985), adaptively weighted (McIntosh and Bessler 1985), unequal (Park and Tomek 1988), covariance (Park and Tomek 1988), and odds-matrix (Colino et al. 2012). These studies have varied on which technique produces the most accurate results. In general, simple averages have outperformed more complex weighting systems in these studies with the exception of Bayesian and shrinkage weights. These results are in line with previous forecasting literature from different sectors such as finance and business (Masih, Masih and Mie 2010). The methods that have gained in reputation appear to be shrinking weights (Stock and Watson 2004).

The shrinking weight methods involves using derived weights which are unequal yet bounded by one, and then reducing them towards a central point, usually towards equality. It has received a considerable amount of attention due to its good performance in empirical studies. An example from agriculture is Colino et al. (2012) who found that shrinkage outperformed simple composite averages in one-quarter ahead hog forecasts in Missouri. This idea is supported with macro-economic data from Diebold and Pauly (1990) whom reported that directly shrinking the weights of real and nominal GNP towards equality performed strongly.

Timmerman (2006) demonstrated in a Monte Carlo simulation that shrinkage does perform well. These results could also be enhanced by “cleaning” the data by various using techniques such as trimmed means. These studies were supported by Stock and Watson (2012) in their mathematical formulation of shrinkage methods. Through both empirical and mathematical examples Stock and Watson illustrated that shrinkage does indeed perform well with composite methods. These results have been replicated in numerous studies all confirming the aforementioned results.

Concise Advice on Combining Forecasts

Much has been written in this treatise and within the literature about the costs, benefits, mathematics, exceptions, and applications of combining forecasts. This thesis does not claim, nor have as its purpose, to provide a full understanding of such a voluminous topic but rather offers a summary of the literature and the main findings in the literature. Armstrong (2001, pp. 2-6), has given sound advice in a condensed paper on the dos and don'ts of forecasting. A summary of the points Armstrong offers is as follows:

1) Use different data and methods to derive an estimate in order to avoid unnecessary duplication. When not possible, use different forecasters who can then derive different forecasts using the same data (Baker et al. 1980; Lobo and Nair 1990).
2) At least five to nine forecasts should be used in combination but marginal returns to forecast errors decreases after five and tappers to 'approximately zero' at thirteen or more forecasts (Libby and Blashfield 1978)

3) "Combining should be done mechanically and the procedure should be fully described" (p. 4) (Rowse, Gustafson, and Ludke 1974; Lawrence, Edmundson, and O'Connor 1986).
4) Use trimmed means in the forecasts (Agnew 1985; McNees 1992)
5) Keep track of forecast track records to vary the weights accordingly (Armstrong 1983; Shamseldin, O'Connor, and Liang 1997)
6) Use the knowledge and experience from professionals to vary the weight of the combined forecasts to ensure greater accuracy (Bessler and Brandt 1981)

In a subsequent paper by Graefe et al. (2014, p. 4) on political elections, the aforementioned list is further condensed to three main points for when gains of combining forecasts is greatest, namely:

1) A number of evidence-based forecasts can be obtained
2) The forecasts draw upon different methods and data
3) There is uncertainty about which forecast is most accurate

"In combining the results of two methods, one can obtain a result whose probability law of error will be more rapidly decreasing" (Laplace 1818, as quoted in Clemen 1989). This quote shows that indeed this 'novel' idea of combining is not new nor will it fade. Numerous industries including hedge funds, finance portfolios, meteorology and even sports have found numerous numerical gains from combining or commonly known as "diversification."

While many industries have realized gains from composite forecasting, agricultural forecasting has not fully developed such procedures to similarly realize these gains. While it is common that producers diversify in crop, livestock, and cash placements, a diversification in forecasting these numbers has been seldom used – particularly in the agricultural sub-sector of basis. In summary, this paper builds upon t composite forecast research applying it to cattle basis in Utah and Western Kansas.

Theories that Develop Basis Forecasts

As mentioned initially, grain and cattle producers are generally interested in the price a given commodity is selling for at an explicit time and location. This idea is reflected in how basis is commonly defined in the literature – a difference between two prices (Leuthold and Peterson 1983):

(9) $\text{Basis}_{l,c,t} = \text{Cash price}_{\,l,c,t} - \text{Futures price}_{l,c,t}$

where 'l' refers to the l^{th} geographical location, 'c' refers to the c^{th} commodity with its corresponding grade/quality and 't' refers to the t^{th} time period (Dhuyvetter 1997). Because the cash price and futures price are both linked to an exact location, grade/quality, and time variations, basis is said to reflect geographical supply and demand. This idea differentiates agricultural products from other commonly traded commodities such as currencies and stocks that are not geographically specific in terms of trading the commodity (Taylor, Dhuyvetter, and Kastens 2006).

As shown above, basis is the residual of two prices – local cash and futures. While many farmers and producers are comfortable with the idea of a local cash price, there has been much controversy surrounding the establishment and use of commodity future exchanges. Many of these arguments have centered on fears of potential price manipulation, spot price volatility, and the overall objectives of exchanges (Campbell 1957; Chandler 1977; House of Representatives 1984).

As Rothstein states (1966), “Many contemporary [nineteenth century] critics were suspicious of a form of business in which one man sold what he did not own to another who did not want it” (p. 61). This may partially be due to the fact that four times the amount of grain produced in the United States (US) was traded during years in the late 19^{th} century while 11 times the amount of grain produced in the US was traded (represented in futures contracts traded on exchanges) in 2002 (Santos 2004). At times this debate has become so heated that legislation has passed the US House of Representatives and the US Senate to ban the futures and options markets (Lurie 1979).

Despite these facts, others defend these institutions indicating that not all commodities are successful on such markets. For example, in 2011 the CME group announced that after 50 years, pork bellies would not be traded on the CME platform. Pork bellies followed numerous other commodity contracts that have expired for various reasons such as fat and potatoes. Commodities that are said to trade successfully in the futures market generally possess five characteristics: (1) uncertainty, (2) price correlations across slightly different products, (3) large potential number of interested participants and industrial structure, (4) large value of transactions, and (5) price freely determined with absence/minimal amount of regulation (Carlton 1984).

Regardless of this continual debate, three main benefits from the futures market have continually emerged in support of it from the academic literature: ability to hedge or reduce risk, speculate about one’s belief of future prices, and a forecast of future price (Carlton 1984; Peck 1985). Of the most importance to this thesis is the ability to reduce ones risk.

It is often stated as a fact among agricultural economists that producers engage in the futures market to exchange cash price risk for seemingly more manageable basis risk (Siaplay et al. 2012). This idea is supported by the continued presence of forward contracts, where the commodity producer tries to maximize basis profit while the commodity buyer hedges in the futures to eliminate price risk. The situation is further aided by the presence of arbitrageurs who give both the futures and cash market liquidity.

In an ideal world, setting a hedge in some sense assumes perfect predictability of the basis (Peck 1985). Since this is never true because basis risk exists, arbitrageurs help bring the futures and cash price into balance by essentially spatially linking the two markets. If prices in two areas are unequal, minus transfer costs, then producers will continually buy in a low priced market and sell in a high priced market. This will continue to occur until prices come back into a spatial equilibrium; an idea known as arbitrage. Due to this mechanism, it is often assumed in agricultural that basis is seasonally determined and is relatively predictable due to "convergence" or that future prices and cash prices will converge to having a difference no greater than actual transportation costs at the maturity of the futures contract.

If the aforementioned statement is valid (producers exchange price risk for seemingly more manageable/predictable basis risk) then two assumptions are made: that the volatility is lower in basis than in the futures and spot[11]market and that the losses accrued through basis movements are more manageable than they are in the cash market by itself. To mathematically illustrate this point, assume two individual price points – cash and basis with their respective errors $e_1 = Cash_t - \widehat{Cash}_{t+1}$ and $e_2 = Basis_t -$

[11] Spot and cash market are used interchangeable in the academic literature and in this paper.

$\widehat{Basis}_{t+1}$. Further assume that the covariance between $e_1$and e_2 is $e_1 \sim N\ (0, \sigma_1^2)$, $e_2 \sim N\ (0, \sigma_2^2)$ and where $\sigma_1^2 = var(e_1), \sigma_2^2 = var\ (e_2), \sigma_{1,2} = \rho_{1,2}\sigma_1\sigma_2$ with $\rho_{1,2}$ is the correlation of the two forecasts; thus:

(10) $e_1 = Cash_t - \widehat{Cash}_{t+1}$

(11) $e_2 = \left(Cash_t - \widehat{Cash}_{t+1}\right) - \ (Futures_t - \widehat{Futures}_{t+1})$

Or substituting equation (10) into equation (11) we gain

(12) $e_2 = e_1 - \ (Futures_t - \widehat{Futures}_{t+1})$

If producers are willing to hedge, then cash price risk must be lower than basis risk or $e_1 > e_2$. After some calculations and solving for the covariance and variance of $e_1$and e_2, we get the following:

(13) $Var(e_1) - Var(e_2) > -\left(Var\left(\hat{F}\right) + Var(F) + 2cov\left(Cash, \widehat{Futures}\right) - 2cov(Cash, Futures) - 2cov\left(\widehat{Cash}, \widehat{Futures}\right) + 2cov\left(\widehat{Cash}, Futures\right) - 2cov(\widehat{Futures}, Futures\right)$

which yields

(14) $\sigma_{\hat{F}}^2 + \sigma_F^2 + 2\rho_{C,\hat{F}}\sigma_C\sigma_{\hat{F}} + 2\rho_{\hat{C},F}\sigma_{\hat{C}}\sigma_F > 2\rho_{C,F}\sigma_C\sigma_F + 2\rho_{\hat{C},\hat{F}}\sigma_{\hat{C}}\sigma_{\hat{F}}$

where ‘F’ represents the futures price, ‘$\hat{F}$’ represents the predicted futures price, ‘C’ represents the cash price, and ‘$\hat{C}$’ represents the predicted cash price. Thus, the condition will almost always hold that $\sigma_{\hat{F}}^2 + \sigma_F^2$ are generally relatively large forecast errors and the correlation portion, $2\rho_{C,\hat{F}}\sigma_C\sigma_{\hat{F}} + 2\rho_{\hat{C},F}\sigma_{\hat{C}}\sigma_F$and $2\rho_{C,F}\sigma_C\sigma_F + 2\rho_{\hat{C},\hat{F}}\sigma_{\hat{C}}\sigma_{\hat{F}}$, will be similar causing a cancelling effect.

Based on these findings, cash price volatility will almost certainly be greater than basis volatility. This conclusion lends support to the ideas of Leuthold and Peterson

(1983) who suggest that the more predictable basis is, the more useful the futures market can become to commercial enterprises. It may also imply a strong reason why futures markets are used to manage some of the price risk that is often inherent in the production cycle (Peck 1985). In summary, if cash price volatility is indeed higher than basis risk, then we should expect an increase in farmers hedging or forward contracting.

Basis Forecasting Models

Since the late 1990s, several studies have been published on forecasting basis in a variety of commodities with the primary focus on corn, wheat, sorghum, and cattle (Dhuyvetter and Kastens 1998; Jiang and Hayenga 1997; Tonsor et al. 2004; Hatchett, Bronsen, and Anderson 2010; Siaplay et al. 2012). A vast majority of these studies, while they have taken different approaches, have mainly evolved from three papers: Working (1949), Paul and Wesson (1967), and Ehrich (1969). The following basis forecasting studies have thus resulted.

Grain Commodities

For grain commodities, Hauser, Garcia, and Tumblin (1990) developed, and subsequently compared, five models for forecasting basis. While many of these were relatively simplistic, using initial basis and naïve forecasts, they learned that forecasts that tended to include implied returns from storage tended to outperform commonly used historical average models.

This work was followed by later studies by Dhuyvetter and Kastens (1998) and Tonsor, Dhuyvetter, and Minter (2004). In summary, they found that longer-term averages ranging from 5-7 years performed best for row crops. Likewise, they modified and subsequently retested Hauser et al.'s (1990) idea of incorporating new information. They found that while it did improve the forecast accuracy it did not statistically perform better than a simple historical average, thus confirming Hauser et al findings.

Subsequent studies have been performed by Siaplay et al. (2012), and Hatchett et al. (2010). Hatchett et al. (2010) attempted to determine which length of historical moving average provides the best forecast of future basis. They concluded that determining an 'optimal' length was futile and that a simple previous year moving average should be used due to the constant occurrence of structural changes. Siaplay et al. (2012) focused on the "importance of the strength and weakness of basis, futures price spread, and futures prices as barometers for producers to hedge [or not]" (2012, p. 15). They found that basis outperformed futures price or that the futures price spread for certain row crop commodities. Their findings essentially confirmed the need for continued research on better basis forecasting models.

These studies suggest that only minor variations have occurred from the traditionally accepted models. Research has been conducted on autoregressive (AR) and moving average (MA) lengths, historical averages, and traditional naïve models. All of these, although different in nature, yield similar results: it is simply difficult to outperform crop/livestock historical averages.

Cattle Basis

While the main focus of most research in forecasting basis has been on grain commodities, cattle basis has also been explored to some degree. Ehrich (1969) and Ivy (1978) examined slaughter (i.e. live cattle) cattle basis and found not only did inventories play a role in determining basis levels but there was a positive correlation between local cash and futures. Erickson (1977) likewise contributed to this literature by showing that basis existed and showed how variability in basis was derived. In the study, Erickson considered slaughter levels, feeder steer price, lagged cash price, cattle on feed, lagged future/cash ratio, and seasonal dummy as determinants of basis- many of which were found to have statistically-significant coefficients in Erickson's regressions.

Leuthold (1979) contributed to the basis literature when he used a multiple regression to explain monthly variations of a single contract before maturity. Specifically, he modeled monthly basis against slaughter prices, corn futures, cash prices of feeder cattle (no weight specified), cash price of fed cattle, cattle on feed, and monthly dummy variables. Leuthold concluded that monthly basis was easier to predict when it was 2-7 months out in comparison to a month prior to maturity.

Naik and Leuthold (1988) built upon these ideas and found that there was indeed greater variability in the cash and futures markets during contract maturity months than at other times in the futures contract's life. Likewise, Liu et al. (1994) used basis spread, lagged basis spread, futures spread, and a variety of other supply and demand variables to forecast basis. While their model had a low R^2 and relatively few significant coefficients on the variables, they concluded that lagged spreads have the ability to explain movements in the live cattle basis.

Dhuyvetter (1997) helped explain some possible misspecifications that occurred when forecasting cattle basis. He found that the day of the week played a significant role in basis levels with the largest amount of cattle being marketed on Tuesday and Wednesday; thus, calculating basis on other days could lead to higher volatility and higher MSE in basis models than if they are modeled using Tuesday or Wednesday quotes. Of particular note, Dhuyvetter reported that for Kansas cattle there was no added benefit in modeling basis on a daily basis compared to modeling basis for weekly prices. Overall, a 2-3 year historical average performed better than a 5+ year average based on Dhuyvetter's study.

Because of these and other difficulties, many different researchers have approached the problem of forecasting basis from different angles. One approach used was trying to understand how captive supplies (cattle under contract to large buyers) influenced basis movement (Eilrich et al. 1990; Elam 1992; Walburger and Foster 1997). Parcell et al. (2000) built upon the aforementioned studies and modeled basis using cold storage, weight of cattle marketed, percent of cattle previously marketed, corn futures, lagged basis, and contract month as explanatory variables in basis forecasting models. The variables choice-select spread and corn price had a significant impact upon live cattle basis whereas changing captive supplies and futures contract specification did not have a statistically-significant impact. In short, although captive supplies are a concern to many with regard to their potential to increase basis volatility, there was no significant evidence this was the case.

In a further attempt to try to understand how to model basis more effectively, Tonsor et al. (2004, p. 228) addressed three questions:

1) What is the impact of adopting a time-to-expiration approach, as compared to more common calendar-date approach?
2) What is the optimal number of years to include in calculations when forecasting livestock basis?

3) What is the effect of incorporating current basis information into a historical-average-based forecast?

They found that time to expiration has little impact upon live and feeder cattle basis and that including current basis improves forecasting procedures but only marginally. Their results confirmed those of Parcell et al. (2000) who found that three years was the optimal amount of time to include in calculating average basis, although they noted that this finding depended on the data being used.

While it is expected that cash price, and subsequently basis, are sensitive to changes in both input and output, Dhuyvetter et al. (2008) wanted to know how changes in lot characteristics had an effect on basis. By incorporating hedonic lot characteristics it was ascertained by Dhuyvetter et al. that weight, contract changes, month, sex, frame, grade, corn, futures prices of live and feeder cattle, and diesel prices had a significant impact on basis lending support to the idea of hedonically-derived basis. Likewise, their results confirmed those of others that feed inputs impact lighter cattle heavily and that incorporating *current* market information can lead to greater forecasting accuracy.

In the most recent up-to-date literature, McElliott (2012) and Swanser (2013) sought to develop econometric solutions to modeling basis for cattle in Kansas and the "Big 5" markets (i.e. Texas, Kansas, Nebraska, Oklahoma, and Colorado), respectively. Their findings coincide with each other and suggest that future price spreads are important in modeling basis in both weekly and monthly intervals.

In conclusion, singular basis forecasting studies have been abundant in the literature. These results have been helpful in understanding the basic characteristics of basis and continue to provide avenues for further research. While helpful, these past papers on grain and cattle fall short in their ability to simultaneously model forecasts as many of these forecasts model unique situations. A more complete review of composite basis forecasting literature would aid in understanding whether singular basis models can either be improved upon or to confirm that the "best" models have already been acquired.

Composite Basis Models

Since the influential Bates and Granger paper (1969), many agricultural composite models have been produced testing different combination methods and procedures in forecasting. The vast majority of the models in agriculture have focused on forecasting either futures or cash prices. As forecasting cash and futures models are not the aim of this paper, the table in the appendix outlines the composite models used, general conclusions, and the reported optimal forecasts of these past studies.

Of particular interest are the studies that have conducted preliminary analyses on composite basis forecasting (Jiang and Hayenga 1997; Dhuyvetter et al. 2008). Jiang and Hayenga (1997) and Dhuyvetter et al. (2008) experimented with simple arithmetic composite basis forecasts. Both reported reasons for doing so was that "averaging two forecasts should have the effect of making the model less sensitive to extreme values" (Dhuyvetter et al. 2008). They separately concluded that composite forecasts perform slightly better than historical averages when forecasting basis (Jiang and Hayenga 1997).

As mentioned previously, Hatchett, Bronsen, and Anderson (2012, p. 19) state, "One of the primary reasons futures markets were created was to let market participants exchange cash price risk for manageable basis risk." Thus, when given the option, producers are more likely to accept basis risk than price risk when considering contrasting alternatives. The ideal outcome for producers then is to have basis risk be lesser than price risk. At the center of composite forecasting is this objective: lower risk/volatility. The published works about cash price composite forecasting have been numerous in comparison to that of basis composite forecasting. In order to understand if basis risk can be reduced, thorough composite forecasting seems like an important line of research.

CHAPTER 3

DATA AND METHODOLOGY

Weekly Cash

Utah Friday weekly cash price data of slaughter cattle steers (LC) were gathered online from the AMS/USDA market news website.[12,13] The aggregate Utah weekly cash data spanned the time period from January 02, 2004 to December 28, 2012. Of the 470 possible observations during this time period, 442 were initially available. After consulting AMS Market News online, an additional 12 observations were included – a total of 454 observations. The remaining 16 (i.e. 3.40%) observations were computed using one of three procedures:

1) Average of the previous and following forecast - used if one week was missing but didn't straddle a contract break.
2) Interpolation[14] - used if two or more weeks were missing but didn't straddle a contract break
3) Same as previous week – used if one or more weeks were missing and did straddle a contract

The vast majority of the missing weeks were in the month of December, predominantly during the last two weeks of that month. This may be due to low trading volume or lack of transaction activity due to the Christian holiday season of Christmas. In

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[12] Thanks are extended to Lyle Holmgren for providing a starting database with the majority of the cattle data already provided.
[13] Several questions have been raised as to the validity of using the slaughter steer cash price in Utah as it principally represents a singular slaughter facility in Hyrum, Utah. Moreover, the price obtained from this facility is a formula that is largely based off prices *outside* of Utah; thus, not truly representing the real prices in Utah (Dillon Feuz, personal conversation, 2014)
[14] Interpolation is defined as a simple arithmetic mean between two numbers divided by '$n+1$' where 'n' represents the number of missing values [e.g. $y = (x_2 - x_1)/(n+1)$ where 'y' is the value added to each value consecutively; x_2 is the newest reported value; x_1 is the oldest reported value; and 'n' is the number of dates that have missing values.

future trading markets, December is seen as a volatile market, which is also reflected in the low number of transactions that occur during that period of the year.

Western Kansas weekly weighted average negotiated live cattle steer prices were gathered from a compiled database provided by the Livestock Marketing Information Center (LMIC). The aggregate Western Kansas weekly cash data spanned the time period from January 02, 2004 to December 28, 2012. All of the possible 470 observations during this time period were available.

Weekly Futures

Weekly futures prices were gathered from the CME Group (2014) and their historical database, as provided by an AMS-USDA representative. The price data spanned from January 02, 2004 to December 28, 2012, and encompassed 470 individual observations with no missing observations for live cattle. The live cattle nearby contract was always used to calculate basis. The contract expiration months for LC were February, April, June, August, October, and December. The live cattle futures contract specifications are found in Appendix B.

The weekly futures price was calculated using a Friday $_t$ to Friday $_{t+1}$ simple arithmetic average, which included five unique daily price observations. Dhuyvetter (1997) noted the day that was used to calculate a weekly average had a statistically-significant impact on basis calculations; thus, a Friday weekly average was chosen to correlate with the Friday Utah cash slaughter prices reported by USDA. On weeks where the Friday to Friday spread straddled two contracts, an average from Friday to the last traded day of the contract was recorded. For example, if the contract LC-FEB ends on the

28th, a Thursday, then Monday the 25th through the 28th would be averaged (e.g. four days rather than the typical five).

Weekly Basis

Basis is modeled after the following assumption:[15]

(15) $\text{Basis}_{\text{l,c,t}} = \text{Cash price}_{\text{l,c,t}} - \text{Futures price}_{\text{l,c,t}}$

where 'l' refers to a geographical location, 'c' refers to an exact commodity with its corresponding grade/quality and 't' refers to an explicit time measurement. This calculation was consistent across commodity, sex, and model type. The local cash and future price variables used in the basis calculation are described above for both Utah and Western Kansas.

Summary Statistics

Table 1 and 2 were the summary statistics for the Utah and Western Kansas live cattle steer prices for the data used in the study. The in-sample data for Utah and Western Kansas live cattle spanned from 2004 – 2009 and the Utah and Western Kansas live cattle out of sample data spanned from 2010-2012.

Data Limitations

One concern with the way basis was calculated is the reported aggregation of Utah live cattle steer prices starting in January 01, 2007. Before this date, cash prices

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[15] Some literature defines basis as Basis = Futures – Cash with the difference being in the sign of the coefficient.

Table 1. Live Cattle In-sample Summary Statistics, 2004-2009

Statistics	**Utah**			**Western Kansas**		
	Cash	Futures	Basis	Cash	Futures	Basis
Mean	86.89	88.36	(1.47)	87.88	88.36	(0.47)
Median	86.50	87.93	(1.67)	87.71	87.93	(0.61)
Maximum	100.00	104.16	7.88	101.00	104.16	10.19
Minimum	74.50	73.60	(14.66)	74.06	73.60	(12.94)
Std. Dev.	5.22	5.89	3.12	5.39	5.89	2.59
Skewness	0.22	0.25	0.11	0.15	0.25	0.20
Kurtosis	2.33	2.86	4.29	2.47	2.86	5.93
Jarque-Bera	8.27	3.45	22.45	4.84	3.45	114.24
Probability	0.02	0.18	0.00	0.09	0.18	-
Observations	313	313	313	313	313	313

were generally reported as a single price rather than a spread of two prices (e.g. the high and low bid).

In order to understand whether this aggregation had a statistical impact on Utah live cattle steer basis, a correlated ANOVA was computed. Preference was given to the correlated one-way ANOVA because a t-test would compare the group means. The results displayed in Table 3 for Utah live cattle basis indicate that the aforementioned aggregation of weights and prices had a statistically-significant impact on steer basis calculations. In accordance with these results, using the average cash price may produce different results than if the low and/or high prices were used. Even in light of this information, an average basis was used for simplicity reasons.

Table 2. Live Cattle Out-of-sample Summary Statistics, 2010-2012

Statistics	Utah			Western Kansas		
	Cash	Futures	Basis	Cash	Futures	Basis
Mean	110.13	110.58	(0.45)	110.65	110.58	0.07
Median	113.50	114.03	(0.82)	113.93	114.03	(0.10)
Maximum	126.50	129.19	5.22	129.89	129.19	5.76
Minimum	79.50	84.63	(5.63)	84.02	84.63	(4.65)
Std. Dev.	12.82	12.73	2.63	12.70	12.73	1.87
Skewness	(0.44)	(0.40)	0.30	(0.39)	(0.40)	0.29
Kurtosis	1.84	1.82	2.31	1.83	1.82	3.39
Jarque-Bera	13.89	13.29	5.52	13.03	13.29	3.27
Probability	0.00	0.00	0.06	0.00	0.00	0.19
Observations	157	157	157	157	157	157

Weekly, rather than daily, data were used. Using weekly data may not allow for trading volume on other days to be fully captured, especially with live cattle. While a valid concern, Dhuyvetter (1997) noted that there was little observed difference in the basis price and volatility when daily or weekly cash prices were used for Kansas live cattle. These results could not be confirmed nor negated as Utah live cattle prices are only reported using a Friday weekly average of slaughter prices. For Western Kansas live cattle steer prices it is assumed that the slaughter prices follow a similar trend noted by Dhuyvetter (1997).

Using a Friday weekly average may not accurately reflect true market conditions on a given day. Dhuyvetter (1997) noted that in Kansas the majority of slaughter cattle were sold on Tuesday and Wednesday (24% and 27 %, respectively) with only 11% sold on

Table 3. Utah Live Cattle Steer Basis p-value(s) on Aggregate Price, 2007-2012

	Steer		
	Low	High	Average
Low	1	0.000	0.000
High		1	0.000
Avg.			1

Friday – the lowest amount of any day of the week. Because of this disparity in marketing between days of the week, it may not be proper to use a weekly average. If these results are representative of the US national cattle market, then this may prove to be problematic for Utah. Rather, a weighted daily average may be more appropriate. Since daily slaughter volume is not reported by the USDA for Utah live cattle, this too was unable to be confirmed nor negated. Although for Western Kansas cash price information, it is reported by the LMIC that the stated price is a weighted average negotiated price; thus, possibly capturing the fluctuations in price over the week. Due to data constraints, post hoc ANOVAs and regression dummies were unable to confirm whether this assumption impacted our results – although one would assume that the results may be slightly different.

A major concern that could be levied against some of the sample data used is that it may not produce representative results, as Utah only represents 1.79% of all slaughter cattle marketing's from year to year in the US (NASS 2013). Western Kansas likewise represents 18.55% of slaughter cattle marketing's from year to year. Combining Utah and Kansas slaughter cattle marketing's, 80% of cattle are still unaccounted for. While true that the results for Utah and Kansas may not hold in larger more competitive markets, they provide a proof of concept to be further tested and fleshed out in larger marketing areas[16].

Lastly, when the Utah nearby basis was physically examined, systematic jumps were observed (see Figure 1). The following live cattle nearby basis contract was charted from January 2004 to December 2004. Particular notice should be given to the gaps in the chart that occur during contract switches.

To determine whether this systematic contract breaks were statistically significant, three methods can be used: econometric model with dummy variables, ANOVA or paired t-tests, and/or the LSD Duncan Test. An econometric model examining structural change was created along with a confirmatory ANOVA.

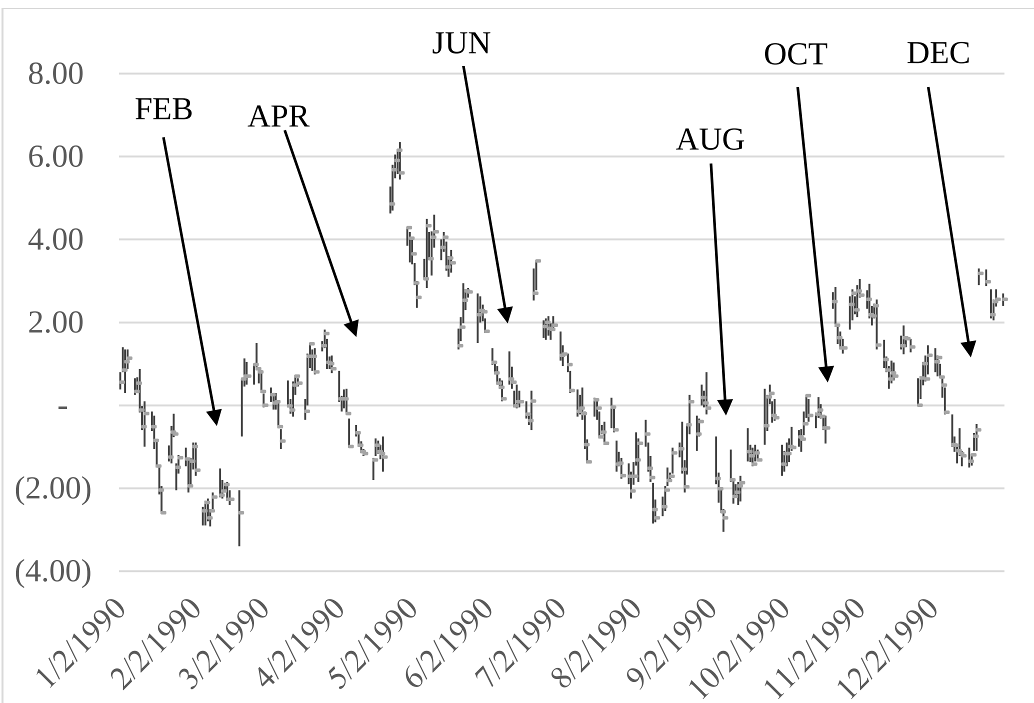

Figure 1. Utah weekly live cattle steer basis: systematic jumps

Source: Data taken from CME Group (2014) and USDA (2014)

[16] A post hoc case study was conducted on basis data from Nebraska and Texas thus accounted for an additional 40%. For more information on the results from these two states, refer to the Appendix.

Assume the following econometric formulation with Utah live cattle future dummy variables, which represent the contract months that live cattle can be bought and sold in Chicago. The February contract has been excluded:

(16) $Basis = \beta_0 + B_1(Apr) + B_2(Jun) + B_3(Aug) + B_4(Oct) + B_5(Dec) + \varepsilon$

The ANOVA results in Table 5 and the regression results in Table 4 show complementary and confirmatory results; there are systematic breaks in Utah live cattle basis prices when there is a switch in futures contracts. Thus, accounting for contract seasonality when calculating nearby basis may lend itself to improved forecasting results and eliminate the aforementioned problem.

Table 4. Regression and Summary Statistics for Utah Live Cattle Basis, 2004-2012

	Sample Data				
Contract Month	Mean	Std. Dev.	Min	Max	Coef.
Feb.	-2.0087	2.0173	-7.4499	3.0100	-
Apr.	0.0934	2.9279	-6.9500	8.4250	2.1027 (.2499)
Jun.	1.8495	2.6204	-3.9749	9.3350	3.8588 (.2514)
Aug.	-1.8431	2.1909	-7.0999	9.3950	.1663 (.2493)
Oct	-2.8389	1.8233	-7.1500	2.8499	-.8295 (.2521)
Dec	-1.3581	2.0964	-5.2249	5.9499	.6518 (.2517)
Dummy Sex					.2002 (.1439)
Constant					-2.1094 (.1931)
R^2	0.3135				
Observations	468				
RMSE	2.3138				

Table 5. ANOVA & Summary Statistics for Utah Live Cattle Basis, 2004-2012

	Sample Data				
Contract Month	Partial SS	df.	MS	F-stat	Prob> F
Model	2510.47	6	418.41	78.15	0.00
Apr.	378.87	1	378.87	70.77	0.00
Jun.	1261.70	1	1261.70	235.67	0.00
Aug.	2.38	1	2.38	0.44	0.00
Oct	57.96	1	57.96	10.83	0.00
Dec	35.89	1	35.89	6.70	0.00
Dummy Sex	10.36		10.36	1.94	0.00
R^2	0.3135				
Observations	468				
RMSE	2.3138				

Model Identification

As noted by Kastens et al. (1998), "[For] some agricultural commodities, locational price differences are more important than differences between cash commodity characteristics" (p. 296). This suggests that to develop an accurate futures-based basis forecast, historical data should be used from a variety of different commodities, locations, and times since basis patterns often differ heavily from location to location. With this in mind, seven singular models were proposed as a foundation for building composite forecasting model(s) for the Utah slaughter cattle basis. These models were chosen and modified from the agriculture cash and basis forecasting literature.

The criteria for inclusion in this analysis of the various forecasting models were based on the suggestions provided by the composite forecasting literature; namely:

inclusion of additional data, methodological evidence, and model variety. These models represented a sample of current published basis and cash forecasting models. The seven models and their derivatives examined were as follows. [17,18]

Model #1 – Naive Basis Forecast

Model #1 assumed that on any given day, the basis current basis for time 't' was equal to the basis lagged one period,[19] in this case lagged by one week. This model is fairly standard and adapted from Hauser et al.'s (1990) research findings on soybean basis.

(17) $Basis_{kt} = \beta_0 + \beta_1 (Basis_{kt-1}) + \varepsilon$

where k refers to the k^{th} location being considered and 'ε' is a white noise error term. This is often referred to in the literature as a naïve model and used as a benchmark for understanding more complex models. Kastens et al. (1998) found that a simple naïve model proved more effective than more complex models.

Model #2 – Previous Basis Forecast

Model #2 assumed that basis could also be modeled as a function of last year's basis, represented as:

(18) $Basis_{kt} = \beta_2 + \beta_3(Basis_{kt-52}) + \varepsilon$

where k refers to the k^{th} location and 'ε' is a white noise error term. In this case, rather than simply including a lagged time period of one week, a yearly lagged time period is

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[17] All of the equations presented were forecasted using E-views 8 using a Static forecast as no lagged dependent variables and/or ARIMA terms were used. A static forecast is described in the E-views help guide as follows (E-views 2013, p. Forecasting from Equations in E-views): "Static calculates a sequence of one-step ahead forecasts, using the *actual*, rather than forecasted values for lagged dependent variables, if available"
[18]To review the output from the individual models, please refer to Appendix E.
[19] One time period in this treatise is defined as a singular week

often deemed more representative because it captures that weeks' variability (seasonality).

Model #3 – 3-Year Average Forecast

The expected basis was also calculated using a historical average (Model #3) as demonstrated by Dhuyvetter and Kastens (1998).

(19) $$Basis_{kjm} = \beta_4 + \frac{1}{i}\sum_{i-1}^{I} \beta_5(Basis_{kjm}) + \varepsilon$$

where 'k' refers to the location, 'j' refers to the week of the year, 'm' refers to the commodity, 'i' refers to past years included in the historical average (for a four-year historical basis i = 2, 3, 4, 5 or I = 5)and 'ε' is a white noise error term.

Dhuyvetter and Kastens (1998) found that a four year historical average performed well when forecasting crops. For Utah live cattle, historical average basis using averages calculated using 2, 3, 4, and 5 years of data were econometrically tested using the aforementioned equation. Each regression was then evaluated based upon whether the variables resembled reality and an appropriate goodness of fit (e.g. R^2) The results indicated that a three-year historical average performed best; thus for Utah live cattle steers, a three-year historical average was used. For the consistency measures, a three-year average was used for Western Kansas as well.

Model #4 – Seasonal Trend Forecast

Model #4 assumed that the expected basis was calculated using monthly dummy variables to capture the effects of seasonality effect (Dhuyvetter and Kastens 1998).

(20) $$Basis_{kjm} = \beta_5 + \beta_6(DV_l) + \varepsilon$$

where 'k' refers to the location, 'j' refers to the week of the year, 'm' refers to the commodity, 'DV' are monthly dummy variables for months 'l' excluding March (i.e., l = Jan, Feb, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov, Dec), and 'ε' is a white noise error term. It is often assumed that seasonality occurs in agricultural markets. These models have been shown to perform well historically and provide insight into the seasonal variations that occur in cattle markets. The results from the regression analysis confirm that seasonality does occur for Utah live cattle basis.

Model #5 – Interest Supply Forecast

Model #5 assumed the expected basis was calculated adapting a similar formulation as proposed by Garcia et al. (1988). Their model was a composite supply and demand formulation. The model used here used only the supply side formulation as explanatory variables in the regression. Garcia et al. (1988) supply side formulation included US cattle slaughter prices per cwt. at Omaha, NE for 1,100-1,300 pounds choice slaughter steers lagged six months, average prices of feeder steers for eight markets (per cwt.) lagged six months, the price of US corn (per bushel) lagged six months, US prime interest rates lagged six months, and monthly dummy variables. Due to the data constraints imposed upon by weekly intervals, this formulation was modified slightly. The following formulation was used:

$$(21) \quad Basis = \beta_7 + \beta_8(Boxed\ Beef_{t-26}) + \beta_9(Feeder_{t-26}) + \beta_{10}(Corn_{t-26}) + \beta_{11}(Interest_{t-26}) + \beta_{12}(DV_l) + \varepsilon_t$$

'Boxed Beef' was the Friday weekly average of the reported choice slaughter boxed beef prices lagged six months; 'Feeder' was the Friday weekly average lagged six months of the feeder futures; 'Corn' was the Friday weekly average of the corn futures price lagged six months; 'Interest' was the Friday weekly average of the US national prime bank loan rate lagged six months; and 'DV' were monthly dummy variables, 'l', with March being excluded.

Model #6 – Contract

Basis is often assumed to be seasonal. Previously used seasonal models have generally only included monthly seasonal variables to explain basis. The results from Tables 4 and 5 show that contractual seasonal dummies that are econometrically modeled can be used (Model #6). Model #6 is defined as follows:

(22) $$Basis_t = B_{13} + B_{14}\left(CD_q\right) + \varepsilon_t$$

where 't' was the time, 'CD' was the contractual dummy variables for contracts 'q' excluding the April live cattle contract, and 'ε' was a white noise error term. This model may prove to be more accurate than monthly dummies in explaining the seasonality that occurs within basis. Likewise, time series data that relies heavily on recent past observations can see systematic and statistically-significant jumps as the futures contract "rolls" from one contract to the next causing potential issues if not accounted for in other models.

Model #7 – Meat Demand

The demand for beef model (Model #7) was adapted from Garcia et al. (1988) paper where they modeled supply and demand. To model beef demand they used US cattle slaughter price per cwt. The variables used in Garcia et al. (1988) formulation were Omaha 1,100-1,300 pounds choice slaughter steers, US hog slaughter per 1,000 head, US broiler slaughter in million pounds, US personal income per capita, and 11 dummy variables for the months of the year at the levels in time "t". This thesis' regression was adapted from this formulation due to weekly time constraints on the data. The final formulation used in this thesis was as follows:

(23) $$Basis_t = \beta_{15} + \beta_{16}(Boxed\ Beef_t) + \beta_{17}(Hog_t) + \beta_{18}(Broiler_t) + \beta_{19}(ELI_t) + \beta_{20}(DV_l) + \varepsilon_t$$

where '*Boxed Beef'* is the Friday weekly average of the reported choice slaughter boxed beef prices; 'Hog' were Friday weekly average cash price for 230-250 barrow and gilts for Iowa and southern Minnesota; 'Broiler' were Friday weekly average of cash broiler prices; 'ELI' were Friday weekly average of the US Economic Leading Indicator; and 'DV' were dummy variables for months '*l*' with March being excluded as the base month.

One modification in Model #7 from Garcia et al. should be noted. The variable 'ELI' was substituted in place of "per capita income." Two reasons support this decision. First, per capita income aims at capturing available cash in the US market supporting the idea that the more money available the more likely people are to purchase meat. Likewise, 'ELI' captures movements in the overall economy which eventually reflect available cash flow; thus, anticipating cash flow in time, 't' would reflect current purchasing decisions and anticipate changes in the economy. Second, per capita data were not available on a weekly format.

Model Error Identification

The judgment of "success" of a given forecast model is generally determined by the amount of error or variance from the true value being forecasted it produces. Various test statistics have been devised to calculate forecasting error. Some of these methods are the mean square error (MSE), root mean square error (RMSE), percent better (PB)[20], mean absolute percentage error (MAPE), and relative absolute error (RAE). Twenty-one agricultural cash, futures, and basis forecasting studies were reviewed and examined. After a survey of the agriculture, business, and economic literature, 22 widely reported forecast errors were found. The reported forecasting error(s) in the twenty-one papers were reviewed. The most common error statistic reported was the R^2 (90%) followed by the RMSE (48%), and the MSE (43%). This was not much different than the averages within the forecasting community.

In 1981, Carbone and Armstrong surveyed practitioners and academics, and found that 48% of academics and 31% of practitioners used the RMSE consistently while the MAPE was used by 24% and 11%, respectively. Over 10 years later, Mentzer and Kahn (1995) found that the MAPE was used by 52% of forecasters and the RMSE was used by 11% – signifying a change in forecaster preference. On average, 2.76 forecasting error measures were reported per study with a high of four and a low of two. Likewise, 90% of the studies examined reported the R^2, 48% reported the RMSE, and only 19% of the studies used the MAPE. A full breakdown of the studies examined and a table demonstrating the raw data can be found in Appendix C. The bar chart in Figure 2 shows the overall percentage of studies that used a given forecasting error measure.

The aforementioned results raise some questions as to current basis, cash, and futures forecasting practices within the agricultural sector. It indicates that many studies rely on two to three forecast error methods or measures. Further, 45% of the error

[20] The error term “percent better” is sometimes referred to as “percent worse” depending upon whether the author(s) are talking about a singular forecast or an error term. See Armstrong (2001) for an example.

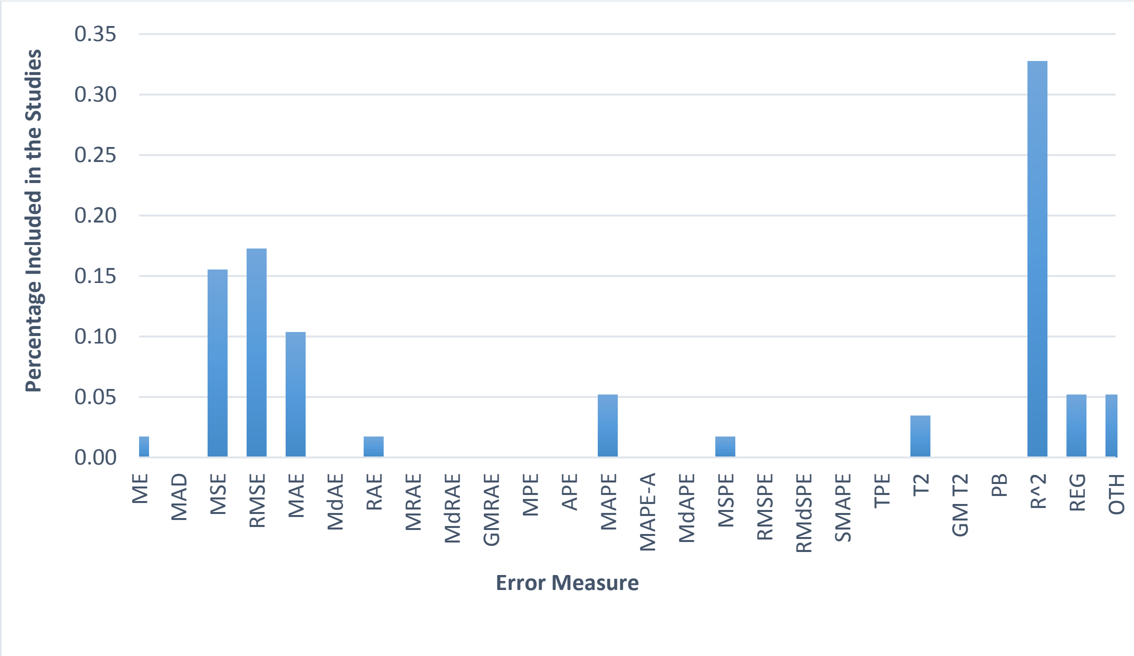

Figure 2. Error measures used in basis literature
Source: Calculated based upon the data gathered from the 21 articles
[a.] Scale dependent errors are ME – MdAE
[b.] Relative errors are RAE – GMRAE
[c.] Percentage errors are MPE – TPE
[d.] Relative measures are T2 – PB
[e.] Miscellaneous error methods reported are REG - OTH

measures reported were scale dependent and another 33% can be accounted for with the R^2. Problems arise in the ability to make business decisions when scale-dependent errors and the R^2 are used. Chatfield (1988) points this out after a thorough reexamination of the notoriously famous “M-competition.” His article refutes and challenges claims reported previously by Zeller (1986) who concluded that the Bayesian method of forecasting were the most accurate because it produced the lowest RMSE. Fildes and Makridakis (1988) likewise criticized Zellner’s results and indicated that the performance of the RMSE could be contributed to five of the 1001 data series; thus, the results were skewed. Fildes and Makridakis (1988) continue their claim that even with the exclusion of these five results there were major issues in the interpretation of the RMSE. Rather, they recommend that results be reported using a unit-less error term.

Armstrong (2001) claims that a body of research has accumulated in which the RMSE has been effectively ruled out as a means of comparison across forecast models. This implies that RMSE analyses that have been conducted within cash, futures, and basis studies are theoretically questionable as to their *current* economic importance. These claims were preceded by Armstrong and Collopy (1992), who confirmed that both the RMSE and MSE should not be used in generalizing error reductions across forecasts. Their conclusion thus denotes that when a group of forecasts are modeled, using the RMSE cannot tell us whether one forecast is better than another. Armstrong and Collopy (1992) conclusions was foreshowed by numerous academic articles that reported the "fit" in time-series data is unreliable in the predictive validity of the model. Armstrong (2001) further quotes many studies that show how the R^2 can be manipulated to produce results from random uncorrelated data.[21]

Fildes and Makridakis (1988), along with Armstrong and Collopy (1992), call into question whether or not the cash, basis, and futures agricultural basis forecast reported errors are appropriate to use as a decision-making tool. Although somewhat controversial, their results offer insight into how certain errors are affected by reliability, construct validity, outlier protection, sensitivity, and relationship to decisions. While the Fildes and Makridakis study is reasonably comprehensive, it is limited in two areas: 1) It does not offer a wide variety of error measures based on the findings of Hyndman and Koehler (2006), and 2) Since basis positive, negative and zero numbers, the conclusions that the authors have made may be inaccurate as they relate to basis forecasting errors.

[21] For further insight into how R^2 is misleading, please refer to Ames and Reiter (1961), Armstrong (1970), and Anscombe (1973) as found pp. 12-13 in Armstrong (2001).

Spearman Rank Correlation

What is more beneficial in determining which error term to use is: 1) calculating the error terms for each singular or composite model; 2) ranking the error terms, lowest to highest, for each forecast; and 3) running a Spearman rank correlation on the errors to test continuity in error ranking.[22] This would afford the error terms to be reported and compared with other forecasts, in addition to determining whether certain errors perform better or worse over time, horizon, and certain data.

Following the logic of Hogg, McKean, and Craig (2005, p. 574), assume that (X_1, Y_1)….(X_n, Y_n) are a random sample with a population coefficient of ρ between the variables X and Y. Assuming a bivariate continuous CDF of $F(x, y)$ the Spearman rho coefficient is given as follows:

$$(24) \qquad r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}}$$

A rank correlation is derived from the equation above by replacing X_i with $R(X_i)$ where "R" represents the rank of X_i from X_1…..X_n. The same holds true for Y_i, Y_i with $R(Y_i)$ where "R" represents the rank of Y_i from Y_1…..Y_n. Substituting and solving the Spearman rho rank correlation can be defined as:

$$(25) \qquad r_s = \frac{\sum_{i=1}^{n}(R(X_i) - \frac{n+1}{2})(R(Y_i) - \frac{n+1}{2})}{n(n^2-1)/12}$$

If $0 < r < 1$, then a positive relationship exists between X_i and Y_i, and vice versa, whereas a perfect relationship is represented with rho being one. Hence, finding the rho coefficient would yield a numerical measure that essentially quantifies the statistical relationships between error measures being estimated for "N" forecasting models. In

[22] It should be noted that Colino et al. (2012) used the DMD test statistic in comparing the RMSE's of hog forecasts for three different states. They found using this statistic provided more valuable results.

short, if a given statistical relationship holds over “h” horizons, then that error measure can be assumed to be of greater validity to that particular time series data.

Armstrong and Collopy piloted this idea among forecasting error terms in 1992. They first tested six individual error terms for 18 annual time series models and found that the MAPE to MdAPE (0.83) and GMRAE to MdRAE (0.79) shared the most agreement. The other correlations were all below 0.60. After increasing to 90 annual time series, the majority of the errors began to converge – indicating that the error terms truly were measuring the same thing. A major benefit to this process is that it helps ensure construct validity and reliability in the error terms. Likewise, by performing the Spearman rank correlation over various time horizons, it helps solidify which error terms are most reliable at certain time periods. Table 6 is an example of the Spearman rank correlation as reported in Armstrong and Collopy (1992).

Stochastic Dominance

In order to determine which forecast has the least amount of variance, the forecast that produces the lowest forecasting error is often used. While a forecast may produce a low error value (e.g. RMSE of 0.52), it may have a relatively wide distribution (e.g. 4.52) thus making the forecast less appealing under risky conditions. In order to determine whether singular forecasts in fact produce better forecasts, a systematic procedure should be developed to judge and eliminate forecasts.[23] One solution is to stochastically rank the cumulative distribution functions for each forecast. Decision makers can then

[23] It should be noted here that the forecasting horizon may play a part in which forecasts are chosen and eliminated.

Table 6. Spearman rank correlation among 18 annual time series

Error [a] Measure	RMSE	MAPE	MdAPE	Percent Better	GMRAE	MdRAE
RMSE	1	0.44	0.42	0.11	0.03	(0.31)
MAPE		1	0.83	0.17	0.68	0.28
MdAPE			1	0.09	0.40	0.06
Percent Better				1	0.46	0.65
GMRAE					1	0.79
MdRAE						1

[a] See Appendix A for a full break down of error measure abbreviations

determine whether or not to accept a certain forecast. Hence two primary questions can be answered using this procedure:

1. Will every producer prefer forecast A [F(a)] to forecast B [F(b)] ?
2. If a producer is indeed risk adverse, will they prefer forecast A [F(a)] to forecast B [F(b)] ?

These questions can be answered using stochastic dominance. Stochastic dominance's main function is to help decision makers' screen out methods, choices, and forecasts that are inefficient. It has also been used to determine the level or risk associated with certain choices. Agricultural economists have found this particularly helpful in screening risky decisions in budgeting (Lien 2003) and crop production (Ritchie et al. 2004). The results thus far have been promising

To illustrate this point and to answer the two questions above, assume two forecasts (X and Y) with generic distribution functions (0, σ^2) that are bounded by [a, b] with X (a) = Y (a) = 0 and X (b) = Y (b) = 1. The first question can be answered using what is commonly referred to as first order or absolute stochastic dominance. A simple definition is (see Figure 3):

a. X is absolutely dominant over Y if P(Y ≤ X) = 1 and there is at least one y such that $F_Y(y) > F_X(y)$ (or equally $\bar{F}_Y(y) > \bar{F}_X(y)$

or

b. X has a greater chance of being larger than Y for any given value of y

When this condition is met (e.g. satisfied), it is commonly notated as $X \geq_{SD} Y$ or $Y \leq_{SD} X$ and graphically illustrated in Figure 3.

Under normal conditions, a given producer would always choose forecast F_X over F_Y. The second condition is more problematic as it does not reveal which forecast is preferred by all producers (Richardson 2008). Rather, it allows for risk preferences to be determined, thus selecting a forecast, or combination of forecasts, that satisfy a producer's risk preference.

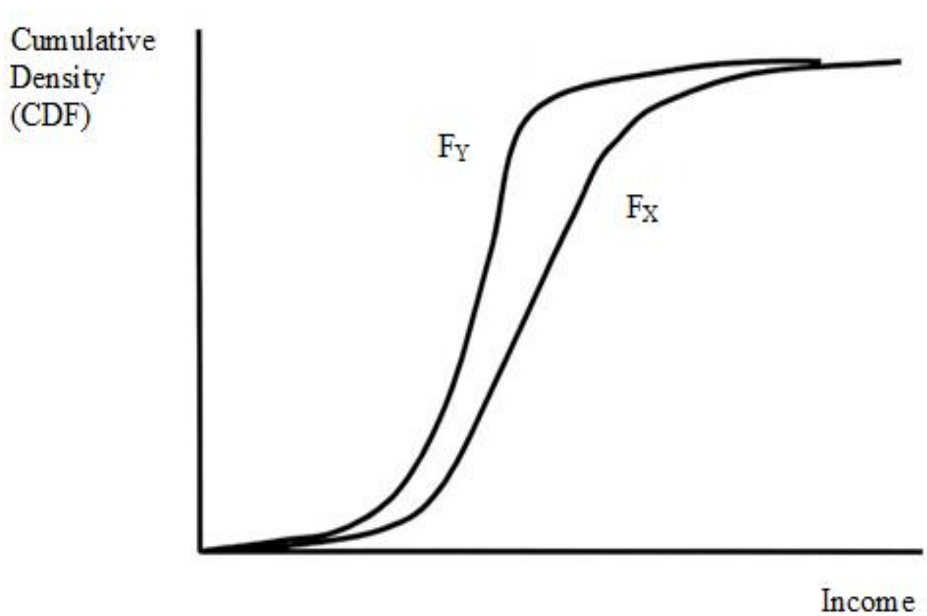

Figure 3. First order stochastic dominance
Source: agronomy.com

The second order stochastic dominance is defined as (see Figure 4):

c. Y is second-order stochastically dominant over X if $\int_{-\infty}^{x} F_Y(y)dy \ \leq$

$\int_{-\infty}^{x} F_X(y)dy$

or

d. For all x's there is at one value of x that restricts the inequality

This condition allows for only restricted or qualified decisions to be made. For certain values of 'x' we would prefer forecast Y and for other values of 'x' we could prefer forecast X not providing a concise decision. This dilemma is illustrated in Figure 4.

The second-order decision thus allows risk preference to be analyzed. Risk is incorporated into stochastic dominance using the Pratt-Arrow's risk aversion coefficient as shown by Meyer (1977).[24] Using lower and upper bound coefficients, one can stochastically order forecasts based on risk preference (see Figure 4).

Meyer states that one must identify a producer's utility function $[U_0(y)]$ which minimizes:

(26) $\int_0^1 [X(y) - Y(y)]U_0'(y)dy$

and is subject to

(27) $r_1(y) \leq \frac{-U_0''(y)}{-U_0'(y} \ \leq \ r_2(y)$

where $r_1$and r_2 are the lower and upper bounds of the RAC, respectively (Bailey 1983). Hence, this allows risk preferences to be considered. It bears noting that this logic tends to deviate from the common assumption that all agricultural producers are risk adverse, but does allow for a variety of risk preferences to be accounted for. Raskin and Cochran

[24] The Pratt-Arrow's risk aversion coefficient (RAC) is written as r(x) = - u''(x) / u '(x) where 'r' represents the resulting RAC, 'u' is the given utility function.

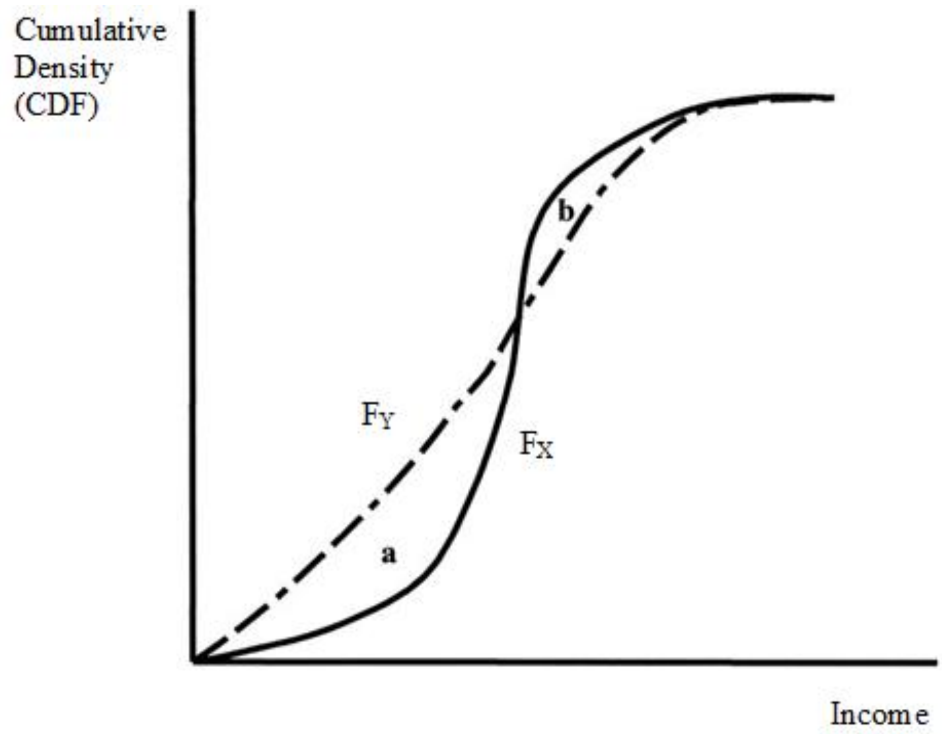

Figure 4. Second order stochastic dominance
Source: agronomy.com

(1986) suggested one possible alternative in their critical review of agricultural economists' arbitrary selection of RAC's. They noted that RAC could be used to explore changes in risk preferences over forecasted time periods (p. 209). Likewise, they also found that, depending upon the RAC chosen, the ranking and preferences could change. Thus properly selecting these bounded RAC's stochastic dominance ensures proper use and interpretation of the stochastic solutions.

Numerous studies have already touted the benefits of using RAC's in stochastic dominance in enhancing decision making preferences, particularly in finance. Within the economic forecasting literature, its popularity has been less so. Some studies have used it to select models based upon their distribution (de Menezes and Bunn 1993; de Menezes and Bunn 1998), while others use it to determine a singular model. Holt and Brandt (1985) used stochastic dominance to rank forecasts based on risk preference when hedging and forecasting hog prices. Of particular mention is that Holt and Brandt used a simple average composite forecast. They found that people who ranged from risk neutral to highly risk adverse would prefer using a composite ARIMA econometric model.

Timmerman (2006) confirms these ideas saying that the main aim of composite forecasts is to reduce risk and overall loss. Thus, composite forecasts should stochastically dominate singular forecasts in risk and the overall loss sustained (p. 3). These findings lend credence to the idea that stochastic dominance can be used to rank forecasts, evaluate risk preference, and determine marking strategies. In order to do this, the generic interpretation of stochastic dominance may not be able to be applied when using basis. For example, in this thesis the objective is to *minimize* variance of a singular forecast rather than maximize wealth. Moreover, this objective implies that an ideal basis forecast will have a low standard deviation that is distributed around zero. Hence, when looking at a very accurate forecast one would expect to see a tighter probability density function (PDF) centered on zero. When a "tight" (e.g. more accurate) singular forecast PDF is then converted to a CDF, it generates a CDF that crosses and lies closest to the vertical axis. The generic interpretation of stochastic dominance, as aforementioned, is the forecast that lies farthest to the right and lowest. Thus, when evaluating which forecast produces the smallest distribution and lowest forecasting error the singular or composite forecast that lies farthest to the left and highest would be deemed most favorable. This is illustrated by the PDFs placed in Appendix G.

Stochastic Efficiency

Stochastic dominance provides an objective criterion under which each composite forecast can be analyzed. One limitation is that it does not provide a way to analyze a range of risky situations. Since the aim of composite forecasts is to eliminate as much risk as possible, it is appropriate to determine whether or not a forecast unilaterally dominates another forecast over a range of risk. In 2004, Hardaker et al. introduced the idea that stochastic efficiency be used to rank risky alternatives. They cite as their major finding as it ranks risky alternatives simultaneously rather than separate pair-wise comparisons. This allowed them to determine a specific range of risk that a forecast would be useful. Likewise, the authors claim using stochastic efficiency provides six main findings (pp. 266-267):

1) Can be used to identify a more efficient set of risk alternatives in comparison to stochastic dominance
2) Provides an ordinal ranking between the upper and lower risk aversion bounds
3) The one step process allows for simultaneous interpretation with the stochastic efficiency graph
4) Allows for more useful policy analysis
5) Used to process data in different formats
6) Is in keeping with Meyer's (1977) original intention of stochastic dominance

While Hardaker et al. (2004) explain in detail how stochastic efficiency is derived, the following section provides a simple mathematical explanation of their findings based upon the assumption of a negative utility function.[25] To illustrate their findings, assume a generic four quadrant chart where the vertical axis is represented by the certainty equivalents (CE) for two generic forecasts X and Y. The horizontal axis is represented by the risk aversion coefficients (RAC) lower RAC, $RAC_L(w)$, and upper

[25] The negative utility function is the generic function used in stochastic efficiency analysis. The following functions are used in other papers published: negative exponential, power, expo-power, quadratic, log, exponent and HARA.

RAC, $RAC_U(w)$.[26] Based upon the given parameters, the following interpretation of the results offers (Hardaker et al. 2004):

1) X(y) is preferred to Y(y) over the range of RACs where the CE_X line is above the CE_Y line,
2) Y(y) is preferred to X(y) over the range of RACs where the CE_Y line is above the CE_X line, and
3) Decision makers are indifferent between forecasts Y and X at the RAC where the CE lines intersect.

The three points provides a systematic interpretation of risky alternatives between $RAC_L(w)$ and $RAC_U(w)$. This allows for decision makers to classify which forecasts should be used based upon their risk preferences. For example, the graph below, taken from Hardaker et al. (2004), represents a prototypical stochastic efficiency output for three different forecasts that are constrained by a non-negativity variable. Figure 5 demonstrate that two utility efficient forecasts, namely Alt. 1 and Alt. 2. Alt. 1 is utility efficient from $RAC_L(w)$ to $RAC_2(w)$. Alt. 2 dominates Alt. 1 and becomes utility efficient from $RAC_3(w)$ to $RAC_U(w)$; Thus, business decision makers who had a risk preference between $RAC_L(w)$ and $RAC_2(w)$ would prefer to use forecast Alt. 1 and those whom had a risk preference from $RAC_3(w)$ to $RAC_U(w)$ would prefer Alt. 2.

Many industries realize the potential in using stochastic efficiency analysis including dairy farms (Flaten and Gudbrand 2007), sheep farming (Tzouramani et al. 2011), and corn and soybean cropping (Fathelrahman et al. 2011). Stochastic efficiency has not been

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[26] As mentioned above during the discussion on the stochastic dominance, RAC's are to be chosen by the forecasters but general range from -4 to 4.

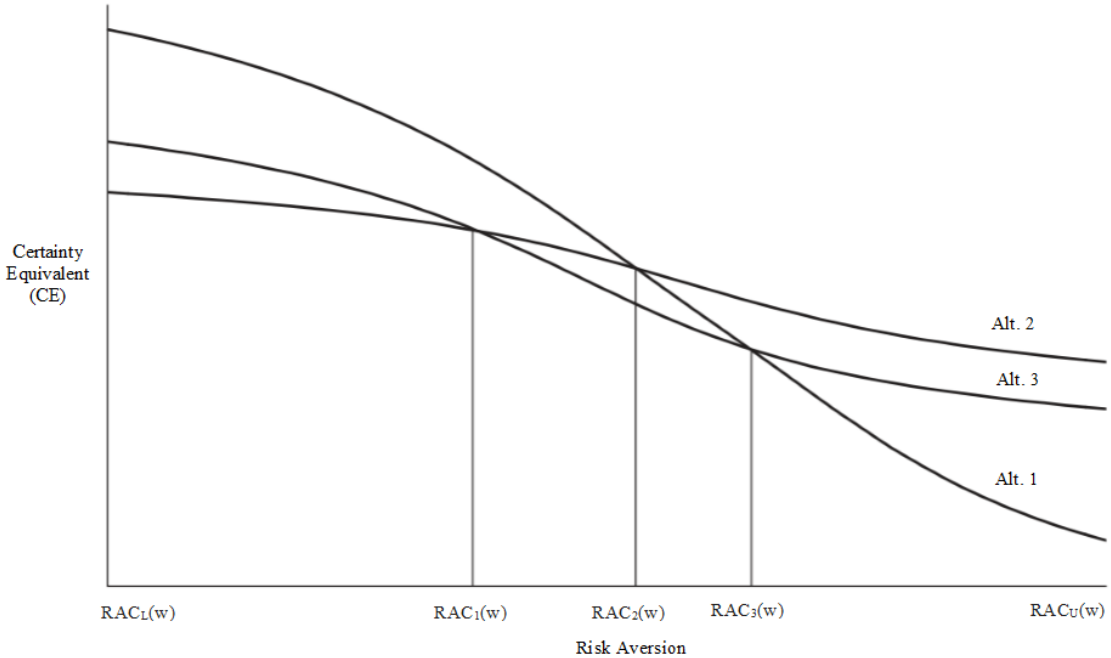

Figure 5. Stochastic efficient graph simultaneously comparing three risky alternatives
Source: Hardaker et al. (2004)

widely used in the cattle industry. The majority of studies using stochastic efficiency have centered on cattle disease prevention (Van Asseldonk et al. 2005). For cattle producers, understanding the increase in profitability that can be gained in using a singular or composite forecast is particularly important for this thesis.

This thesis offers an alternative interpretation to Hardaker et al. (2004) for stochastic efficiency that stems from their definition of CEs. They affirm that when ranking CEs more is far better than less. This interpretation deviates from that assumption since the objective of forecasting is to reduce deviation (e.g. tighter distribution). Thus, CEs that are smaller are far better than higher values. Under these conditions, once again assume a generic four quadrant chart where the vertical axis is represented by the certainty equivalents (CE) for two generic forecasts X and Y. The horizontal axis is represented by the risk aversion coefficients (RAC) lower RAC, $RAC_L(w)$, and upper

RAC, $RAC_U(w)$.[27] Based upon the given parameters, the standard interpretations would be modified to be:

1) X(y) is preferred to Y(y) over the range of RACs where the CE_X line is below the CE_Y line,
2) Y(y) is preferred to X(y) over the range of RACs where the CE_Y line is below the CE_X line, and
3) Decision makers are indifferent between forecasts Y and X at the RAC where the CE lines intersect

This modified interpretation allows for the residuals of singular or composite forecasts to be used in a stochastic efficiency analysis.

Risk Premiums

One of the benefits of using stochastic efficiency is that Certainty Equivalents are calculated. Certainty Equivalents (CE) are used under the assumption that rational individuals act in a way that they strive to maximize their own utility. Richardson et al. (2008) quoted Freund (1956) who proposed a calculation for CEs that was a function of expected income or wealth ($\bar{Z}$) absolute risk aversion (r_a), and the variance of the income or wealth (V). Mathematically it is:

(28) $$CE = \bar{Z} - 0.5 r_a V$$

Hardaker, in 2000, subsequently suggested using CEs to rank risk alternatives, making them practical for business managers. In the context of stochastic efficiency, CEs represent the vertical distance between two forecasts. The standard interpretation of CEs

[27] As mentioned above during the discussion on the stochastic dominance, RAC's are to be chosen by the forecasters but general range from -4 to 4.

are if the CE remains positive, then on the average rational producers will prefer risky alternatives to risk free alternatives (Richardson et al. 2000). If the CE is negative, then the contrary would be true. Thus, the standard interpretation is that if a line remained positive and above all other CEs, then it would be the most preferred out of all the forecasts. Certainty Equivalents are also useful in calculating risk premiums at a given RAC. A risk premium is obtained by subtracting the base scenario from a proposed scenario. Mathematically it is:

(29) $RP_i = CE_{Scenario\ i} - CE_{Base\ i}$

for a given RAC_i (Richardson et al. 2010). The standard interpretation is that if RP line is positive then it shows that value it has over the base scenario. Likewise, the RP shows how much a producer would need to be compensated before switching to another ranching method (see Figure 6).

In this analysis, the lowest forecast and farthest to the left was deemed as the most efficient because the objective once again is the reduction of the residuals. This implies that if a forecast is more accurate, then a producer would be better able predict price and allocate resources appropriately to maximize profit. The value of the RP in this thesis is viewed as the amount a producer would need to be compensated (\$/cwt) to use another forecast.

To illustrate this point, let’s assume that risk premiums are calculated for three forecasts, Alt. 1, Alt.2, and Alt. 3. Using the modified interpretation of risk premiums, Alt. 1 is deemed as the most efficient forecast between a range of risk. Modifying the formula in Equation 29, the risk premiums were calculated as follows:

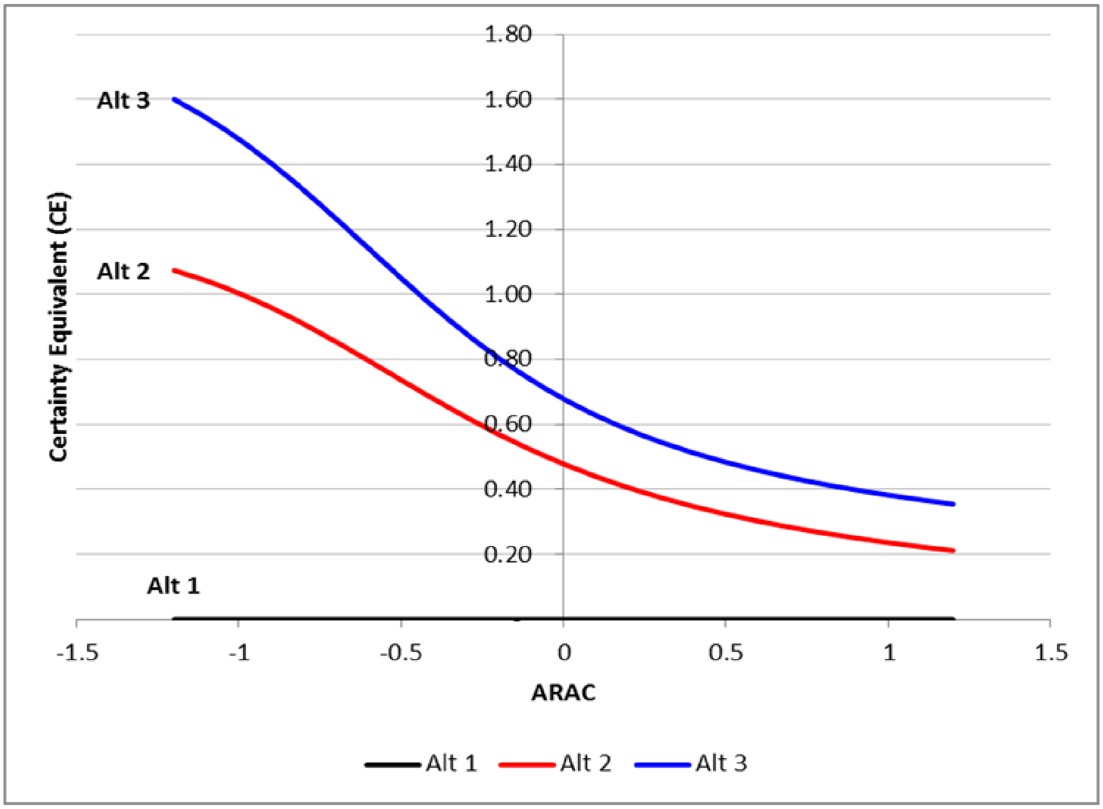

Figure 6. Adjusted risk premiums comparing three risky alternatives

(30) $RP_i = |CE_{Scenario\ i} - CE_{Base\ i}|$[28]

The risk premium between Alt. 1 and Alt. 2 at an RAC of 0 is 0.48 (see Figure 6). Thus, a producer who has the choice between these two forecasts, Alt. 1 and Alt. 2, would need to be compensated $0.48/cwt to be incentivized to use Alt. 2. Using this interpretation, forecasts can be ranked properly.

Error Measures

With many errors to choose from, the debate is often which one should I use?[29] The answer is that it depends. Often the answer is determined by the structure of the time

[28] The only modification here is a change in the sign. For example, when calculating basis we have an actual cash price of $105.25/cwt and a futures price of $107.25/cwt. Applying the basis formula we get Basis = 105.25 – 107.25 or Basis = $(2.00)/cwt. Taking the absolute of this value would be Basis = | -2.00 | or Basis = $2.00/cwt. Thus, a mere change in the sign.

[29] For a list of names that correspond with the error term abbreviations used please refer to Appendix A

series being used and its historical performance.[30] In their informative yet critical review of forecast measures and subsequent accuracy, Hyndman and Koehler (2006) classify commonly-used error measures based upon what these measures rely upon. This explanation mimics their reasoning (pp. 682-686).

Categorizing Forecasting Errors

Scale-dependent error measures are some of the most commonly used error measures. They include MSE, RMSE, MAE, and MdAE. These are most often used to compare different methods within the same data set. A violation of this measure is most commonly seen when forecasters compare scale-dependent error measures across different data scales as seen in the M-2 competition, which was criticized by Chatfield (1988). Due to its popularity, the RMSE is most commonly used and often preferred over the MSE when using the same data. This assumption holds likewise for agricultural commodities where the RMSE was most popular followed by the MSE (see Figure 2).

Measures based upon percentage errors are likewise very popular because they allow for comparisons across datasets because they are not scale-dependent. These include measures such as the MAPE, MdAPE, RMSPE, and RMdSPE. The majority of the complaints filed against these types of errors are that they generally have a skewed distribution, infinite/undefined when the observation at time “t” is zero (i.e. $Y_t = 0$), have a meaningful zero, and place a heavier penalty on positive errors than on negative errors. In agriculture basis forecasting, for example, this produces a problem since many values can be positive and negative. Some of the alternatives to these complaints have been the

[30] While not ethically vocalized, researchers may experiment with a variety of error measures finally settling on the one that produces the lowest error with their data.

development of symmetric percentage error terms (Makridakis 1993) and logarithmic transformations (Swanson, Tayman, and Barr 2000).

Some forecasters dislike using scale dependent error measures. An alternative to divide each error by the error obtained (i.e. $\varphi_t = \varepsilon_t/\varepsilon_t^*$ where ε_t is the error term and ε_t^* is the obtained error) assuming a random walk. The measures based on relative errors, as they are commonly referred to, are MRAE, MdRAE, GMRAE, and their derivatives. This approach has been preferred among forecasters as a reasonable alternative although it is often not reported in published literature. One possible explanation provided is due to its complexity and possibility of ε_t^* being very small and causing issues. While these concerns are valid, others continue to advocate for the use of these measures as well as providing modifications to the aforementioned measures based on relative errors.[31]

Lastly, rather than using the relative errors mentioned above, it has been proposed to use relative *measures*. Essentially, the relative measure compares the error term of a given model to that of a benchmark model. This methodology can be used for a variety of error types including the MAE, RMSE, MSE, MdAE etc.[32] To illustrate, use the error term MAE. Assume that MAE_b is MAE for the benchmark model which is generally assumed to follow a random walk.[33]

Following the formulation of Hyndman and Koehler (2006), we get the relative MAE measure by using the formulation $RelativeMAE = MAE/MAE_b$. In a similar vein, the error terms Percent Better and Worse can be derived. Using this formulation we can derive empirically which forecast is more accurate. If $MAE > MAE_b$ then the proposed

[31] See Armstrong and Collopy (1992) for their use of Winsorzed means.
[32] It should be noted that the relative RMSE measure is often referred to as Thiel's U Statistic or just U2
[33] The random walk is sometimes referred to as the "naïve" model or that the forecasted observation in "t+h" is equal to the present observation or simply "t" (i.e. $MAE_t = MAE_{t+h}$)

model is worse than the benchmark model, and vice versa. It is exactly for these reasons that these errors are reported – they are easy to interpret.[34]

Select Error Measures

Numerous times within this thesis the term "error measurement" and its derivatives have been used. In order to avoid further confusion, a summary of the accuracy measures used in this thesis are explained below. The formulation for these terms is based on Mahmoud (1987), Armstrong (2001), and Makridakis (1985). While this list cannot claim to be comprehensive or complete, it does provide a singular error measurement from each measurement category as shown by Hyndman and Koehler (2006). The forecast errors used were systematically chosen as to reflect different categories and forecasting error variety.

As mentioned above, error terms can be classified into four main categories: scale-dependent, percentage errors, relative errors, and relative measures. The four error terms chosen for this study are mean absolute deviation (MAD) for scale-dependent, symmetric mean absolute percentage error (SMAPE) for percentage error, relative absolute error (RAE) for relative error, and Theil's U2 (TU2) for relative measures.[35] These error terms are formulated as follows.

Let us assume that an error, or ε_t , in time "t" is defined as[36]:

Error (ε)

(31) $\varepsilon_t = A_t - F_t$

---

[34] The most popular forecasting error of the relative measures is the Theil's U2 which is the relative measure of the RMSE

[35] As other forecasting errors were also used to supplement these errors, the formulas can be found in Appendix I

[36] It should be mentioned here that the subscripts for time horizon, method, and commodity, have been excluded for simplicity reasons, although some authors have chosen their inclusion for a more dynamic model.

when A_t represents the actual historical values in time period "t" and F_t represents the forecasted values in time period "t".

Mean Absolute Deviation (MAD)

(32) $MAD = \frac{1}{n}\sum_{t=1}^{n}|F_t - A_t|$

where 'n' is the number of observations included in the calculation, when A_t represents the actual historical values in time period "t" and F_t represents the forecasted values in time period "t".

One primary benefit in using the MAD when basis forecasting is that it disregards whether the value is positive or negative avoiding that negatives and positives would cancel each other out. With basis, this is particular useful because we are forecasting around a true zero.

Systematic Mean Absolute Percent Error (SMAPE)

(33) $SMAPE_t = 100 * \sum_{t=1}^{n}\left|\frac{A_t - F_t}{(F_t + A_t)/2}\right|$

where 'n' is the number of observations included in the calculation, when A_t represents the actual historical values in time period "t," and F_t represents the forecasted values in time period "t". The SMAPE is an alternative to the MAPE and is often used when there are zero or near zero values as with basis. Since the error term is constrained to 200%, in theory, it reduces the influence of low value items. While many researchers suggest using this error measure, Goodwin and Lawton (1999) demonstrated that when the forecasted and actual values have opposite signs, very large sMAPE values can be seen.

Relative Absolute Error

(34) $RAE_t = \frac{\sum_{t=1}^{n}|A_t - F_t|}{\sum_{t=1}^{n}|A_t - \overline{A_t}|}$

whereA_t represents the actual historical values in time period "t," and F_t represents the forecasted values in time period "t", and $\overline{A_t}$ is the average of the actual values over time period 't' (Gepsoft 2014). While some argue that the RAE is not useful in making business decisions, it does allow for a useful comparison in determining which method to use. Since the purpose of this study revolves around whether or not a particular method is useful, it has particular significance.

Theil's U2 Statistic

The comparison between a forecasting method and a naïve model (value regressed on its value lagged one time period) is used to determine whether a model is better than simply guessing. This allows business managers to determine which model is best – Theil's U_2 statistic does just that. It compares a forecasted RMSE to that of a naïve RMSE model. Because the error measure RMSE was used by 48% of studies examined it seems appropriate measure to use. While it is sometimes disputed how the Theil's U_2 statistic is calculated, for the purposes of this study it is calculated as the following:

$$(35) \qquad U_{t2} = \frac{\sqrt{\sum_{t=1}^{n}(F_t - A_t)^2}}{\sqrt{\sum_{t=1}^{n}(A_t)^2}}$$

where F_t represents the forecasted values in time "t", and A_t represents the actual historical values in time period "t"(Armstrong 2001). The statistic is interpreted the following:

1) 'x' < 1 – the forecasting technique is better than guessing
2) 'x' = 1 – the forecasting technique is about as good as guessing
3) 'x' >1 – the forecasting technique is worse than guessing

As ‘x’ approaches zero it is said the forecast is becoming more accurate; hence, a value of 0.0001 signifies near perfection in the forecasting model.[37]

Nonlinear Programming

Many management decisions can be made in a linear and orderly fashion such as paying the utilities before taking a salary. Yet other questions, such as those faced by a hedge fund manager as to which stocks to choose, may prove to be too problematic for a linear assumption to be made. Under these circumstances, nonlinear assumptions need to be examined.

Simply stated, nonlinear programming (NLP) is the process by which a decision maker can optimize a function subject to a number of constraints that are not linear in nature. By and large, optimization comes in the form of minimizing or maximizing a given function. A generic notation for a nonlinear programing is shown as follows (Bradley, Hax, and Magnanti 1977, p. 410):

Maximize

(36) $f\,(x_1, x_2, \dots, x_n)$,

subject to:

(37) $g_1(x_1, x_2, \dots, x_n) \leq b_1$,

$$\vdots \qquad\qquad \vdots$$

$g_m(x_1, x_2, \dots, x_n) \leq b_m$,

where the constraint functions g_1 through g_m are given.

---

[37] The Theil’s U_2 statistic is often reported as three separate values: bias, variance, and covariance proportion. These are important in determining structural change and will likewise be reported.

While most commonly seen in the field of operations research and finance, agriculture has likewise found use for it. Areas in agriculture that have found particular use of NLP are related to climate change (Luo et al. 2003), cropping (McCarl and Spreen 1997), and dairy milking (Doole and Romera 2013). A prototypical example of how NLP can be used to help producers minimize production costs or maximize profits is seen in its application to water irrigation rights. For example, a farmer needs to water his/her crops through the duration of the summer without them withering. To ensure that the optimal water supply is used, a nonlinear program is needed that accounts for plant nutrition uptake, weather, and input costs; thus, the complexities presented in the risky situation of lack of water and return on investments can be accounted for using NLP.

NLP has particular use in the finance industry. A representative example is a hedge fund manager who has to decide which stock, options, equities etc. will maximize his/her profit. This situation is commonly known as the mean-variance (MV) model. This formulation takes into account a stock's average return as well as its variance-covariance relationship with other available stocks. The model, whose aim is to maximize profit, then selects the stock and quantity of shares to buy. In agriculture, this is also applicable. For example, a farmer has four crops he/she is able to plant subject to a number of constraints (e.g. labor, working capital, land, and government regulations). Knowing the historical data allows the famer to formulate a MV model that selects the crops to plant that would maximize his/her profitability in a given year. Using the same principles from agriculture and finance, individual and composite forecasts can be examined.

Segura and Vercher (2001) experimented with the idea of using software to optimize nonlinear forecasting functions. Modeling the Holt-Winter method they were able to optimize a given set of nonlinear parameters. In 2006, these results were replicated using the additive and multiplicative forms by Bermudez, Segura, and Vercher (2006). The results were unanimous – optimized forecast values can be obtained using a nonlinear programming methodology. In recent years, Kasotakis (2007) tested whether composite time-series forecasts would produce lower error terms. The results showed that composite models outperformed singular models. Likewise, they tested whether forecasting horizon had an impact on composite forecasting accuracy. Similarly, the results showed that shorter horizons and simple models performed the best. These results are consistent with time-series forecasting properties of short half-lives. Lastly, these ideas were further illustrated by Balakrishnan, Render, and Stair (2007), who found that optimal weights could be found for a weighted moving average technique.

The aforementioned results confirm the findings from Makridakis and Winkler (1983), Makridakis (1993), and Makridakis and Hibon (2000) who found that on average, a combination of forecasts outperformed simple singular models. Specifically, this thesis builds on these ideas as they relate to composite forecasting within the cattle industry in Utah. One of the major limitations with NLP is whether or not the program has solved for a global minimum/maximum. Under the conditions where there are no constraints, this guarantees that the function will be concave and a global maximum/minimum found (McCarl and Spreen 1997). In instances where there are indeed constraints, certain tests such as Newton Method and Gradient Search could to be conducted to ensure a global maximum/minimum is found.

Parameters Used in the NLP

Summation to One

As suggested by Timmerman (2006, p. 14), composite model weights should be constrained to one (see Equation 8). This implies that all the models combined cannot equal more than 100%. From a practical business perspective, this constraint is necessary and is imposed upon all composite weight NLP formulations.

Weights

Seven separate weight constraints were sequentially examined in the NLP formulation. In other words, in addition to the constraint that the weights summed to one, seven additional weight constraints were sequentially individually added. The weighting constraints examined are as follows:

1) *Optimal* – This is considered the base model and no additional constraints besides summation to unity were added.
2) *Equal* – In keeping with the literature, equal weights is examined. This implies that all forecasts simultaneously were counted, divided by that number and then constrained to that value. For example, if five forecasts were used, then each forecast weight would be constrained to equal 0.20.
3) *Expert Opinion* – Five industry experts were given the seven forecasts used in the study and given 100 points. They were then asked to divide up those points among the provided forecasts how they wished. These results were then averaged (Brandt and Bessler 1981).

4) *Ease of use* – In agriculture, simplicity is best due to the fact that producers are often not trained in econometrics and advanced mathematics. Under this assumption, four forecasts are chosen that represent current cattle producers mindsets and quantitative ability. These are then the weights were divided equally (e.g. $100\%/'n' forecasts$).

5) *Restricted Optimal* – When forecasts are examined, the forecast that produces the lowest forecast error is used (Makridakis and Winkler 1983).[38] This formulation draws from this logic and chooses four forecasts that individually produce the lowest error and then divide the weights equally (e.g. $100\%/'n' forecasts$). This weight constraint was used for the three different forecasting errors.

NLP Formulation

In 1989, Clemen suggested that mechanical weights could be estimated rather than trying to derive other elaborate weighting techniques (see also Bunn 1985). Makridakis et al. in 1998 confirmed this and reported that it would be possible to use a nonlinear optimization algorithm to help identify given parameters that would *minimize* the MSE or other measurements. This NLP objective formulation takes into account these suggestions, along with Timmerman's (2006, p.14) counsel that weights we estimated upon the variance and covariance of the individual forecasts as shown in equations (4-6). Following this logic, the objective function of the NLP based on each weighting scenario, that was solved using the computer program GAMS, is the following:

[38] See Colino et al. (2010) who used a composite MSE as one of their weighting schemes

Scenario 1 – Optimal

Minimize:

(38) $Min \sum_{i=1}^{7} w_i^2 \sigma_i^2 + 2 \sum_{i \neq j}^{7} w_i w_j \sigma_{ij}$

subject to:

(39) $\sum_{n=1}^{7} w_i = 1$

(40) $\omega_i \geq 0 \;\; \forall\, i$

where:

w_i= the weight of each forecasting model

σ_i^2= is the variance of the forecasting error of each model

σ_{ij}= is the covariance of the forecasting error of each model

Scenario 2 – Equal

Minimize:

(41) $Min \sum_{i=1}^{7} w_i^2 \sigma_i^2 + 2 \sum_{i \neq j}^{7} w_i w_j \sigma_{ij}$

subject to:

(42) $\sum_{n=1}^{7} w_i = 1$

(43) $\omega_i = \omega_j \;\forall\, i \neq j$

(44) $\omega_i \geq 0 \;\; \forall\, i$

where:

w_i= the weight of each forecasting model

σ_i^2= is the variance of the forecasting error of each model

σ_{ij}= is the covariance of the forecasting error of each model

Scenario 3 – Expert Opinion

Function:

(45) $\sum_{i=1}^{n} w_i^2 \sigma_i^2 + 2 \sum_{i \neq j}^{n} w_i w_j \sigma_{ij}$

subject to:

(46) $\frac{1}{5} \sum_{i=1}^{5} \sum_{n=1}^{n} w_{in} = 1$

where:

w_i= the average weight of each forecasting model depending upon the expert opinion

σ_i^2= is the variance of the forecasting error of each model

σ_{ij}= is the covariance of the forecasting error of each model

w_{in}= the weight of each forecasting model for each expert

where five cattle experts were asked their opinion on the weight that should be given to each forecast.

Scenario 4 – Ease of use

Minimize:

(47) $Min \sum_{i=1}^{4} w_i^2 \sigma_i^2 + 2 \sum_{i \neq j}^{4} w_i w_j \sigma_{ij}$

subject to:

(48) $\sum \omega_i \quad = 1$

(49) $\omega_i \geq 0 \;\; \forall\, i$

where:

w_i= the weight of each forecasting model

σ_i^2= is the variance of the forecasting error of each model

σ_{ij}= is the covariance of the forecasting error of each model with four models being chosen based upon producers ability to access data and simplicity of the model and each given equal weight.

Scenario 5-7 – Restricted Optimal

Minimize:

(50) $Min\ \sum_{i=1}^{3} w_i^2 \sigma_i^2 + 2\sum_{i \neq j}^{3} w_i w_j \sigma_{ij}$

subject to:

(51) $\sum \omega_i \quad = 1$

(52) $\omega_i \geq 0 \ \ \forall\, i$

where:

w_i= the weight of each forecasting model

σ_i^2= is the variance of the forecasting error of each model

σ_{ij}= is the covariance of the forecasting error of each model

with the three models with the lowest error measure being used and given equal weight.

Procedures

Three main contributions to the literature are made by this thesis. First, evidence suggests that forecasting error measures currently reported in the forecasting basis literature may provide misleading information about which forecasting models are most accurate and should be used by producers. Second, this thesis shows that stochastic dominance and efficiency tests can be used to systematically select the forecasts that could create the most profit for cattle producers if used. Third, it shows that composite basis forecasts can be used to reduce forecast error for live cattle basis in Utah. Together, these contributions suggest that profitability could be increased for Utah and Western Kansas live cattle steer producers.

Part 1

Seven individual econometric models were used to forecast Utah and Western Kansas live cattle steer basis. The forecasts were then checked for heteroskedasticity and serial auto correlation. In forecasts where these issues were found, the Newey-West standard errors were used to rectify these issues (see Appendix E for the regression output results). Eight forecasting errors (FE) were calculated and ranked. A Spearman rank correlation was then used on the ranked forecasting errors to determine consistency across the different error measures. Upper and lower risk aversion coefficients (RAC) were calculated from the singular forecasting residuals using a formula from McCarl and Bessler's (1989). An average of the standard deviations of the seven forecasts was taken.

Using the upper and lower RAC's, and the residuals of each individual forecast, stochastic dominance (SD) was applied to determine which forecasts were the most acceptable based on risk preference. The individual forecasts were once again ranked based upon how they performed. The stochastic efficiency (SE) procedure tested between the upper and lower RAC's to bolster the findings obtained from stochastic dominance and forecast errors. Based on the calculated stochastic efficiency graphs, risk premiums were obtained.

Part 2

Using the formula from Equations 35 to 37, a NLP model was created in GAMS. A variance-covariance matrix of the forecasted residuals of the singular forecasts for

Utah and Western Kansas live cattle steers was calculated. The NLP model then solved to minimize this variance-covariance while constraining the proportion (e.g. weight) given to the models to sum to one. The weights were then recorded. New composite residuals were obtained by taking the singular forecast residuals and multiplying them by the calculated proportion (e.g. weight).

After summing the new calculated residuals together across each time period, new composite residual was obtained for time periods *'t'* to '*t + n'*. These steps were then repeated with the other weighing techniques with minor variations. After the composite residuals were calculated, specific forecasting errors were calculated. These FE were then ranked and a Spearman rank correlation was conducted to determine content validity among the forecasting error measures. Upper and lower risk aversion coefficients (RAC) were calculated from the new composite forecasting residuals using a formula from McCarl and Bessler's (1989). An average of the standard deviations of the seven forecasts was taken.

Using the upper and lower RAC's and the residuals of each individual forecast, stochastic dominance (SD) was applied to determine which forecasts were the most acceptable based on risk preference. The individual forecasts were once again ranked based upon how they performed. Stochastic efficiency (SE) procedure tested between the upper and lower RAC's to bolster the findings obtained from stochastic dominance and forecast errors. Based on the calculated stochastic efficiency graphs, risk premiums were obtained.

Part 3

After both the singular and composite forecasts were calculated and analyzed for Utah live cattle steers, the procedures were then repeated for Western Kansas Live Cattle. The results were summarized, general trends reported, and recommendations given. Limitations with the data and methodology were also explained. Lastly, suggestions for further research for live cattle steers in general were provided.

CHAPTER 4

RESULTS

Singular Forecasts

Singular forecasts should be evaluated based upon a variety of forecast evaluation techniques. Hyndman and Koehler (2006) have urged that forecasts be evaluated using four different categories of forecasting errors: scale-dependent (RMSE-MSE), percentage error (MAPE-sMAPE), relative error (RAE), and relative measure (Theil's I-Theil's U2). The pre-screened singular forecasting models were evaluated based on the four forecasting error categories. Tables 7 and 8 are a summary of the forecasting errors, arraigned by forecasting error category, for Utah and Western Kansas live cattle steers.

Forecast Errors

The error results were very consistent with previous literature on live cattle basis. Lag-1 was the most responsive to changes in basis for both Utah and Western Kansas. Depending on which error term was used, a producer could come to different conclusions as to which forecasts would improve overall profitability. The Western Kansas live cattle steers had lower forecasting error values than Utah which should be expected as it represents a larger portion of live cattle marketed in the US.

In examining the different types of forecasting error, the Theil's U2 indicates that all of the forecasts proved to be better than guessing as the forecasting error values were less than one. This indicates that producers could be better off if they chose to use a forecast to predict prices rather than guessing. The 3-yr-avg. forecast did not perform

Table 7. Forecast Accuracy for Utah Live Cattle Steer Basis, 2010-2012

Forecast	Forecast Error							
	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Lag-1	1.75	1.35	3.07	630.2	129.0	0.63	0.387	0.66
Lag-52	2.65	2.13	7.00	479.1	407.0	0.99	0.617	1.00
3-yr. avg.	2.72	2.21	7.37	661.0	522.8	1.02	0.566	1.03
Seasonal	2.42	1.96	5.88	704.4	645.7	0.91	0.489	0.91
Interest Supply	2.18	1.72	4.75	511.5	207.0	0.80	0.490	0.82
CD	2.46	1.99	6.03	703.4	952.1	0.92	0.504	0.93
Meat Demand	2.33	1.93	5.45	588.2	1,007.5	0.90	0.474	0.88

Table 8. Forecast Accuracy for Western Kansas Live Cattle Steer Basis, 2010-2012

Forecast	Forecast Error							
	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Lag-1	1.44	1.05	2.08	152.1	342.2	0.73	0.490	0.77
Lag-52	1.87	1.46	3.50	192.1	521.4	1.02	0.760	1.00
3-yr. avg.	1.85	1.49	3.43	257.7	396.9	1.04	0.660	0.99
Seasonal	1.71	1.38	2.93	306.6	426.2	0.96	0.530	0.92
Interest Supply	1.80	1.42	3.23	308.8	346.9	0.99	0.533	0.96
CD	1.75	1.41	3.07	332.2	646.2	0.98	0.553	0.94
Meat Demand	1.66	1.37	2.74	317.2	470.3	0.95	0.516	0.88

well in comparison to the other forecasts for both Utah and Western Kansas raising some concerns about whether or not this a useful forecast to use when predicting live cattle prices. The Meat Demand and Interest Supply forecasts proved to perform particularly well indicating that while auto regressive techniques are useful, standard supply and demand models can add a substantial amount of information. Using forecast percentage errors (e.g. MAPE and sMAPE) also proved to be problematic for Utah and Western Kansas live cattle steers. The MAPE values are very high, indicating that distortion may have occurred in calculating basis due to outliers and small values that are centered on zero. This causes some trepidation in making conclusions about which forecast was the best based solely using the MAPE. The sMAPE is often used to reduce/trim the outliers and compress the results to less than 200. For Utah and Western Kansas live cattle basis, this did not occur. Large values were reported for the sMAPE also confirming the results from other studies that indicated that when using both positive and negative values, the sMAPE can become distorted.

Spearman Rank

In order to determine which forecast was the most consistent, an ordered rank was conducted. Following the logic of Armstrong (2001), the seven forecasts that were used as base models are ranked based upon the previously calculated forecast evaluation measures (e.g. most accurate =1, least accurate =7). If indeed the error measures were measuring the same thing, and doing so in a reliable manner, then the cross-correlations between the forecast error terms should be high – close to one. The error rankings are in Tables 9 and 10. The Spearman rank correlation results are in Tables 11 and 12.

The Spearman rank correlation results for Utah live cattle steers (see Table 11) indicated that the forecasting measures *generally* do not measure the same construct because of the low correlations (<0.50). For example, the sMAPE and RAE are either

Table 9. Forecast Rankings for Utah Live Cattle Steer Basis, 2010-2012

Forecast Forecast	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
	Forecast Error							
Lag-1	1	1	1	4	1	1	1	1
Lag-52	6	6	6	1	3	6	7	6
3-yr. avg.	7	7	7	5	4	7	6	7
Seasonal	4	4	4	7	5	4	3	4
Interest Supply	2	2	2	2	2	2	4	2
CD	5	5	5	6	6	5	5	5
Meat Demand	3	3	3	3	7	3	2	3

Table 10. Forecast Rankings for Western Kansas Live Cattle Steer Basis, 2010-2012

Singular Forecast	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
	Forecast Error							
Lag-1	1	1	1	1	1	1	1	1
Lag-52	7	6	7	2	6	6	7	7
3-yr. avg.	6	7	6	3	3	7	6	6
Seasonal	3	3	3	4	4	3	3	3
Interest Supply	5	5	5	5	2	5	4	5
CD	4	4	4	7	7	4	5	4
Meat Demand	2	2	2	6	5	2	2	2

negative or generally have a correlation < 0.50 with all other forecasting error measures. The rank correlation did indicate a clustering of error terms based upon the forecasting error category. For example, the scale dependent errors showed a perfect correlation (1.00) between RMSE and MSE, and a high correlation (0.50) between the RAE and

Table 11. Spearman Rank of Utah Live Cattle Steer Forecast Errors

Forecast Error	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
RMSE	1.00	1.00	1.00	0.14	0.36	1.00	0.86	1.00
MAD		1.00	1.00	0.14	0.36	1.00	0.86	1.00
MSE			1.00	0.14	0.36	1.00	0.86	1.00
MAPE				1.00	0.39	0.14	(0.21)	0.14
sMAPE					1.00	0.36	0.04	0.36
RAE						1.00	0.86	1.00
Theil's I							1.00	0.86
Theils U2								1.00

Theil's I. Problems were also noted with the Theil's I, which were negatively correlated with MAPE forecasting error. On average, the Theil's Inequality Coefficient was highly correlated with the scale dependent error values (0.86). Lastly, the Theil's U2 was highly correlated with many of the forecasting errors.

The results for Western Kansas live cattle steers (see Table 12) produced much less consistent results. The MAPE - RAE had a negative correlation of (0.04) and the majority of the scale dependent errors were highly correlated (0.96 to 1.00) with one another. This was of particular interest because it indicated some consistency in rankings across the forecast accuracy categories. The MAPE forecasting error produced the least consistent results being negatively correlated with the majority of the other forecasting errors. The Theil's I, on the other hand, once again performed well in comparison to the other forecasting errors.

Table 12. Spearman Rank of Western Kansas Live Cattle Steer Forecast Errors

Forecast Error	Forecast Error							
	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
RMSE	1.00	0.96	1.00	(0.07)	0.32	0.96	0.96	1.00
MAD		1.00	0.96	(0.04)	0.21	1.00	0.93	0.96
MSE			1.00	(0.07)	0.32	0.96	0.96	1.00
MAPE				1.00	0.54	(0.04)	-	(0.07)
sMAPE					1.00	0.21	0.50	0.32
RAE						1.00	0.93	0.96
Theil's I							1.00	0.96
Theils U2								1.00

These findings across Utah and Western Kansas produce similar results. On one hand, the rank correlation indicated a clustering of error terms based upon the forecasting error category but on the other, there are very few error terms that were highly correlated with all error categories. These findings confirm Armstrong and Collopy (2001) who found that rankings among time series models were low. Further, the Spearman correlations indicate that using an alternative method to determine which forecast should be used may be requisite.

Stochastic Dominance

Due to the fact that the forecasting errors produced conflicting results across the different error measures, stochastic dominance was used. The purpose was to to determine which singular forecasts produced the least amount of variance (e.g. risk) for producers. Stochastic dominance offers a systematic procedure to judge and subsequently select the forecasts that meet a given criteria. In order for the forecast to be considered “efficient” or “accurate,” it must dominate all other forecasts in the lower and upper RAC’s. To find the lower and upper RAC’s, this thesis followed McCarl and Bessler’s (1989) formulation of:[39]

(53) $$RAC = \pm \frac{5}{StDev.}$$

For each forecast, the standard deviation from the residuals was calculated for all seven forecasts. An average of the standard deviation of the seven forecasts was then taken. As previously mentioned, the generic interpretation of stochastic dominance cannot be applied when forecasting basis. The objective in this thesis was to minimize the variance of the singular forecast residual. Hence, a tighter PDF centered on zero was desired. When a “tight” (e.g. more accurate) singular forecast PDF was converted to a CDF, it generated a CDF that lies closer to the axis (i.e. closer to the left and highest). The direct inverse of the normal interpretation.

A graph of the probability density functions in Appendix G confirms this assumption. Table 13 displays the results for the Utah and Western live cattle singular forecasts for steers with the transformed ranks.

For Utah live cattle steers, Lag-1 and Interest Supply were both considered efficient forecasts because they dominated all other forecasts on both the lower and upper RAC bounds. The worst singular forecasting models were Lag-52 and 3 yr. avg. as they were the lowest and farthest to the right. Two forecasts in particular produced stirring

[39] In reviewing this thesis with other industry and academic experts, some have expressed some concern over the large RACs used. Upon discussing the item further, making the RACs smaller would cause nearly perfect horizontal lines. This is partially due to the formula used. Since basis is generally bounded by -5 and 5, the standard deviation will be relatively small thus causing a smaller dominator, inflating the RAC. Possibly using a different RAC formula could lower the RAC.

Table 13. Stochastic Dominance Forecast Rank Preference

Singular Forecast	Utah		Western Kansas	
	Risk Adverse[a]	Risk Loving[b]	Risk Adverse[c]	Risk Loving[d]
Lag-1	1	1	1	1
Lag-52	6	6	7	3
3-yr. avg.	7	7	6	7
Seasonal	4	3	3	4
Interest Supply	2	2	5	2
CD	5	4	4	6
Meat Demand	3	5	2	5

[a] Risk Adverse implies an RAC of -1.5
[b] Risk Loving implies an RAC of 1.5
[c] Risk Adverse implies an RAC of -1.0
[d] Risk Loving implies an RAC of 1.0

results. First, Meat Demand was considered a good forecast when a producer was risk loving but changed when a producer became risk adverse. In referencing Table 7 and 9, Meat Demand produced the second lowest forecasting error values. Thus, confirming assumptions that when a forecasting error is calculated it indicates a point estimate of accuracy rather than a range of accuracy. Second, the Contract Dummy forecast produced similar results but to a lesser extreme. Of particular interest is Lag-52 and 3-yr-avg. were not deemed “safe” or risk free forecasts. Rather, the stochastic dominance results indicate that using these forecasts would produce volatile and risky results; hence, they should be avoided by Utah live cattle producers.

For Western Kansas Steers, Lag-1 was considered an efficient forecast. For Meat Demand, when a producer was risk adverse, he/she would not use this forecast; but, when

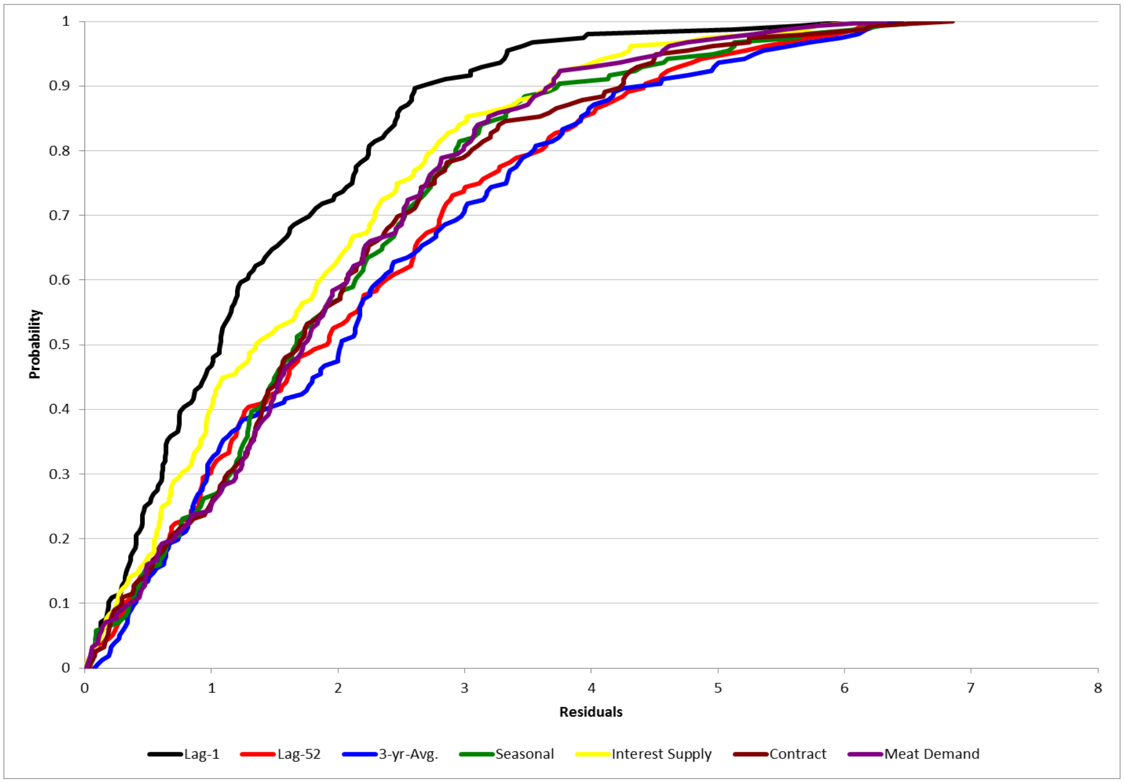

Figure 7. CDF comparison of singular forecasts for Utah live cattle steers

they were risk loving Meat Demand would be a very favorable forecast. The contrary was true for Lag-52. Similar to the forecast Meat Demand from Utah live cattle steers, Lag-52 for Western Kansas live cattle steers produced a very high forecasting error in comparison to the other forecasts; yet, it was the most preferred by cattle producers that were very risk adverse. These findings once again lend support to the idea of evaluating forecasts using a range of criteria. The forecasts that should be avoided when forecasting Western Kansas live cattle steers were 3 yr. avg. and Contract Dummies, both of which were the lowest and farthest to the right of all the CDF's. These results confirm the previous findings on forecasting errors which both produced high forecasting errors (see Table 8).

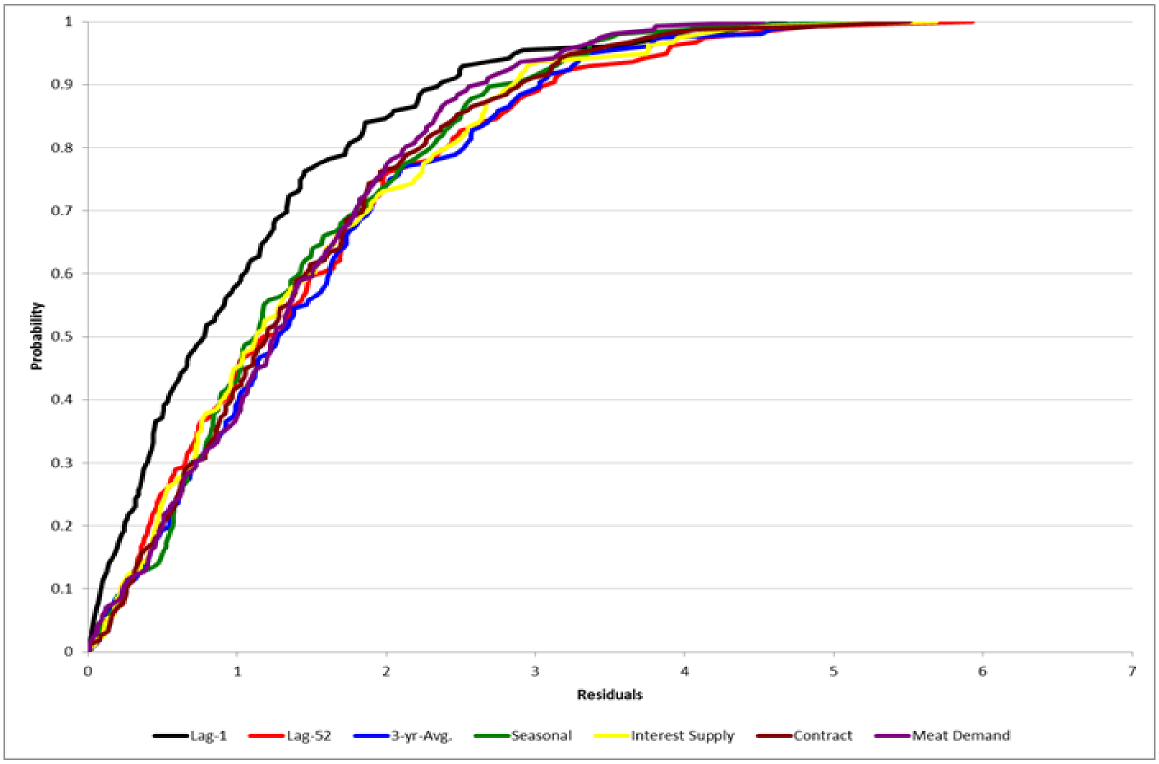

Figure 8. CDF comparison of singular forecasts for Western Kansas live cattle steers

Stochastic Efficiency

Stochastic dominance provides an objective criterion under which each singular forecast can be analyzed. One limitation of stochastic dominance was that, while it expanded upon forecasting errors, it did not provide a way to analyze a complete range of risky situations simultaneously. Because the objective of this thesis was to help producers eliminate some of the risk they faced through better forecasting, it was appropriate to determine whether or not a given forecast unilaterally dominated another forecast over a situations. Stochastic efficiency utilized this concept to analyze and rank the singular forecast model residuals for each scenario.

Since the stochastic efficiency varied the level of the risk aversion coefficient over a defined range and ranked the alternatives in terms of certainty equivalence (CE), it was helpful to determine to what degree a certain forecast was acceptable to producers. Raskin and Cochran (1986) found that the risk aversion coefficient could greatly impact the results of such analyses. As such, the upper and lower limit risk aversion coefficients (RACs) were defined using the following equation (McCarl and Bessler 1989):

(54) $$RAC = \pm \frac{5}{StDev.}$$

For the singular forecasts, the individual standard deviation was found. This was repeated for all seven forecasts. An average of the standard deviation of the seven forecasts were then taken. Figures 8 and 9 display the rankings of the singular forecasts as they relate to each other. Since the objective was once again aimed at reducing error rather than maximizing wealth, the results were interpreted inversely, or the line that was farthest to the left and closest to the origin (0, 0) was the best.

Of particular note was that the majority of the forecasts converged towards each other when a producer became more risk adverse. This implies that a producer became more risk adverse, he/she became indifferent about which forecast to use. Lag-1 and Interest Supply were the forecasts that produced the most consistent results. These results confirm the findings from stochastic dominance and forecast error measures. Meat Demand was once again preferred by risk loving producers and strongly disliked by risk adverse cattle producers. The 3-yr-avg. and Lag-52 forecasts likewise performed poorly for both risk adverse and risk loving producers. The stochastic efficiency also added a richness to the results indicating that the majority of the forecasts were stationary in their ranking position over a wide range of risk (see Table 14).

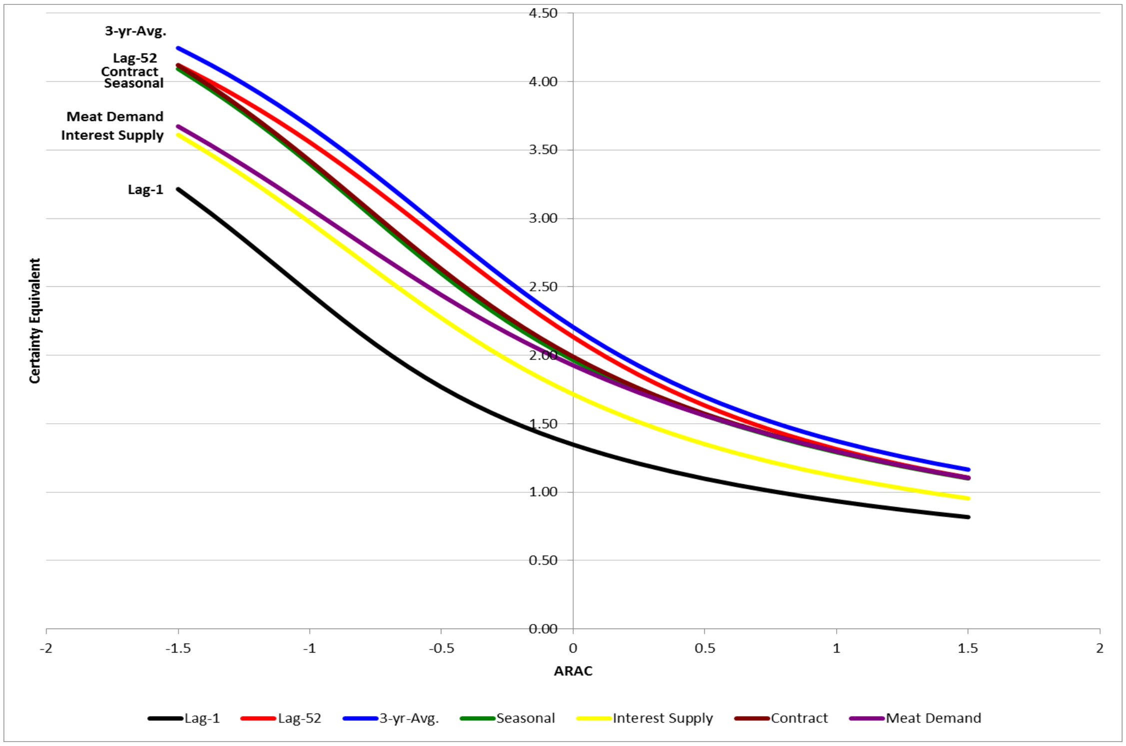

Figure 9. Stochastic efficiency of singular forecasts for Utah live cattle steers

In summary, the results produced by the stochastic efficiency chart were fairly consistent with previous findings for forecasting error, rank correlation, and stochastic dominance that the singular forecasts Lag-1 and Interest Supply were the most accurate forecasts.

Western Kansas live cattle steers (refer to Table 15 and Figure 10) produced similar results to that of live cattle steers. Lag-1 was stochastically efficient over the range of risk. Interest Supply was consistently the worst performing forecast whereas Lag-52 changed dramatically over time. Risk loving producers thought highly of Meat Demand because it varied from the second and third best forecast but risk adverse producers would not use it as it was risky. These findings places scrutiny on whether

Table 14. Stochastic Efficiency Ranks for Singular Forecasts: Risk Preference for Utah Live Cattle Steer

	Risk Preference						
Forecast	Very Risk[a] Loving	Risk[b] Loving	Semi-Risk[c] Loving	Risk[d] Neutral	Semi-Risk[e] Adverse	Risk[f] Adverse	Very Risk[g] Adverse
Lag-1	1	1	1	1	1	1	1
Lag-52	6	6	6	6	6	6	6
3-yr. avg.	7	7	7	7	7	7	7
Seasonal	4	4	4	4	3	3	3
Interest Supply	2	2	2	2	2	2	2
CD	5	5	5	5	5	4	4
Meat Demand	3	3	3	3	4	5	5

a. Very risk loving is equal to -1.50
b. Risk loving is equal to -1.00
c. Semi risk loving is equal to -0.50
d. Risk neutral is equal to 0.00
e. Semi risk adverse is equal to 0.50
f. Risk adverse is equal to 1.00
g. Very risk adverse is equal to 1.50

forecasts could be accurately analyzed solely upon forecasting error. For example, the forecast Meat Demand consistently was the second or third best forecast when analyzed using forecasting errors (see Table 8). But, when analyzed using stochastic efficiency, the results were slightly different. In general, these results were consistent with previous findings based on forecast error, ranking correlations, and stochastic dominance (see Figure 8), but they add validity to which forecasts should be chosen by producers with a given risk preference.

Risk Premiums

Risk premiums help add meaning to the stochastic efficiency results. Tables 16 and 17 present the calculated risk premiums between existing between the alternative

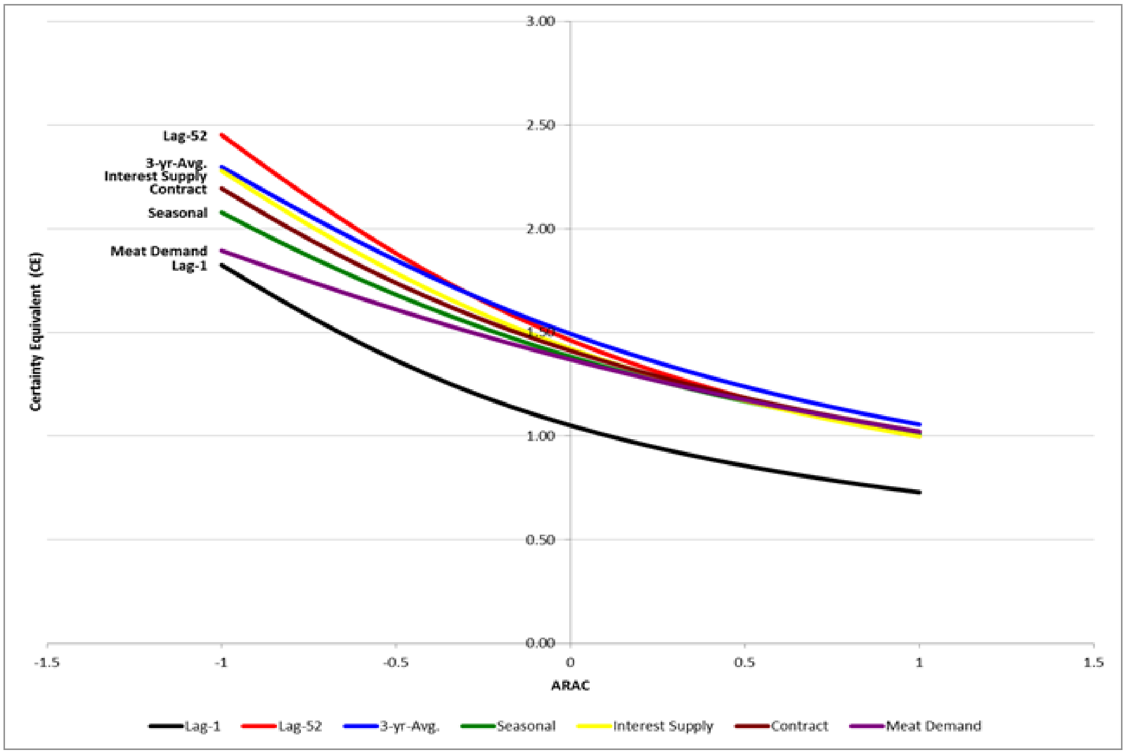

Figure 10. Stochastic efficiency of singular forecasts for Western Kansas live cattle steers

scenarios for Utah and Western Kansas live cattle steers. Because most producers are assumed to be risk adverse, the following scenarios were used: risk neutral, moderately risk adverse, risk adverse, and very risk adverse.

The risk premium is generally thought to represent the amount of money that producers would need to be paid to be indifferent about a decision. In this paper, the risk premium was interpreted as the improvement in the residuals that would need to be achieved before a producer would be indifferent about using another forecast. Lag-1 forecast was used as the base scenario to compare other forecasts because it performed the best overall under forecasting error, stochastic dominance, and stochastic efficiency. For producers in Utah (see Table 16) with that were moderately risk adverse deciding between the two lowest forecast error forecasts, Meat Demand and Lag-1, Meat

Table 15. Stochastic Efficiency Ranks for Singular Forecasts: Risk Preference for Western Kansas Live Cattle Steer

Forecast	Risk Preference						
	Very Risk[a] Loving	Risk[b] Loving	Semi-Risk[c] Loving	Risk[d] Neutral	Semi-Risk[e] Adverse	Risk[f] Adverse	Very Risk[g] Adverse
Lag-1	1	1	1	1	1	1	1
Lag-52	7	7	7	6	6	4	3
3-yr. avg.	6	6	6	7	7	7	7
Seasonal	3	3	3	3	2	3	4
Interest Supply	5	5	5	5	4	2	2
CD	4	4	4	4	5	6	6
Meat Demand	2	2	2	2	3	5	5

[a.] Very risk loving is equal to -1.00
[b.] Risk loving is equal to -0.66
[c.] Semi risk loving is equal to -0.33
[d.] Risk neutral is equal to 0.00
[e.] Semi risk adverse is equal to 0.33
[f.] Risk adverse is equal to 0.66
[g.] Very risk adverse is equal to 1.00

Demand would had to have had improved by 0.46 before a producer would have been indifferent between the two. This results provides a new dynamic to forecasting. With many low forecasting errors, a producer may appear to be indifferent between two forecasts when in fact, profitability could be increased. Lag-1 is the best forecast overall as no improvement in the forecast needs to be made over the given range of risk. Of particular interest was the rate of decrease in the risk premium – decreased exponentially as the RAC increased and maintaining the same order ranking and converging as the risk increased. The graph of the risk premiums are located in Appendix F.[40]

[40] Some academics have indicated some hesitancy in using the RPs to demonstrate payoffs because the cattle ranchers are not necessarily a function of the cattle basis. Further, the results might not indicate a perfect 1-1 tradeoff ratio.

Table 16. Risk Premiums (Difference in Certainty Equivalent) for Singular Forecasts, Utah Live Cattle Steers

Forecast	Risk[a] Neutral	Moderately[b] Risk Adverse	Risk[c] Adverse	Very Risk[d] Adverse
Lag-1	-	-	-	-
Lag-52	0.79	0.54	0.38	0.29
3-yr. avg.	0.86	0.60	0.44	0.35
Seasonal	0.62	0.46	0.36	0.28
Interest Supply	0.37	0.25	0.18	0.14
CD	0.64	0.47	0.36	0.29
Meat Demand	0.58	0.46	0.36	0.29

[a] Risk Neutral is equal to an RAC of 0.0
[b] Moderately Risk Adverse is equal to an RAC of 0.50
[c] Risk Adverse is equal to an RAC of 1.00
[d] Very Risk Adverse is equal to an RAC of 1.50

For Western Kansas producers that were moderately risk adverse would always have chosen to use the Lag-1 model. The graph in Appendix F and Table 17 reveal interesting tendencies related to the preferred forecasting method and the RACs. Further, the risk premiums enrich the rankings of stochastic efficiency. For example the risk premiums are all very similar to each other when a producer is very risk adverse. Hence, rather than a simple order rankings of which forecasts were the most accurate, risk premiums display clustering of forecasts providing more objective criterion for cattle producers. This convergence might also explain some of the discrepancies between the ranks of the different forecasts.

Both Utah and Western Kansas live cattle risk neutral producers were indifferent about the forecast accuracies of the different models and were not incentivized to use a

Table 17. Risk Premiums (Difference in Certainty Equivalent) for Singular Forecasts, Western Kansas Live Cattle Steers

Forecast	Risk[a] Neutral	Moderately[b] Risk Averse	Risk[c] Adverse	Very Risk[d] Adverse
Lag-1	-	-	-	-
Lag-52	0.41	0.35	0.31	0.27
3-yr. avg.	0.44	0.40	0.36	0.33
Seasonal	0.33	0.32	0.30	0.28
Interest Supply	0.37	0.33	0.30	0.27
CD	0.36	0.34	0.32	0.29
Meat Demand	0.32	0.32	0.31	0.29

[a] Risk Neutral is equal to an RAC of 0.0
[b] Moderately Risk Adverse is equal to an RAC of 0.33
[c] Risk Adverse is equal to an RAC of 0.66
[d] Very Risk Adverse is equal to an RAC of 1.00

particular forecast. Moreover, risk neutral could imply that producers do not consider the variance in forecast errors in their decision to use or not use a particular forecast.

Risk Summary - Singular Forecasts

A summary of these findings is useful in comparing the singular forecasts. Table 18 displays the Utah and Western Kansas findings when singular forecasts were used. The singular forecasts were evaluated for how well they performed under the forecasting error, stochastic dominance, and stochastic efficiency tests. Up to two individual forecasts were included under each category. Recommendations are also given as to which forecast should be used by producers.

Table 18. Forecast Risk Summary for Singular Forecasts

Forecast Evaluation	Utah		Western Kansas	
	Best	Worse	Best	Worse
Forecast Error	Lag-1, Internet Supply,	3-yr. avg., Lag-52	Lag-1, Meat Demand	3-yr. avg., Lag-52
Stochastic Dominance	Lag-1, Internet Supply	3-yr. avg., Lag-52	Lag-1	3-yr. avg. , Contract Dummy
Stochastic Efficiency	Lag-1, Internet Supply	3-yr. avg., Lag-52	Lag-1, Meat Demand	3-yr. avg., Lag-52
Recommendations (Yes/No)	Lag-1, Internet Supply	3-yr. avg, Lag-52	Lag-1, Meat Demand	3-yr. avg., Lag-52.

Composite Forecasts

The results from the singular forecasts suggest that all the conditions prescribed by Timmerman (2006) have been met, namely: 1) σ_1 or σ_2 are not equal to zero 2) $\sigma_1 \neq \sigma_2$ and $\rho_{1,2} \neq 1$ and 3) $\rho_{1,2} \neq \sigma_1/\sigma_2$. Based on these findings, a composite forecast could reduce the risk and increase the accuracy of a forecast.

Since the choice was made to combine forecasts (e.g. composite forecasts), particular consideration was given to the weight prescribed to each singular forecast. The gains previously proposed in the literature for combining forecasts have assumed that a simple average will perform the best over time in comparison to other weighting methods. A simple average-weighing scheme and other methods were empirically tested using an NLP minimization model. Specifically, the results answered the question of whether or not using a simple average was the most efficient weighting scheme for Utah live cattle composite forecasts.

For Utah live cattle steers (see Table 19), the "Optimal" composite forecast chose the singular forecasts Lag-1 and Meat Demand. Likewise, the four best singular models were consistently selected (see Table 7). The singular forecasts that were used the least in the composite forecasting equations were 3 yr. Avg. and Contract Dummy. These results concur with previous findings that suggested that Lag-1 and Meat Demand were the best singular models and 3 yr. Avg. and Contract Dummy were the worst.

For Western Kansas live cattle steers (see Table 20), the Optimal composite forecast consisted of Lag-1, Meat Demand, and Internet Supply singular forecasting models. Lag-1, Seasonal, and Meat Demand were the most selected singular forecasts chosen and

Table 19. Composite Forecast Weights for Different Singular Models for Utah Live Cattle Steer

	Singular Forecasts						
Composite Forecasts	Lag-1	Lag-52	3-yr. Avg.	Seasonal	Interest Supply	Contract Dummy	Meat Demand
Optimal	0.79	-	-	-	-	-	0.21
Equal	0.14	0.14	0.14	0.14	0.14	0.14	0.14
Expert Opinion	0.10	0.15	0.35	0.15	0.05	0.05	0.15
Ease-of-use	0.25	0.25	0.25	0.25	-	-	-
Best MSE	0.33	-	-	-	0.33	-	0.33
Best sMAPE	0.33	0.33	-	-	0.33	-	-
Best Theil's I	0.33	-	-	0.33	-	-	0.33
Average	0.33	0.13	0.11	0.13	0.12	0.03	0.17

Table 20. Composite Forecast Weights for the Singular Models for Western Kansas Live Cattle Steers

Composite Forecasts	Singular Forecasts						
	Lag-1	Lag-52	3-yr. Avg.	Seasonal	Interest Supply	Contract Dummy	Meat Demand
Optimal	0.67	-	-	-	0.14	-	0.19
Equal	0.14	0.14	0.14	0.14	0.14	0.14	0.14
Expert Opinion	0.10	0.15	0.35	0.15	0.05	0.05	0.15
Ease-of-use	0.25	0.25	0.25	0.25	-	-	-
Best MSE	0.33	-	-	0.33	-	-	0.33
Best sMAPE	0.33	-	0.33	-	0.33	-	-
Best Theil's I	0.33	-	-	0.33	-	-	0.33
Average	0.31	0.08	0.15	0.17	0.10	0.03	0.16

demonstrates the need for both market conditions and fast reacting time series models. The singular models that were selected among the forecasting error weighting methods (Best MSE – Best Theil's I) were Meat Demand and Lag-1 implying consistency across forecasting error measures in the singular forecasts. On the contrary, singular forecasts Lag-52 through Contract Dummy showed little consistently across error measures as they were sporadically chosen by the composite models. These findings were consistent with the findings from Table 8.

Composite Forecast Errors

New composite forecasting errors were calculated. This was done by taking the individual singular forecast residuals and multiplying them by the calculated weight. After summing the new residuals over each separate time period, a new composite weight was obtained. Forecasting accuracy measures were then calculated and the results are displayed in Tables 20 and 21.

The results from the composite forecasting models for Utah live cattle steers showed a reduction in forecast errors using the Optimal forecast in comparison to the best singular model (see Table 7 for original forecasting error). [41] A reduction in the forecast error for the Optimal forecast was generally consistent across the forecasting error measures with the exception of the MAPE and sMAPE. Theil's U2 indicated that all forecast models yielded better results than simply guessing as the values for Theil's U2 statistics were less than one in all forecasting error measures. Similar to the singular forecast findings, the MAPE and sMAPE forecasting errors were skewed either high or low, respectively (see Table 7). The MAPE forecasting error and its' derivatives were only reported in 5% of the basis forecasting literature (see Figure 2) providing an explanation as to why academics have chosen to shy away from such a measure. These results and findings from the literature suggest that using percentage error measures when forecasting basis may be problematic.

The results for Western Kansas produced slightly different results (see Table 22). While the Optimal composite forecasts generally produced the lowest forecasting error across different measures, it was slightly higher than the lowest singular forecasting error (see Table 8). This indicated that the Optimal composite forecast was slightly inferior in performance to the best performing singular model. Theil's U2 indicated that all composite models were better than guessing. Likewise, the Theil's Inequality Coefficient

[41] A comparison between the forecasting errors of the singular models and the composite models confirm the assumption that the forecasting errors can be improved upon. See Appendix K for the full breakdown of these forecasting error improvements were positive numbers represent that the composite forecasts outperformed the singular models, and vice versa.

Table 21. Composite Forecast Accuracy for Utah Live Cattle Steers

Composite Forecast	Forecasting Error							
	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Optimal	1.76	1.38	3.10	610.1	182.7	0.64	0.399	0.67
Equal	2.19	1.77	4.81	576.6	423.0	0.82	0.491	0.83
Expert Opinion	2.32	1.88	5.40	596.9	2,079.9	0.88	0.514	0.88
Ease-of-use	2.21	1.78	4.91	593.0	439.9	0.83	0.504	0.84
Best MSE	1.92	1.54	3.68	553.9	314.5	0.71	0.434	0.72
Best sMAPE	2.01	1.60	4.05	507.1	221.3	0.74	0.486	0.76
Best Theil's I	2.02	1.64	4.06	621.3	349.9	0.76	0.438	0.76

(Theil's I) produced the lowest bias implying it was the most accurate over time. When using the RAE forecasting error to compare models, the Optimal and Best Theil's U2 composite forecasting models performed the best. The problems with the MAPE and sMAPE were likewise noticeable in Western Kansas live cattle steers.

The findings above support the conclusion that, depending on which error term is used, a producer can make different conclusions about when to buy and sell. In order to determine which weighting method was the most appropriate to use, an ordered rank was conducted to see if there was consistency across the different composite forecasts. The seven weighting methods were ranked based upon the variance and forecast error (e.g. most accurate =1, least accurate =7). Both Utah and Western Kansas live cattle steer rankings were reported.

The numerical rankings of Utah live cattle steers (see Table 21) indicated that the Optimal composite forecast tended to perform well across all forecasting errors. Likewise, the Equal weighting systems proved also very accurate. This indicated that

Table 22. Composite Forecast Accuracy for Western Kansas Live Cattle Steers

Composite Forecast	**Forecasting Error**							
	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Optimal	1.41	1.06	1.99	183.3	790.5	0.74	0.431	0.76
Equal	1.60	1.26	2.56	243.7	350.2	0.88	0.562	0.86
Expert Opinion	1.64	1.30	2.70	234.9	390.3	0.91	0.596	0.88
Ease-of-use	1.60	1.25	2.57	202.3	400.5	0.87	0.604	0.86
Best MAD	1.49	1.18	2.21	240.9	455.4	0.82	0.502	0.80
Best sMAPE	1.56	1.22	2.42	217.9	566.4	0.85	0.553	0.84
Best Theil's I	1.49	1.18	2.21	240.9	455.4	0.82	0.502	0.80

while deriving an optimal combination can be difficult, once obtained it can outperform equal weights. The Best sMAPE and Best Theil's I composite models were continually ranked lower than other composite models. This implies that while equal weights perform well, screening forecasts based solely upon forecasting error rather than inclusion of relevant information may produce inferior results. Moreover, it suggests that the error measure was not helpful in the decision making process when forecasting basis composite weights. Expert Opinion weighting likewise performed poorly or average. This confirms the findings of Colino et al. (2010) who found that extension forecasts proved to be the most inaccurate for live hogs in Iowa and Minnesota.

The forecasts for Western Kansas live cattle steer basis told a similar story. The Optimal composite forecast produced consistent results with relatively little fluctuations across different forecasting error measures. Best MSE produced somewhat consistent results, generally being ranked as the second most accurate error measure of those considered. Overall, Western Kansas steer basis forecasts produced more tenuous results than the forecasts for the Utah live cattle steer basis making generalizations across cattle types more difficult to make.

Spearman Rank

To determine whether or not the different composite forecasting errors were consistent, an analysis of their content validity was conducted. Using the ranked composite forecast errors, a Spearman rank correlation was conducted. If indeed the different forecasting errors were measuring the same thing across the different error measures, then one would expect the cross-correlations between the forecast error terms to be high – close to one. Tables 23 and 24 revealed both consistencies and problems with the ranking of the error terms. Utah live cattle steers showed consistency in the scale-dependent (RMSE – MSE), and in the relative measure (Theil's I – Theil's U2), errors implying that decisions made by producers based on these error measures should be fairly consistent (see Table 25).

Table 23. Composite Forecast Rankings for Utah Live Cattle Steers

	Forecasting Error							
Composite Forecast	RMSE	MAD	MAE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Optimal	1	1	1	6	1	1	1	1
Equal	2	2	2	2	3	2	2	2
Expert Opinion	4	4	4	7	4	4	3	4
Ease-of-use	3	3	3	1	2	3	4	3
Best MSE	5	5	5	3	5	5	5	5
Best sMAPE	7	7	7	5	7	7	7	7
Best Theil's I	6	6	6	4	6	6	6	6

Table 24. Composite Forecast Rankings for Western Kansas Live Cattle Steers

Composite Forecast	Forecasting Error: RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Optimal	1	1	1	1	7	1	1	1
Equal	5	6	5	7	1	6	5	5
Expert Opinion	7	7	7	4	2	7	6	7
Ease-of-use	6	5	6	2	3	5	7	6
Best MSE	2	2	2	5	4	2	2	2
Best sMAPE	4	4	4	3	6	4	4	4
Best Theil's I	3	3	3	6	5	3	3	3

Table 25. Spearman Rank of Utah Live Cattle Steers Composite Forecast Errors

Forecast Errors	Forecasting Errors: RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
RMSE	1.00	1.00	1.00	0.11	0.96	1.00	0.96	1.00
MAD		1.00	1.00	0.11	0.96	1.00	0.96	1.00
MSE			1.00	0.11	0.96	1.00	0.96	1.00
MAPE				1.00	0.14	0.11	-0.11	0.11
sMAPE					1.00	0.96	0.89	0.96
RAE						1.00	0.96	1.00
Theil's I							1.00	0.96
Theils U2								1.00

The composite forecasting Spearman rank correlation coefficients produced much more robust findings than the singular forecasts. Nearly all the correlation coefficients are very high with a few exceptions. The Theil's I – MAPE produced a negative correlation (-0.11). A variation from the findings from the singular models is that the sMAPE forecasting error is highly correlated with the other forecasting weighting schemes. The high correlations enjoyed by the scale-dependent errors allows for producers to choose amongst the RMSE, MAD, and MSE. Overall, the composite findings indicate strong content validity among the weighting schemes.

The cross-correlation findings for Western Kansas steers (see Table 26) among the various forecasting errors yielded inconsistent relationships among the various forecasting error measures. Some error terms were almost perfectly inversely correlated (e.g. MAD – sMAPE of -0.82). The consistency seen in Utah live cattle steers were not present in Western Kansas steers. A possible explanation for this is that the volume of Western Kansas is larger producing divergent results from that of smaller markets. Similarly, the sMAPE produced highly inconsistent results similar to the singular forecasts.

Table 26. Spearman Rank of Western Kansas Live Cattle Steer Composite Forecast Errors

	Forecasting Errors							
Forecast Errors	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
RMSE	1.00	0.96	1.00	0.14	(0.75)	0.96	0.96	1.00
MAD		1.00	0.96	0.32	(0.82)	1.00	0.89	0.96
MSE			1.00	0.14	(0.75)	0.96	0.96	1.00
MAP				1.00	(0.57)	0.32	0.07	0.14
sMAPE					1.00	(0.82)	(0.71)	(0.75)
RAE						1.00	0.89	0.96
Theil's I							1.00	0.96
Theils U2								1.00

Stochastic Dominance

In order to determine which singular forecasts produced the least amount of variance (e.g. risk) for producers, stochastic dominance was used. Stochastic dominance offered a systematic procedure to judge and select forecasts. In order for the composite forecast to be considered "efficient" or "accurate," it must dominate all other forecasts in the lower and upper RAC's. To find the lower and upper RAC's, this thesis followed McCarl and Bessler's (1989) formulation of

(55) $\text{RAC}= \pm \frac{5}{StDev.}$

The standard deviation of each composite forecast's residuals was found. An average of the standard deviation of the composite was then taken. The composite forecasts were evaluated using this methodology for both Utah and Western Kansas live cattle steers.

As previously mentioned, the usual interpretation of stochastic dominance cannot be applied when using basis forecasts. The objective in this study is to develop forecasting methods to minimize the variance of the composite forecasting residual. Hence, a tighter PDF for the forecast errors that is centered on zero was desirable. When a "tight" (e.g. more accurate) composite forecasting PDF is converted to a CDF, it generates a CDF that lies closer to the axis (e.g. closer to the left and highest; this is the direct inverse of the normal interpretation in stochastic dominance analysis). A graph of the PDFs in Appendix G confirms this assumption. Tables 27 displays the results for the Utah and Western Kansas live cattle composite forecasts for steers. The ranks have already been transformed as suggested above.

Several conclusions can be made about how producers selection of a composite forecasting method would change with respect to a given risk preference. First, the Optimal composite forecast dominated most other weighting techniques across all risk preferences. This entails that that while the error measure used may vary, the findings of the optimal weighting system dominating other forecasts will not.

Second, the Equal composite forecast were consistently dominated by other composite forecasting methods across all risk preferences. In fact, the Equal composite forecast that served as the bench mark for all composite forecasts consistently underperformed other weighting methods in terms of the stochastic dominance analysis (see Table 27). While this was consistent with some literature, the degree by which the Equal composite forecast was dominated may be of particular interest to other researchers.

Table 27. Stochastic Dominance Ranks: Risk Preference for Live Cattle Steers

	Utah		Western Kansas	
Composite Forecast	Risk Loving[a]	Risk Adverse[b]	Risk Loving[c]	Risk Adverse[d]
Optimal	1	1	1	1
Equal	6	6	5	6
Expert Opinion	7	7	7	7
Ease-of-use	5	5	6	5
Best MSE	2	2	3	3
Best sMAPE	3	3	4	4
Best Theil's I	4	4	2	2

[a] Risk loving is equal to an RAC of -1.2
[b] Risk Adverse is equal to an RAC of 1.2
[c] Risk loving is equal to an RAC of -0.96
[d] Risk Adverse is equal to an RAC of 0.96

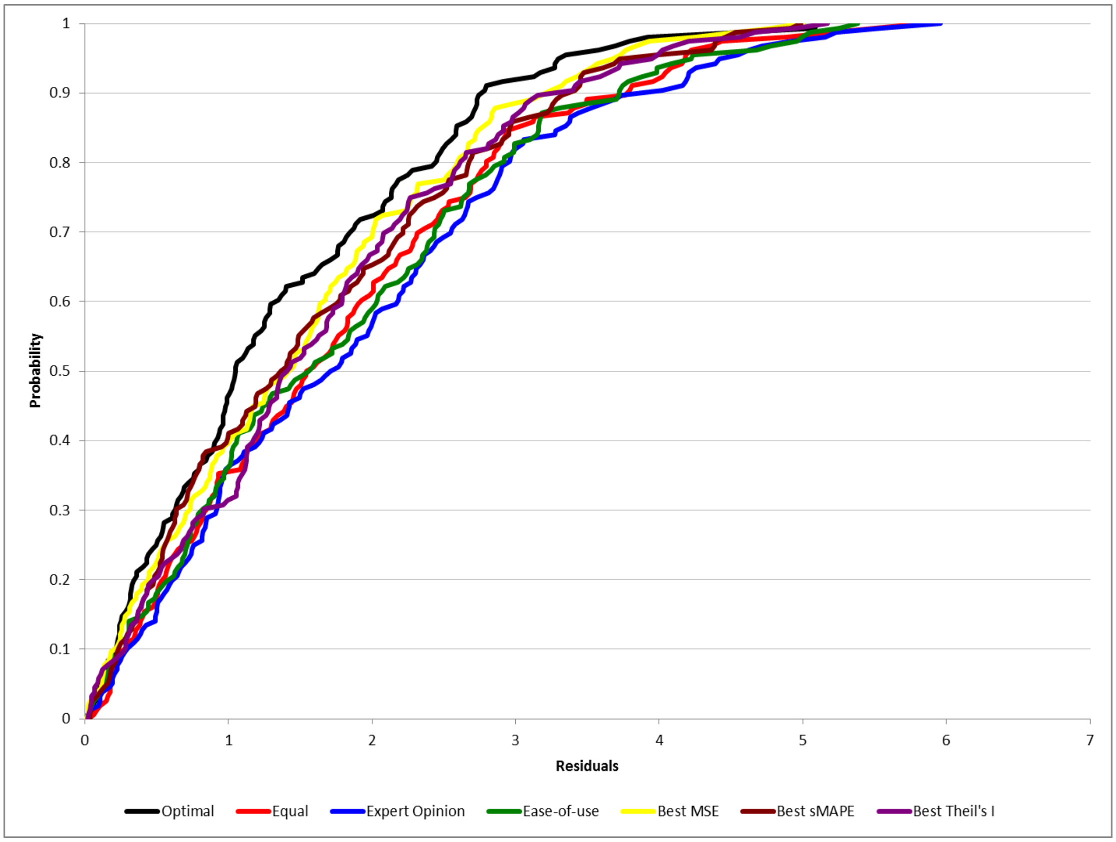

Figure 11. CDF comparison of composite forecast errors for Utah live steers

Third, Ease-of-Use and Expert Opinion were primarily dominated by other forecasting methods across all risk preferences. Both Expert Opinion and Ease-of-Use were common forecasting models for cattle producers, yet they were always found to underperform in the case of this analysis. These findings strengthen the previous findings from the Spearman rank correlation and call into question whether extension forecasting, which is based solely upon Expert Opinion, was reliable compared to other forecasting methods.

Fourth, the seemingly negative results for Equal and Expert Opinion results were most pronounced for Utah and Western Kansas risk loving preference where they were both ranked 6th and 7th, respectively. This suggested that these weighting techniques were not suited if producers are risk loving and seeking to corner markets. This may be due in

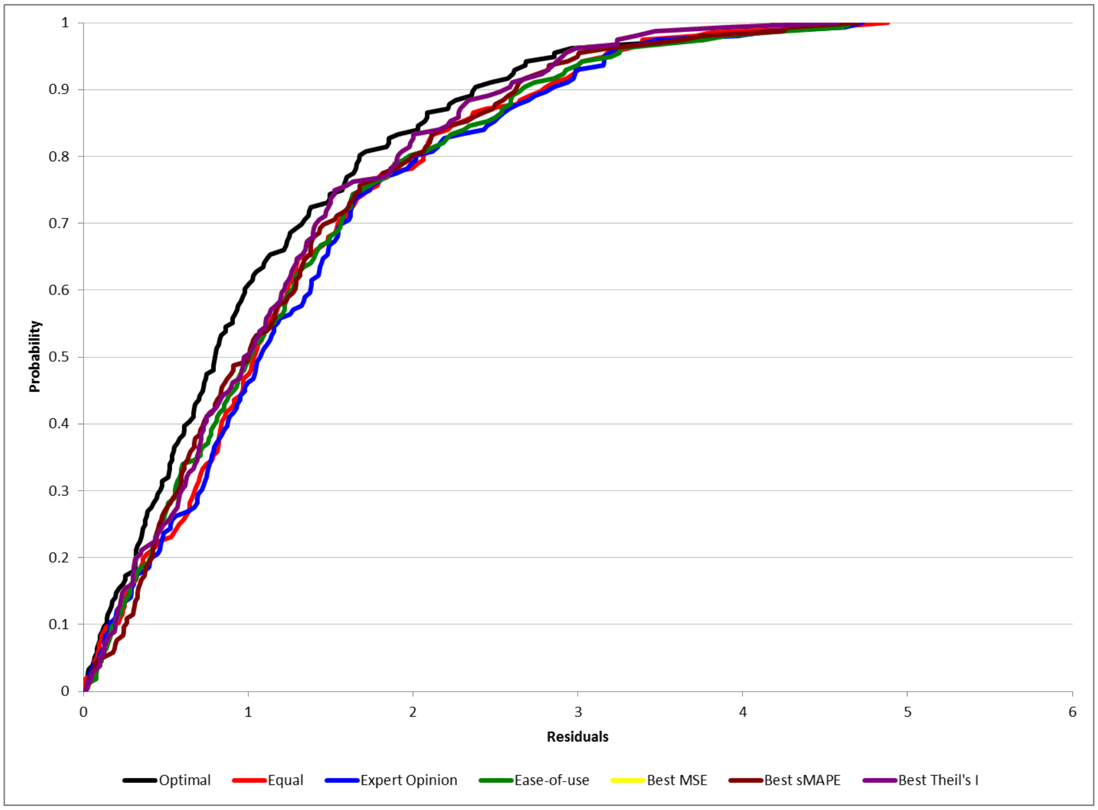

Figure 12. CDF comparison of composite forecast errors for Western Kansas live steers

part that expert opinions are often conservative estimates rather than progressive and optimistic.

Lastly, depending on the producer's forecasting error preference, a different composite forecast was likely to have been chosen. For example, for Utah live cattle steers, the Best MSE model would have been chosen for risk adverse and risk loving producers. For Western Kansas live cattle steers, the forecasting error would have been the best Theil's I. This denoted that risk preferences in producers can enhance composite forecasting decision making. Figure's 11 and 12 confirm these results graphically while providing the corresponding percentages in which certain forecasts were dominated.

Stochastic Efficiency

The stochastic efficiency technique varied the risk aversion coefficient over a defined range and ranked the alternatives in terms of the certainty equivalence (CE). Stochastic efficiency was helpful in determining to what degree a certain forecast was "acceptable" to a cattle producer. The upper and lower limit RACs were defined using McCarl and Bessler 1989) (see Equation 51).[42]

Figures 13 and 14 graphically display the ranking of the singular forecasts as they relate to each other for Utah and Western Kansas live cattle steer basis. As some of the graphs are difficult to interpret visually, an accompanying table is provided. Table 28 and 29 display the rank of each composite forecast over a range of risk preferences. Because the objective was once again aimed at seeking a tight distribution of forecast residuals rather than necessarily maximizing returns, the results must be interpreted inversely from the "normal" stochastic efficiency approach. In other words, the line in Figure 13 that was the closest to the origin was the best and the line farthest away was the worst of the different alternatives considered.

Figure 13 shows that the Optimal composite forecast dominated all forecasts over the range of risk preferences and grew slightly less advantageous to use as a producer becomes more risk adverse for Utah live cattle steers. The composite forecasts that performed poorly were the Equal and Expert Opinion for risk lovers and risk-adverse producers. Table 28 indicates that the Best MSE performed well as a producer goes from being risk-loving to being risk-adverse. The opposite was true for Equal and Expert Opinion which steadily decreased or stayed the same over the range of risk. The results

[42] Please refer to these as Raskin and Cochran (1986) who found that modifying the RACs can have an impact on the stochastic dominance results.

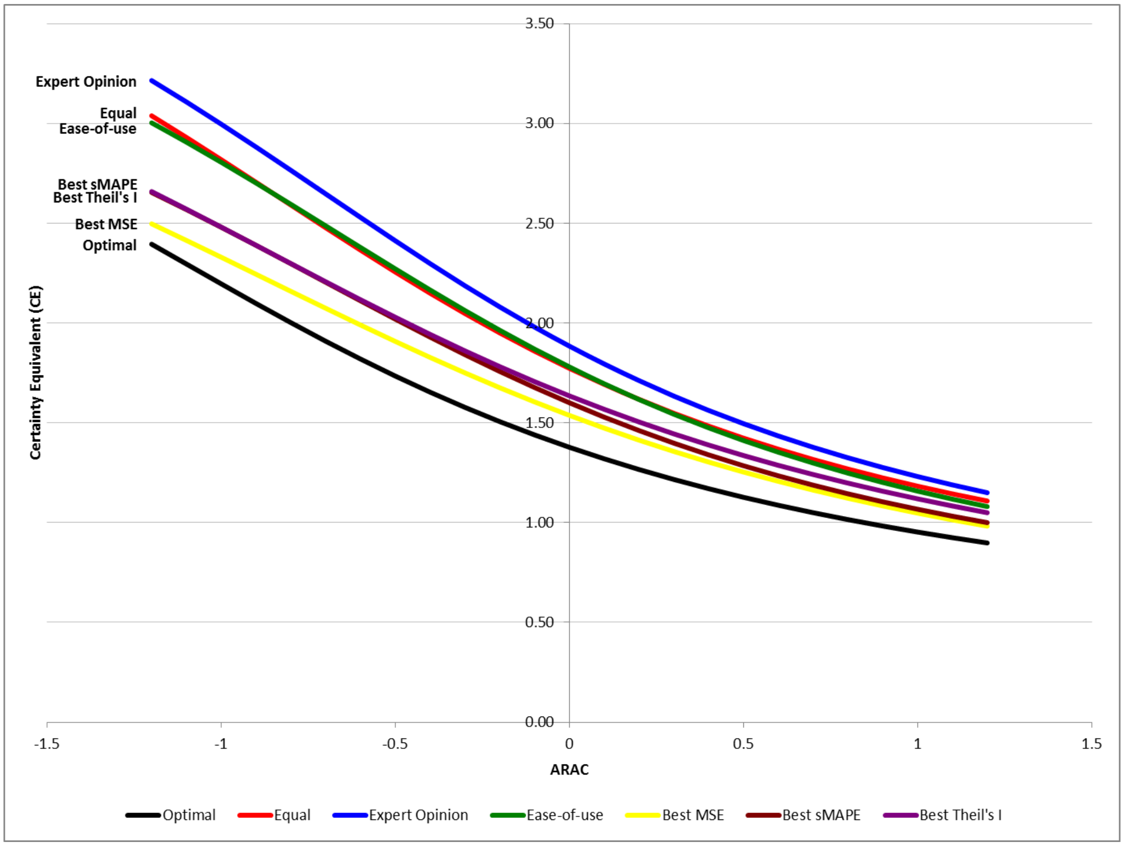

Figure 13. Stochastic efficiency of composite forecasts for Utah live cattle steers

denoted that using the Optimal composite forecast would appeal to both risk-loving and risk-adverse producers.

Whereas the forecasting error analysis for Western Kansas live cattle steers produced conflicting results about which composite forecast should be used to make decisions based on basis forecasting, the stochastic efficiency analysis produced clear results – the Optimal composite forecast should be used based on the stochastic efficiency analysis. The Optimal composite forecast dominated the other composite forecasting models and became more attractive for producers as it producers went from risk-loving to risk-adverse. While the figure shows that the forecasts are fairly grouped together, the CEs indicate that the Optimal dominates all other forecasts.

Table 28. Stochastic Efficiency Ranks for Composite Forecasts: Risk Preference for Utah Live Cattle Steers

	Risk Preference						
Composite Forecast	Very Risk[a] Loving	Risk[b] Loving	Semi-Risk[c] Loving	Risk[d] Neutral	Semi-Risk[e] Adverse	Risk[f] Adverse	Very Risk[g] Adverse
Optimal	1	1	1	1	1	1	1
Equal	6	5	5	5	6	6	6
Expert Opinion	7	7	7	7	7	7	7
Ease-of-use	5	6	6	6	5	5	5
Best MSE	2	2	2	2	2	2	2
Best sMAPE	3	3	3	3	3	3	3
Best Theil's I	4	4	4	4	4	4	4

[a.] Very risk loving is equal to -1.20
[b.] Risk loving is equal to -0.80
[c.] Semi risk loving is equal to -0.40
[d.] Risk neutral is equal to 0.00
[e.] Semi risk adverse is equal to 0.40
[f.] Risk adverse is equal to 0.80
[g.] Very risk adverse is equal to 1.20

Likewise, the second best composite model to use was the Best MSE. The worse models were Equal, Ease-of-use, and Expert Opinion. These two models consistently performed poorly (i.e., were dominated by other alternatives) over the full range of risk preferences pointing producers away from using these methods. There was relatively little change in the order of the composite forecasts as a producer goes from being risk-loving to being risk-adverse in the analysis, with the exception of the Ease-of-Use model, which showed marginal improvements (i.e., was more preferred as a producer became more risk-adverse).

The stochastic efficiency results confirmed that the Optimal composite forecast were preferred to all other models over the entire range of risk preferences. It also

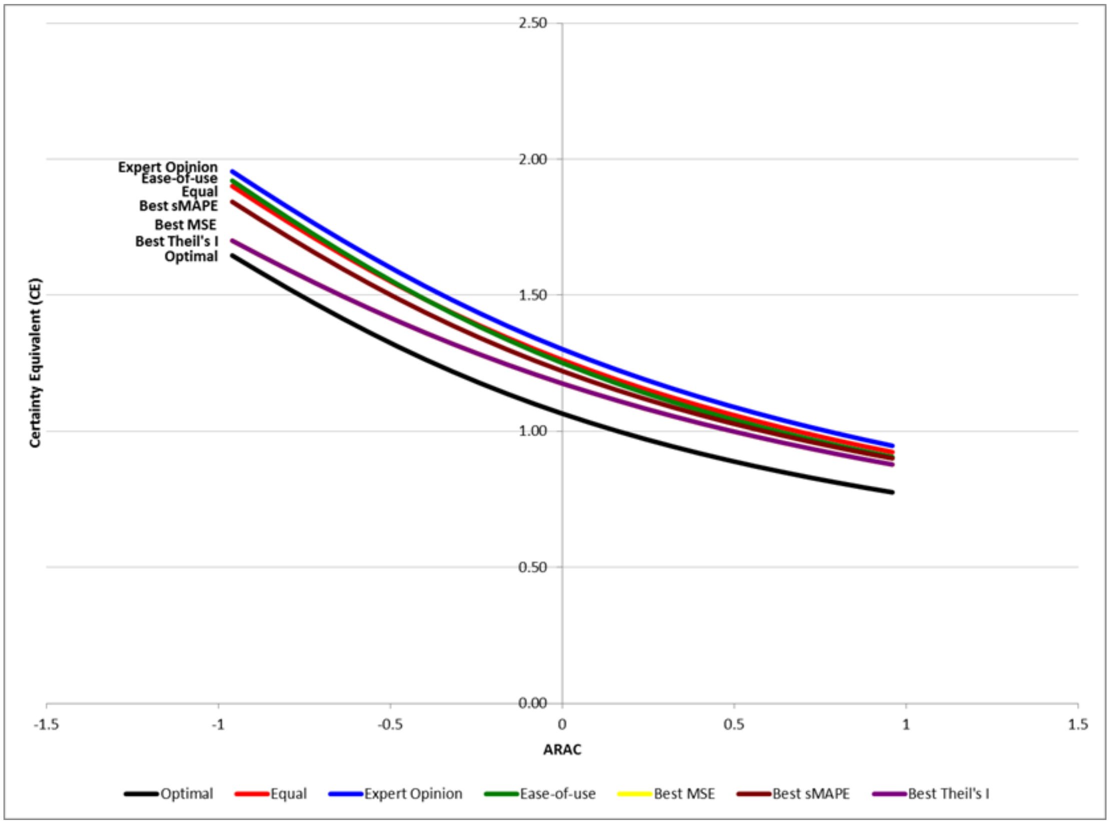

Figure 14. Stochastic efficiency of composite forecasts for Western Kansas live cattle steers

clarified which models were preferred between the upper and lower risk levels. These findings added support to the idea that stochastic efficiency could be used as a decision-making tool to determine which composite forecasts can be used by cattle producers.

Risk Premiums

The aforementioned results can be further strengthened by the findings for risk premiums as they relate to each composite forecast. Table 30 presents the calculated risk premiums between alternative scenarios. Because most producers are assumed to be risk-adverse, the following scenarios were used: risk neutral, moderately risk adverse, risk adverse, and very risk adverse. Risk premiums can be visualized in several ways.

Table 29. Stochastic Efficiency Ranks for Composite Forecasts: Risk Preference for Western Kansas Live Cattle Steers

	Risk Preference						
Composite Forecast	Very Risk[a] Loving	Risk[b] Loving	Semi-Risk[c] Loving	Risk[d] Neutral	Semi-Risk[e] Adverse	Risk[f] Adverse	Very Risk[g] Adverse
Optimal	1	1	1	1	1	1	1
Equal	5	5	6	6	6	6	6
Expert Opinion	7	7	7	7	7	7	7
Ease-of-use	6	6	5	5	5	5	5
Best MSE	2	2	2	2	2	2	2
Best sMAPE	4	4	4	4	4	4	4
Best Theil's I	3	3	3	3	3	3	3

[a.] Very risk loving is equal to -0.96
[b.] Risk loving is equal to -0.64
[c.] Semi risk loving is equal to -0.32
[d.] Risk neutral is equal to 0.00
[e.] Semi risk adverse is equal to 0.32
[f.] Risk adverse is equal to 0.64
[g.] Very risk adverse is equal to 0.96

First, referring back to the stochastic efficiency graph in Figure 9, the difference between the two lines represents the risk premium that a given producer will place over another given alternative at a given risk preference. Hence, it was generally thought to represent the amount of money that producers would need to be paid to be indifferent about the two models in making a decision.

In this paper, it can be interpreted as the improvement in the composite forecasting residual that needs to be achieved before a producer is indifferent about using another composite forecast.

As the Optimal composite forecast dominated the other composite forecasting models, it was used as the basis for comparison with all the other composite forecasts. Table 30 displays the risk premiums for Utah live cattle steers and Table 31 displays the

Table 30. Risk Premiums (Improvement in Residuals) for Composite, Utah Live Cattle Steers

Composite Forecast	Risk[a] Neutral	Moderately[b] Risk Adverse	Risk[c] Adverse	Very Risk[d] Adverse
Optimal	-	-	-	-
Equal	0.40	0.31	0.25	0.21
Expert Opinion	0.51	0.39	0.31	0.25
Ease-of-use	0.40	0.30	0.23	0.18
Best MSE	0.16	0.13	0.11	0.08
Best sMAPE	0.22	0.17	0.13	0.10
Best Theil's I	0.26	0.22	0.18	0.15

[a] Risk Neutral is equal to an RAC of 0.0
[b] Moderately Risk Adverse is equal to an RAC of 0.40
[c] Risk Adverse is equal to an RAC of 0.80
[d] Very Risk Adverse is equal to an RAC of 1.20

Table 31. Risk Premiums (Improvement in Residuals) for Composite, Western Kansas Live Cattle Steers

Composite Forecast	Risk[a] Neutral	Moderately[b] Risk Adverse	Risk[c] Adverse	Very Risk[d] Adverse
Optimal	-	-	-	-
Equal	0.20	0.18	0.16	0.15
Expert Opinion	0.24	0.21	0.19	0.17
Ease-of-use	0.19	0.16	0.15	0.13
Best MSE	0.11	0.11	0.11	0.10
Best sMAPE	0.16	0.14	0.13	0.12
Best Theil's I	0.11	0.11	0.11	0.10

[a] Risk Neutral is equal to an RAC of 0.0
[b] Moderately Risk Adverse is equal to an RAC of 0.50
[c] Risk Adverse is equal to an RAC of 1.00
[d] Very Risk Adverse is equal to an RAC of 1.50

risk premiums for Western Kansas live cattle steers with accompanying graphs in Appendix F.

For Utah live cattle steers, the Optimal composite forecast would always be used among producers who were risk neutral, moderately risk adverse, and risk adverse. The rank of the forecasts remained relatively constant. There was a shrinking risk premium for Best sMAPE and Best Theil's I as a producer became more risk adverse implying that a producer was less incentivized to use another composite forecast as they become more risk adverse. Western Kansas steers show similar results to those of live steers with one exception. The exception being that the Best sMAPE showed a decreasing risk premium.

Risk Summary – Composite Forecasts

A summary of these findings is useful in comparing the composite forecasts. Table 32 displays the Utah and Western Kansas live cattle steer findings when composite forecasts were used. The singular forecasts were evaluated for how well they performed under the forecasting error, stochastic dominance, and stochastic efficiency tests. Up to two weighting methods were included under each category. Recommendations are also given as to which weighting methods should be used by producers.

Table 32. Forecast Risk Summary for Composite Forecasts

Forecast Evaluation	**Utah**		**Western Kansas**	
	Best	Worse	Best	Worse
Forecast Error	Optimal, Equal	Best Theil's I, Best sMAPE	Optimal	Expert Opinion, Ease-of-use
Stochastic Dominance	Optimal, Best MSE	Expert Opinion, Equal	Optimal, Best Theil's I	Expert Opinion, Ease-of-use
Stochastic Efficiency	Optimal, Best MSE	Expert Opinion, Equal	Optimal	Expert Opinion, Equal
Recommendations (Yes/No)	Optimal, Best MSE	Expert Opinion	Optimal	Expert Opinion, Ease-of-use

CHAPTER 6

CONCLUSIONS

Within the live cattle basis market in Utah, there is a need to provide accurate tools that are accessible to cattle producers. Cattle producers can increase profitability in their respective enterprise by reducing costs or increasing revenues. This thesis proposes a simple and time-effective way for Utah and Western Kansas cattle producers to increase revenues by more accurately predicting movements in price.

Three main contributions to the literature discussed in this thesis were the following: First, that composite basis forecasts can be used to reduce forecast variance and error in Utah and Western Kansas live cattle basis. Second, stochastic dominance and efficiency tests could be used to systematically select forecasts that would create the most profitability for cattle producers. Third, the thesis provided evidence that the forecasting error measures that are currently being used in the agricultural forecasting literature can provide misleading information about which forecasting models are most accurate and should be used by producers.

Lessons Learned

The results indicated that Utah and Western Kansas fed cattle producers' profitably can be increased by combining forecasts while reducing their exposure to basis risk. The main lessons learned from this study are as follows:

Singular and Composite Forecasts

Central to the argument of combining forecasts is the notion that it is difficult to produce a weight distribution across forecasts that will outperform a simple arithmetic mean. The results from this thesis indicate that the Optimal composite forecast consistently outperformed the Equal composite forecast for Utah and Western Kansas live cattle steers across a range of risk preferences.

A principal goal in forecasting is to create a model that depicts reality while being as accurate as possible. Strong evidence was found in this study in support of creating better singular forecasts. When stronger singular models are created, it provides a better mixture of composite forecasting weights. This was seen with Lag-1 and Meat Demand. These forecasts were individually the most accurate. Consequently, they were chosen the most often in the composite forecast combinations. Thus, producers should seek out ways to create or improve forecasting models in an effort to increase the benefits of using composite weights. This is particularly useful for extension agencies, whose job it is to provide free and accurate price forecasts to producers. These results should also strengthen their commitment to provide increasingly accurate forecasts to producers so they can forecast basis more precisely and increase overall profitability.

In an effort to improve seasonality forecasting for Utah and Western Kansas live cattle steer basis, Chicago futures contract dummies replaced the traditional monthly dummy variable model. The forecasting accuracy was significantly improved when futures contract dummies were used (see Table 39). This finding has a direct impact upon cattle ranchers who sell to slaughter houses. Since futures price data is assumed to be unbiased and an efficient price forecast, slaughter houses use this data to generate pricing offers to cattle ranchers. The rancher then has the opportunity to sell at that given price. Since the price offered to the cattle producer was derived from the futures market, logic might dictate that, ceteris paribus, a forecasting model that represented contract breaks would perform well. The results indicated that it does perform mediocre for Utah and Western Kansas live cattle steers. For producers who are looking for a simple and more efficient way to forecast basis, using live cattle future contract dummies provides a plausible useful alternative.

Consistency in Forecasting Errors

Scale dependent forecasting errors are rampant in the basis forecasting literature. This research suggests that using this type of forecasting error may lead producers to make inaccurate conclusions about whether or not to use a given forecast. For example, a producer may conclude, based on the RMSE that a given forecast is the most accurate; however, if the Theil's U2 is calculated, it may indicate that in fact another forecast is more accurate. These results imply that when live cattle basis forecasts are reported, they display a variety of forecasting error measures that should be provided to increase producers' confidence that the model they have selected is the most accurate and reliable.

A Spearman rank correlation that statistically displays the errors' content validity—and that they measure what they are intended to measure—should accompany the reporting of a variety of error measures.

The results from this thesis indicated that among certain forecasting error categories (e.g. scale-dependent, percentage error etc.) content validity was lacking. When extension reports are made available, these correlations would assist producers in selecting the forecast that they deem to be the most accurate. Methods and futures studies should detail why the errors were not consistent. When the errors are not consistent and produce different results, alternative forecasting evaluation methods such as stochastic dominance and stochastic efficiency should be used to determine which singular or combination of forecasts are the most accurate.

This thesis also detailed how forecasting errors must be adjusted for data series, such as basis, that have a meaningful zero. This limitation causes a distortion in the data and generally inflates certain forecasting error measures such as the MAPE (see Tables 7, 8, 21, and 22). An explanation of the forecast errors that produce biased or misleading results when forecasting basis will also be helpful to producers. As extension economists understand the limitations and adjustments when forecasting basis, they would be able to provide more accurate information having a positive effect on a producers overall profitability.

Stochastic Dominance, Stochastic Efficiency, and Risk Premiums

Cattle producers in Utah especially are exposed to high levels of basis volatility because of low trading volume in comparison to other states. This volatility, as shown above, can produce forecasting errors that are not as consistent. Stochastic dominance and stochastic efficiency provide a pragmatic alternative to screening singular and composite forecasts. The results also provide a rich amount of pertinent information for cattle producers.

For example, the stochastic dominance analysis indicated that, on average, the Optimal composite forecast was the most effective for Utah and Western Kansas live cattle steers. These findings were enhanced by the findings from the stochastic efficiency figures. The findings inform producers that the Optimal weighting technique is upheld over a range of risk preferences, further strengthening its usage by producers as it provides a risk diversified alternative.

By comparing the best singular forecasts with the Optimal composite forecast, the best forecast sometimes out performs the Optimal composite forecast, but at a minimum level. These findings support the idea for using composite forecasts. Using a composite forecast will produce low forecasting error while also providing a security against structural breaks with a diversified portfolio of forecasts.

Risk premium measures can help quantify the amount that each individual forecast will need to be improved in order for a producer to be indifferent about two forecasts. For example, for Utah and Western Kansas live cattle steers, the composite forecasts Expert Opinion and Equal Weights will need to greatly improve before a risk loving and risk adverse producer will use them. In essence, Utah cattle producers can use the risk premiums as a decision making tool. Risk premiums, coupled with experience, can help producers determine which forecast to use and if diversification is requisite in a given year.

Stochastic efficiency allows a producer to determine how his/her production decisions will change based upon his/her risk preference. Sometimes these changes are dramatic, as seen with Western Kansas live cattle steers. The results indicated that the statistical difference between weighting techniques for risk lovers was much larger than risk adverse. Further, the different weighting techniques were inclined to converge as a producer became more risk adverse. The Optimal composite forecast also provided the most accurate information for Utah live cattle steer producers. Overall, producers can properly select which forecast is the most accurate over a range of risk.

Limitations & Further Research

While the results of this study are promising, the results are limited in some areas. First, there a low number of observations for the Spearman rank correlations. Statistically speaking, there was reduced validity in these findings. Armstrong and Collopy (1992) used 18 different data series and then increased that number to 90 data series. They found that the results tend to converge. A possible way to remedy this is to use an increased variety of forecasting models and forecasting error evaluation methods. While the variety of models will increase the N-size, the results may still limited in their ability to compare forecasting errors across different forecasting error categories, as there are a finite number of forecasting error methods in each forecast error category (e.g. scale dependent, percentage error, etc.).

One main complaint that can be levied against these findings is that they are not representative of the US live cattle market as a whole. Since Utah accounts for ~2% of all live cattle marketed in the US each year, and Western Kansas ~ 20%, these results may prove to be a mere anomaly. Irrespective to this statement is that the purpose of this study was to apply a variety of techniques to Utah and Western Kansas in an effort to provide a proof of concept model. With this in mind, an extension to this study may be to expand the results to larger live cattle markets (e.g. Nebraska and Texas).

Lastly, a possible bias may have been introduced into the methodology through the selection of the forecasting error measures. These measures reflect the best decision of the author and may not reflect the same preferences of other professionals. As such, different forecasting error measures may supply contradictory findings. To eliminate this limitation, a variety of errors need to be considered, tested, and then empirically compared against these findings to determine the consistency of these findings.

Recommendations

Cattle producers constantly strive to accurately forecast basis for a given commodity, time, and location in order to make informed marketing decisions about current and future commodity prices. In essence, "without a knowledge of the usual basis and basis patterns for [a] particular commodity, it is impossible to make fully informed decisions, for example, whether to accept or reject a given price." (CBOT 1990, p. 23)

This thesis provides knowledge to Utah and Western Kansas live cattle steer producers by: 1) Creating new strategies to allow Utah and Western Kansas fed cattle producers become better informed; and 2) Providing some suggestions for extension economists to aid in supplying that information. Specifically, it recommends that stochastic dominance and efficiency methods be used in live cattle basis forecasting. This thesis provides recommendations for singular and composite models. Further, this thesis confirms Clemen's (1989, p.559) comments, who said, "The results have been virtually unanimous: combing multiple forecasts leads to increased forecast accuracy….in many cases one can make dramatic performance improvements by simply averaging the forecasts."

Irrespective of these results, producers should determine what works well in his or her unique situation. As Winkler (1989) suggests, "In many situations there is no such thing as a 'true' model for forecasting purposes. The world around us is continually changing, with new uncertainties replacing old ones” (p. 606). The same can be said for Utah live cattle basis.

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APPENDICES

Appendix A

Table 33. Error Terms – Complete List

Category	Abbreviation	Error Measure Name
Scale-dependent	ME	Mean Error
	MAD	Mean Absolute Deviation
	MSE	Mean Square Error
	RMSE	Root Mean Square Error
	MAE	Mean Absolute Error
	MdAE	Median Absolute Error
Relative Errors	RAE	Relative Absolute Error
	MRAE	Mean Relative Absolute Error
	MdRAE	Median Relative Absolute Error
	GMRAE	Geometric Mean Relative Absolute Error
Percentage Errors	MPE	Mean Percentage Error
	APE	Absolute Percentage Error
	MAPE	Mean Absolute Percentage Error
	MAPE-A	Adjusted Mean Absolute Percentage Error
	MdAPE	Median Absolute Percentage Error
	MSPE	Mean Square Percentage Error
	RMSPE	Root Mean Square Percentage Error
	RMdSPE	Root Median Square Percentage Error
	SMAPE	Symetric Mean Absolute Percentage Error
	TPE	Turning Point Error
Relative Measures	T2	Theil's U2
	GM T2	Geometric Mean Theil's U2
	PB	Percent Better
Other	R^2	R-Squared
	REG	Regression
	OTH	Other

Appendix B

<table>
<tr><td>Contract Size</td><td colspan="2">40,000 pounds (~18 metric tons)</td></tr>
<tr><td>Product Description</td><td colspan="2">55% Choice, 45% Select, Yield Grade 3 live steers</td></tr>
<tr><td>Pricing Unit</td><td colspan="2">Cents per pound</td></tr>
<tr><td>Tick Size (minimum fluctuation)</td><td colspan="2">$.00025 per pound (=$10 per contract)</td></tr>
<tr><td>Daily Price Limits</td><td colspan="2">$.03 per pound above or below the previous day's settlement price</td></tr>
<tr><td rowspan="2">Trading Hours (All times listed are Central Time)</td><td>CME Globex (Electronic Platform)</td><td>MON 9:05 a.m. - FRI 1:55 p.m. Central Time
Daily trading halts 4:00 p.m. - 5:00 p.m. Central Time</td></tr>
<tr><td>Open Outcry (Trading Floor)</td><td>MON-FRI: 9:05 a.m. - 1:00 p.m. Central Time</td></tr>
<tr><td>Last Trade Date/Time</td><td colspan="2">Last business day of the contract month, 12:00 p.m.</td></tr>
<tr><td>Contract Months</td><td colspan="2">Feb, Apr, Jun, Aug, Oct, Dec</td></tr>
</table>

Figure 15. Abbreviated live cattle contract specifications
Source: *CME Group, 2014*

Appendix C

Table 34 below was taken from Hatchett, Bronsen, and Anderson (2010) and outlines the main studies that have been published along with which the optimal forecasts and the conclusions from the equivalent author(s).

Table 34. Grain Basis Forecasting Studies

Study	Optimal Forecasts	Conclusions
"Basis Expectations and Soybean Hedging Effective" – Hauser, Garcia, and Tumblin (1990)	• 1 or 3-year historical basis during pre-harvest. • Futures price spreads after the harvest	• Forecasts that include the implied return to storage outperform historical averages • Historical average models perform comparably to models incorporating current market information
"Forecasting Crop Basis: Practical Alternatives"- Dhuyvetter and Kastens (1997)	• 4-year moving average for wheat. • 7-year moving average for corn. • 7-year moving average for soybeans. • 5-year moving average for milo.	• Futures price spreads were best • Diminishing returns were achieved beyond 4-12 weeks
"Corn and Soybean Basis Behavior and Forecasting: Fundamental and Alternative Approaches" - Jiang and Hayenga (1998)	• 3-year moving average plus current market information best for corn. • Seasonal ARIMA best for soybeans.	• The 3-year moving average out performed by models that include current market information and seasonal ARIMA models
"Incorporating Current Information into Historical-Average-Based Forecasts to Improve Crop Price Basis Forecasts" – Taylor, Dhuyvetter, and Kastens (2006)	• 3-year moving average for wheat. • 2-year moving average for corn. • 3-year moving average for soybeans. • 2-year moving average for milo.	• Futures price spreads and current basis deviations from historical levels only helpful 4 weeks prior to harvest • As the post-harvest horizon approached, the optimal amount of current market information increased.
"Forecasting Basis Levels in the Soybean Complex: A Comparison of Time Series Methods" - Sanders and Manfredo (2006)	• ARMA model best for soybeans. • VAR model best for soybean meal. • Previous year's basis best for soybean oil.	• The accuracy of the 1 and 5-year moving averages do not diminish over time[43]

[43] While this table does not include every article, it merely illustrates the point that relatively few changes have occurred within forecasting crop basis.

Appendix D

Table 35. Cash and Futures Basis Composite Forecasting Results

Study	Composite Forecasts	Conclusions	Optimal Forecast(s)
Brandt, J. A., & Bessler, D. A. (1981). Composite forecasting: An application with US hog prices.	• Two period adaptive and simple average for econometric and ARIMA • Minimum variance and single average for econometric, ARIMA, and expert opinion	• Composite performed better than singular • Weight based upon previous results • Advised to use composite without prior knowledge	• Minimum variance and single average for econometric, ARIMA, and expert opinion on quarterly live hog
Brandt, J. A., & Bessler, D. A. (1983). Price forecasting and evaluation: An application in agriculture.	• Simple average of exponential smoothing (simple, Holt-Winters), ARIMA, econometric, and expert judgment	• Composite outperformed singular models • Expert opinion is advised to be supplemented with composite models	• Simple average, expert opinion, and ARIMA for quarterly live hogs
Brandt, J. A. (1985). Forecasting and hedging: an illustration of risk reduction in the hog industry.	• Simple average of ARIMA and expert judgment • Adaptive average of Econometric and ARIMA	• Composite models produced the lowest MSE & RMSE • Reduced price risk and fluctuations by combining • Different data and models prove beneficial	• Simple average, adaptive average, and ARIMA for quarterly live hogs
Harris, K. S., & Leuthold, R. M. (1985). A comparison of alternative forecasting techniques for livestock prices: a case study.	• Simple composite of econometric and ARIMA models for hogs and cattle	• Few efficiencies gained by combining econometric and time series • ARIMA does not predict turn points well • Different weighting criteria for composite models	• ARIMA (integrated & individual) and composite models for live cattle • Composite and individual econometric & ARIMA for live hogs
McIntosh, C. S., & Bessler, D. A. (1988). Forecasting agricultural prices using a Bayesian composite approach.	• Matrix beta Bayesian composite • Simple average of expert opinion, futures, and one-step ahead ARIMA • Restricted ordinary least squares • Adaptive weight on forecast errors	• For quadratic loss functions, composite models work best • Lack of historical data favors the Bayesian method • Simple average performed well with little work required	• Adaptive, Bayesian, and simple average for quarterly hog futures

Table 35 cont.

Study	Composite Forecasts	Conclusions	Optimal Forecast(s)
		•	•
Park, D. W., & Tomek, W. G. (1988). An appraisal of composite forecasting methods.	• 18 distinctive models were created out of ARIMA, trend-seasonal, lagged prices, & ARIMA using adaptive smoothing, unequal weighting, and covariance terms *For a full explanation of the forecasts used, the authors have asked that you contact them	• Composite models provide the means for reducing model misspecification • Composite models tend to be robust (i.e. smaller MSE) • Covariance terms in future composite models should be avoided • Composite models should be used if specification risk is high	• Based on the charts provided, it is inconclusive which model is linked with each MSE reported. Please contact the author for further insight.
Cole, C., Mintert, J., & Schroeder, T. (1994). Forecasting Cash Feeder Steer Prices: A Comparison of the Econometric, VAR, ARIMA, Feeder Cattle Futures and Composite Approaches	• Simple average of econometric, futures, naïve, VAR, and ARIMA	• Composite model outperformed all other models in MAPE, MAD, and % turning points • Derived econometric models performed well	• Simple average, ARIMA, and naïve performed the best for 700-800 feeder steers
Colino, E. V., Irwin, S. H., Garcia, P., & Etienne, X. (2012). Composite and Outlook Forecast Accuracy.	• Equal weight, equal weight-rolling window, MSE-weight, MSE weight-rolling window, OLS (restricted & unrestricted), shrinkage (0-1 by 0.25) & odds matrix for State Var., Futures, VAR,and ARMA *For a complete breakdown of all models used please refer to the authors paper	• A variety of composite forecasts provided better models than outlook forecasts • Equal weighted composites generally reduced the error the most and produce largest trading profits • Results favored using futures for short horizons and composite for longer horizons	• Hog (Iowa) h=1 - > Restricted OLS, Shrinkage (0.25), and Best Previous Model • Hog (Missouri) h=1- > Restricted OLS-rolling window, Shrinkage (0.25)-rolling window, & Shrinkage (1.0)-rolling window

Table 35 cont.

Study	Composite Forecasts	Conclusions	Optimal Forecast(s)
Manfredo, M. R., Leuthold, R. M., & Irwin, S. H. (2001). Forecasting fed cattle, feeder cattle, and corn cash price volatility: the accuracy of time series, implied volatility, and composite approaches	• Simple average of GARCH-t & IV • Simple average of (GARCH-t and IV), (GARCH-t, IV, & HISTAVG), (RM97 and IV), (RM94 and IV), (RMOPT and IV), (NAÏVE and IV) • Regression weights of (GARCH-t and IV), (GARCH-t, IV, & HISTAVG), (RM97 and IV), (RM94 and IV), (RMOPT and IV), (NAÏVE and IV) • Option contracts and regression weights of (GARCH-t and IV), (GARCH-t, IV, & HISTAVG), (RM97 and IV), (RM94 and IV), (RMOPT and IV)	• Regression composite models do better in shorter time horizons • Risk Metrics work well as a GARCH proxy • Still ambiguity in assigning model superiority through time	• H=1 Live Cattle - > regression weights for (GARCH-t and IV), (RMOPT and IV) (GARCH-t, IV, & HISTAVG) • H=1 Feeder Cattle - > (Naïve), Simple average of (NAÏVE and IV), regression weights of (RMOPT and IV) • H=1 Corn - > option contract and regression weight of (GARCH-t and IV), (IV), & contract and regression weight of (GARCH-t, IV, & HISTAVG) *"H" intervals were 1,2,4,16, & 20; for a complete list of superior models refer to authors paper

List of articles used in review of forecasting errors

1) Tonsor et al. (2004)
2) Liu et al. (1994)
3) Schroeder et al (1988)
4) Bailey, Gray, and Rawls (2002)
5) McElliott (2012)
6) Dhuyvetter et al. (2008)
7) Parcelll et al. (2000)

8) Hauser, Garcia, and Tumblin (1990)

9) Dhuyvetter and Kastens (1997)

10) Jiang and Hayenga (1998)

11) Taylor, Dhuyvetter, and Kastens (2004)

12) Sanders and Manfredo (2006)

13) Brandt, J. A., & Bessler, D. A. (1981)

14) Brandt, J. A., & Bessler, D. A. (1983)

15) Brandt, J. A. (1985)

16) Harris, K. S., & Leuthold, R. M. (1985)

17) McIntosh, C. S., & Bessler, D. A. (1988)

18) Park, D. W., & Tomek, W. G. (1988)

19) Cole, C., Mintert, J., & Schroeder, T. (1994)

20) Manfredo, M. R., Leuthold, R. M., & Irwin, S. H. (2001)

21) Colino, E. V., Irwin, S. H., Garcia, P., & Etienne, X. (2012)

Appendix E

Table 36. Live Cattle Lag-1 Regression Results, 2004-2009

Variables	Utah				Western Kansas			
	C	S.E.	T-stat	Prob.	C	S.E.	T-stat	Prob.
Intercept	(0.54)	0.17	(3.13)	0.00	(0.18)	0.15	(1.25)	0.21
Lag-1	0.64	0.06	10.14	-	0.57	0.08	6.82	-
No. of obs.	313				313			
Adjusted R^2	0.41				0.35			
F-stat	216.94				165.29			

Table 37. Live Cattle Lag-52 Regression Results, 2004-2009

Variables	Utah				Western Kansas			
	C	S.E.	T-stat	Prob.	C	S.E.	T-stat	Prob.
Intercept	(1.18)	0.32	(3.68)	0.00	(0.46)	0.26	(1.74)	0.08
Lag-52	0.31	0.08	3.83	0.00	0.19	0.06	3.06	0.00
No. of obs.	313				313			
Adjusted R^2	0.11				0.05			
F-stat	37.58				16.04			

Table 38. Live Cattle 3-yr. avg. Regression Results, 2004-2009

	Utah				**Western Kansas**			
Variables	C	S.E.	T-stat	Prob.	C	S.E.	T-stat	Prob.
Intercept	(0.94)	0.31	(3.05)	0.00	(0.42)	0.25	(1.69)	0.09
3-yr. avg.	0.60	0.11	5.58	-	0.45	0.10	4.34	-
No. of obs.	313				313			
Adjusted R^2	0.20				0.11			
F-stat	76.83				40.29			

Table 39. Live Cattle Contract Dummy Regression Results, 2004-2009

	Utah				**Western Kansas**			
Variables	C	S.E.	T-stat	Prob.	C	S.E.	T-stat	Prob.
Intercept	1.08	0.64	1.70	0.09	1.53	0.65	2.36	0.02
Contract-February	(3.00)	0.81	(3.70)	0.00	(2.78)	0.81	(3.46)	0.00
Contract-June	(0.62)	0.81	(0.77)	0.44	(0.66)	0.79	(0.84)	0.40
Contract-August	(3.44)	0.87	(3.96)	0.00	(3.01)	0.76	(3.96)	0.00
Contract-October	(4.48)	0.78	(5.74)	-	(2.89)	0.74	(3.92)	0.00
Contract-December	(3.72)	0.90	(4.14)	-	(2.68)	0.85	(3.18)	0.00
No. of obs.	313				313			
Adjusted R^2	0.27				0.22			
F-stat	23.96				16.96			

Table 40. Live Cattle Seasonal Regression Results, 2004-2009

Variables	**Utah**				**Western Kansas**			
	C	S.E.	T-stat	Prob.	C	S.E.	T-stat	Prob.
Intercept	0.47	0.72	0.65	0.52	1.16	0.73	1.60	0.11
January	(2.48)	0.93	(2.66)	0.01	(2.86)	0.91	(3.14)	0.00
February	(2.28)	0.96	(2.37)	0.02	(1.94)	0.92	(2.10)	0.04
April	1.23	1.00	1.24	0.22	0.75	1.01	0.75	0.46
May	1.37	1.07	1.28	0.20	0.42	1.12	0.37	0.71
June	(1.37)	1.02	(1.34)	0.18	(0.99)	1.02	(0.97)	0.33
July	(2.71)	1.22	(2.23)	0.03	(2.79)	0.97	(2.88)	0.00
August	(2.94)	0.82	(3.57)	0.00	(2.48)	0.79	(3.13)	0.00
September	(4.09)	0.88	(4.64)	-	(2.55)	0.86	(2.98)	0.00
October	(3.65)	1.06	(3.44)	0.00	(2.48)	0.92	(2.70)	0.01
November	(3.23)	1.03	(3.13)	0.00	(2.02)	1.03	(1.97)	0.05
December	(2.98)	1.06	(2.81)	0.01	(2.57)	0.93	(2.76)	0.01
No. of obs.	313				313			
Adjusted R^2	0.30				0.21			
F-stat	12.92				8.63			

Table 41. Live Cattle Interest Supply Regression Results, 2004-2009

Variables	**Utah**				**Western Kansas**			
	C	S.E.	T-stat	Prob.	C	S.E.	T-stat	Prob.
Intercept	1.63	4.87	0.34	0.74	2.96	4.27	0.69	0.49
January	(2.12)	1.14	(1.87)	0.06	(2.86)	1.08	(2.64)	0.01
February	(2.42)	1.03	(2.34)	0.02	(2.18)	1.05	(2.08)	0.04
April	1.66	1.19	1.39	0.16	0.95	1.20	0.79	0.43
May	1.92	1.34	1.43	0.15	0.73	1.32	0.56	0.58
June	(0.61)	1.20	(0.51)	0.61	(1.10)	1.21	(0.91)	0.36
July	(2.05)	1.50	(1.37)	0.17	(2.76)	1.32	(2.10)	0.04
August	(2.24)	1.19	(1.88)	0.06	(2.36)	1.14	(2.06)	0.04
September	(3.43)	1.26	(2.72)	0.01	(2.46)	1.16	(2.12)	0.03
October	(2.99)	1.37	(2.18)	0.03	(2.37)	1.20	(1.97)	0.05
November	(2.59)	1.26	(2.05)	0.04	(1.86)	1.26	(1.49)	0.14
December	(2.53)	1.21	(2.09)	0.04	(2.42)	1.07	(2.27)	0.02
Boxed Beef: Lag-26	(0.02)	0.03	(0.59)	0.55	(0.00)	0.02	(0.03)	0.98
Feeder: Lag-26	0.03	0.06	0.59	0.56	0.00	0.05	0.02	0.99
Corn: Lag-26	(0.16)	0.25	(0.66)	0.51	(0.26)	0.20	(1.30)	0.20
Interest: Lag-26	(0.37)	0.21	(1.76)	0.08	(0.18)	0.19	(0.91)	0.36
No. of obs.	287				287			
Adjusted R^2	0.31				0.23			
F-stat	9.56				6.73			

Table 42. Live Cattle Meat Demand Regression Results, 2004-2009

	Utah				Western Kansas			
Variables	C	S.E.	T-stat	Prob.	C	S.E.	T-stat	Prob.
Intercept	16.76	12.02	1.39	0.16	10.10	11.00	0.92	0.36
January	(2.37)	1.15	(2.05)	0.04	(3.17)	1.06	(3.00)	0.00
February	(2.46)	1.11	(2.23)	0.03	(2.14)	1.02	(2.10)	0.04
April	1.55	1.08	1.43	0.15	0.69	1.07	0.64	0.52
May	1.81	1.15	1.57	0.12	0.68	1.18	0.58	0.56
June	(0.62)	1.06	(0.58)	0.56	(0.37)	1.01	(0.37)	0.71
July	(1.74)	1.28	(1.37)	0.17	(1.92)	1.18	(1.63)	0.10
August	(1.99)	1.03	(1.93)	0.05	(1.64)	0.99	(1.67)	0.10
September	(3.21)	1.02	(3.14)	0.00	(1.84)	0.97	(1.90)	0.06
October	(2.91)	1.09	(2.68)	0.01	(1.91)	0.96	(2.00)	0.05
November	(2.70)	1.02	(2.66)	0.01	(1.75)	1.01	(1.74)	0.08
December	(2.58)	1.10	(2.35)	0.02	(2.40)	0.99	(2.42)	0.02
Boxed Beef	0.02	0.03	0.70	0.49	0.04	0.03	1.56	0.12
Hog	0.02	0.03	0.52	0.60	(0.02)	0.03	(0.58)	0.57
Broiler	(0.13)	0.06	(2.01)	0.05	(0.10)	0.06	(1.69)	0.09
ELA	(0.09)	0.05	(1.60)	0.11	(0.05)	0.05	(1.12)	0.26
No. of obs.	313				313			
Adjusted R^2	0.33				0.24			
F-stat	10.75				7.27			

Appendix F

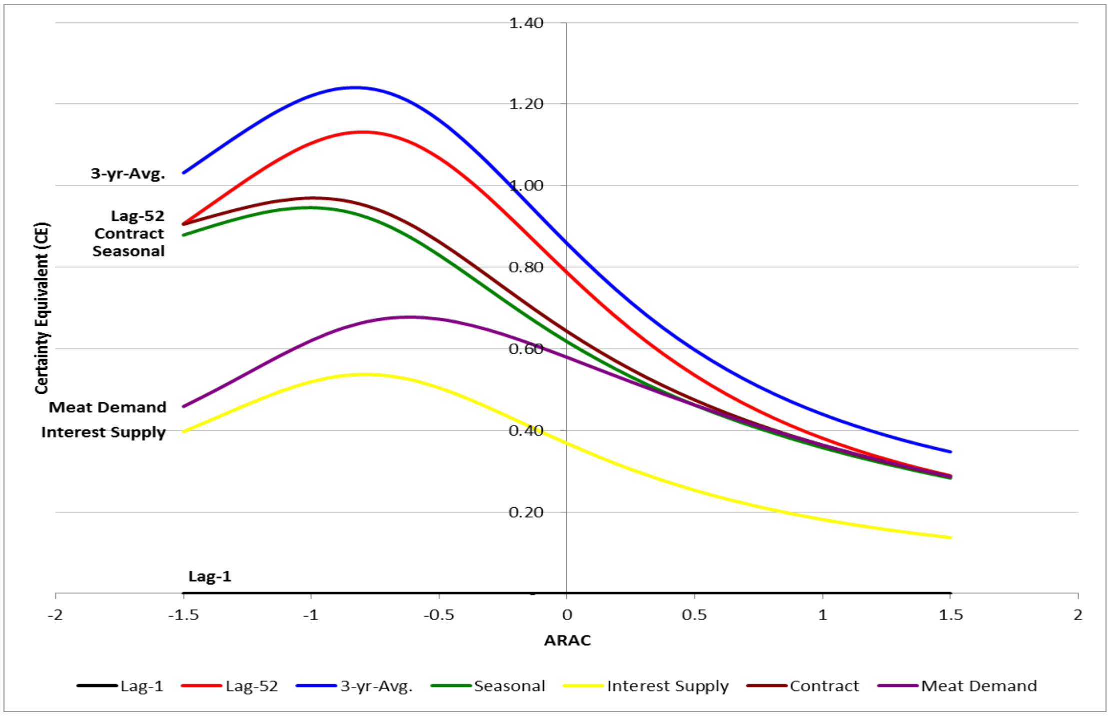

Figure 16. Risk premiums for single forecasts, Utah live cattle steers

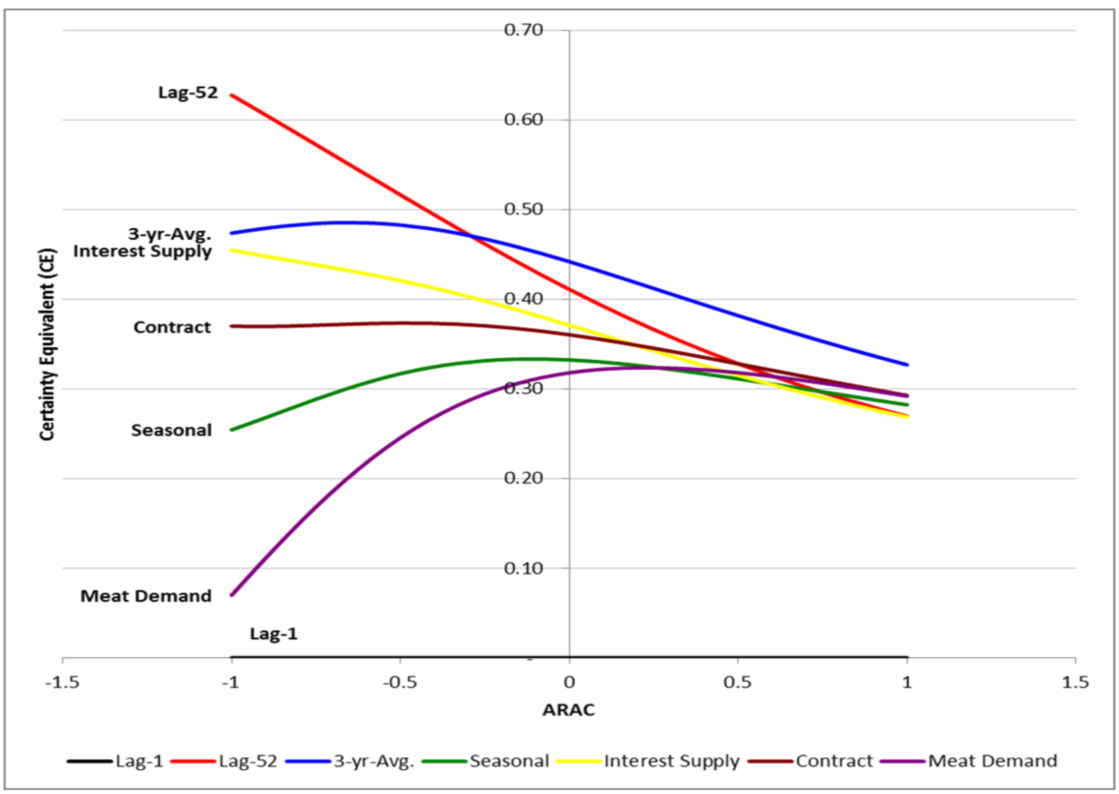

Figure 17. Risk premiums for singular forecasts, Western Kansas live cattle steers

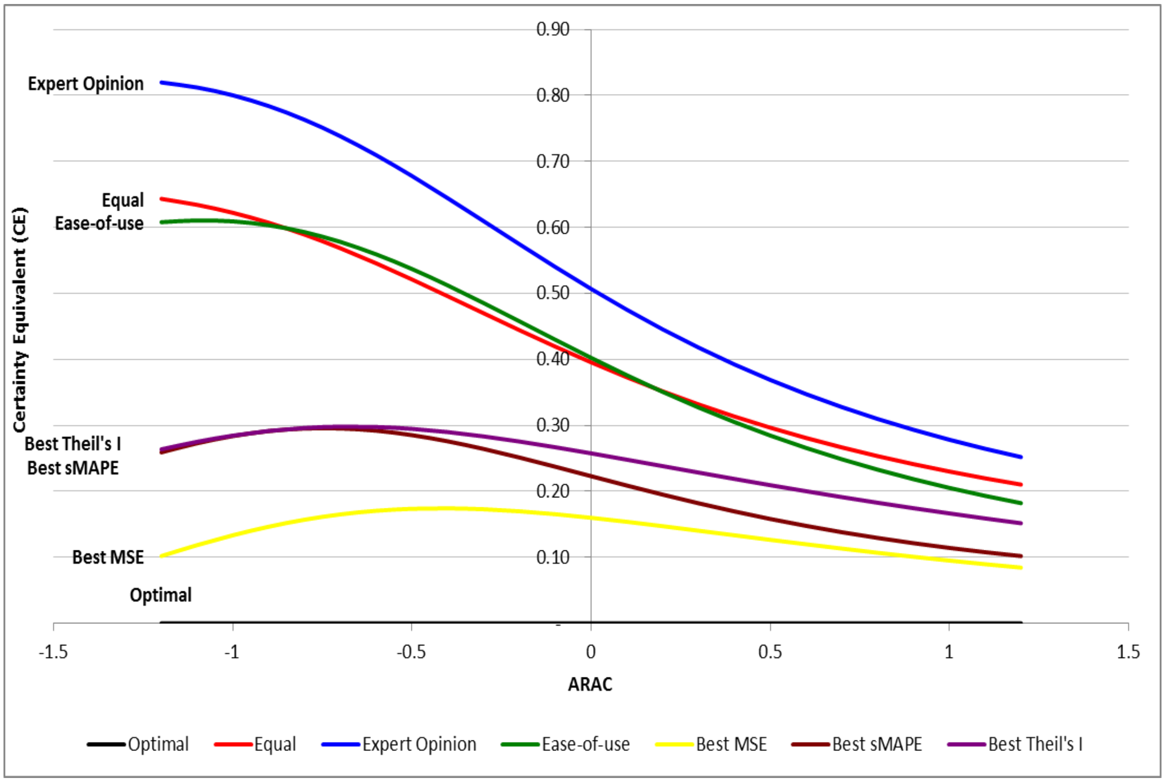

Figure 18. Risk premiums for composite forecasts, Utah live cattle steers

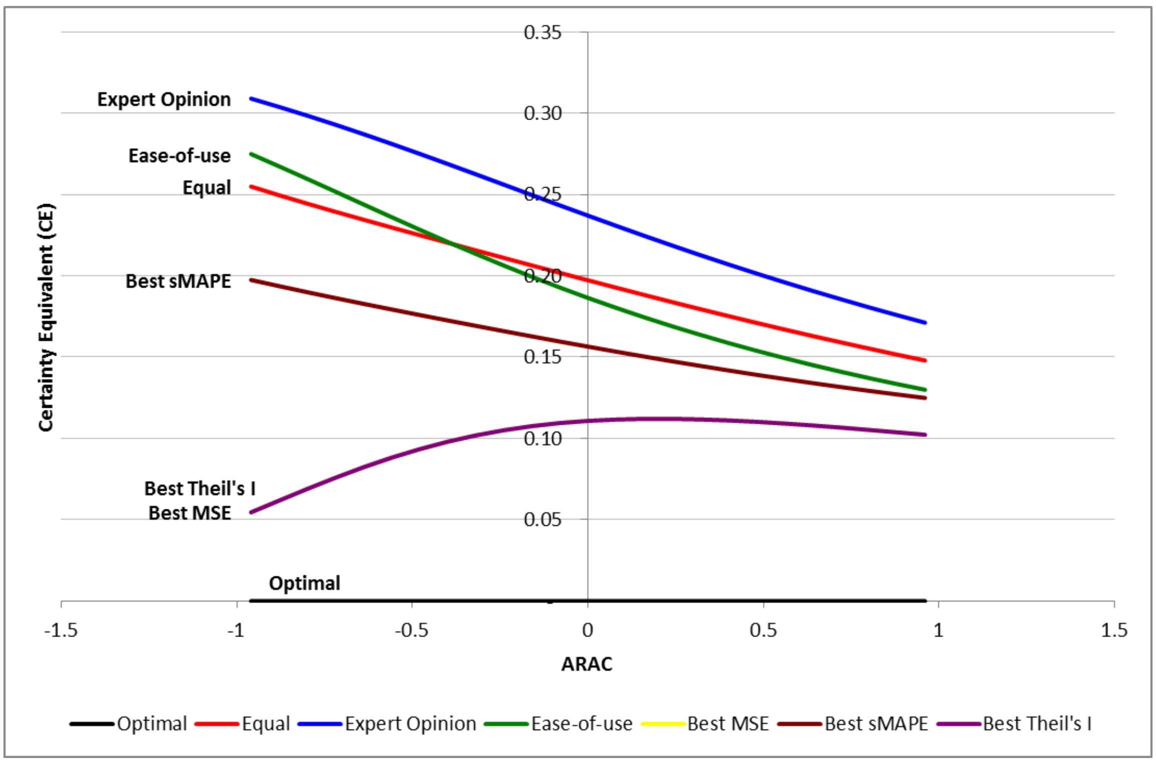

Figure 19. Risk premiums for composite forecasts, Western Kansas live cattle steers

Appendix G

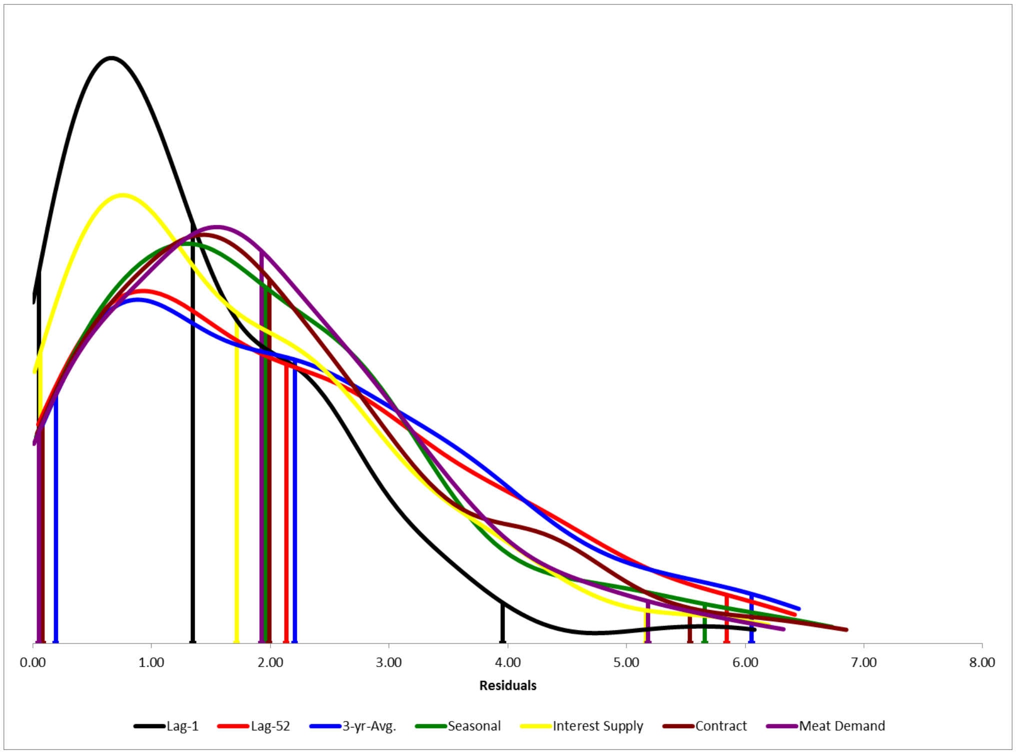

Figure 20. PDF of Utah live cattle steers, singular forecasts

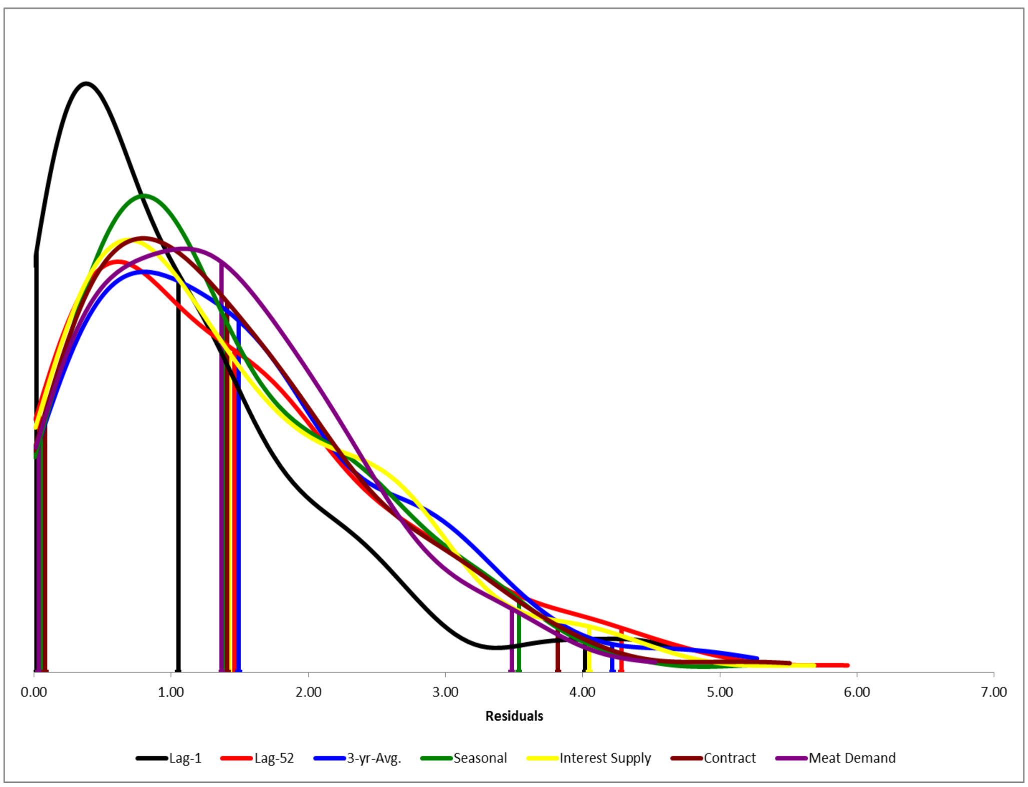

Figure 21. PDF of Western Kansas live cattle steers, singular forecasts

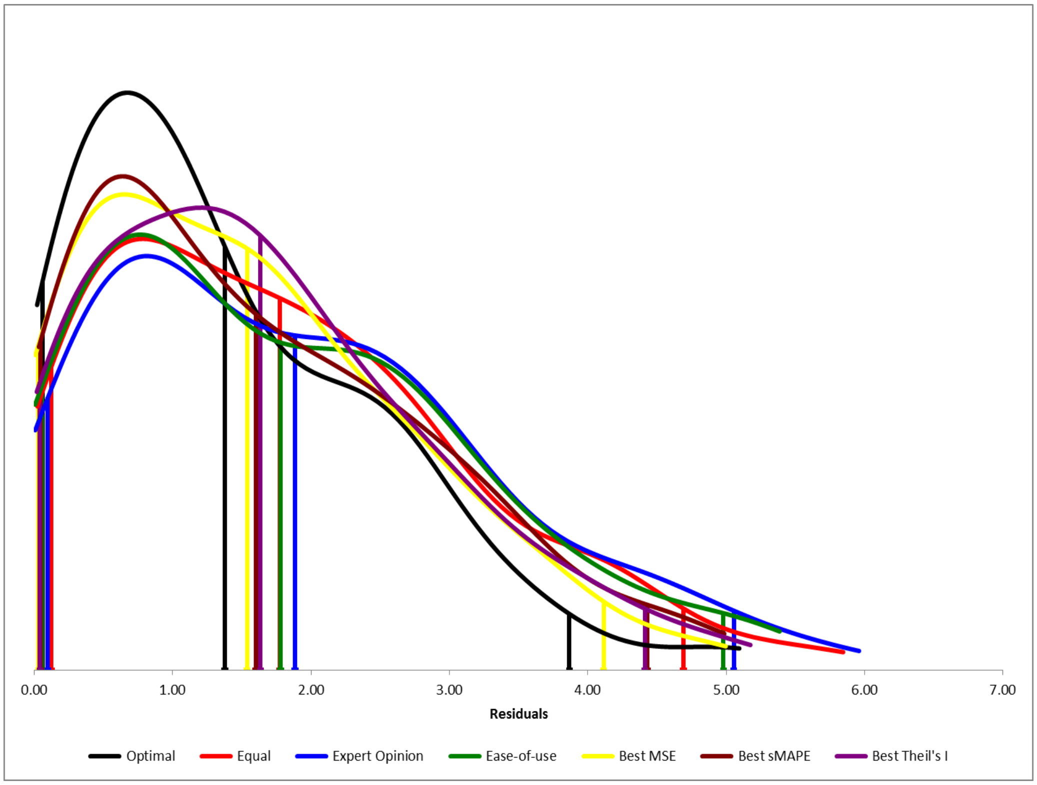

Figure 22. PDF of Utah live cattle steers, composite forecasts

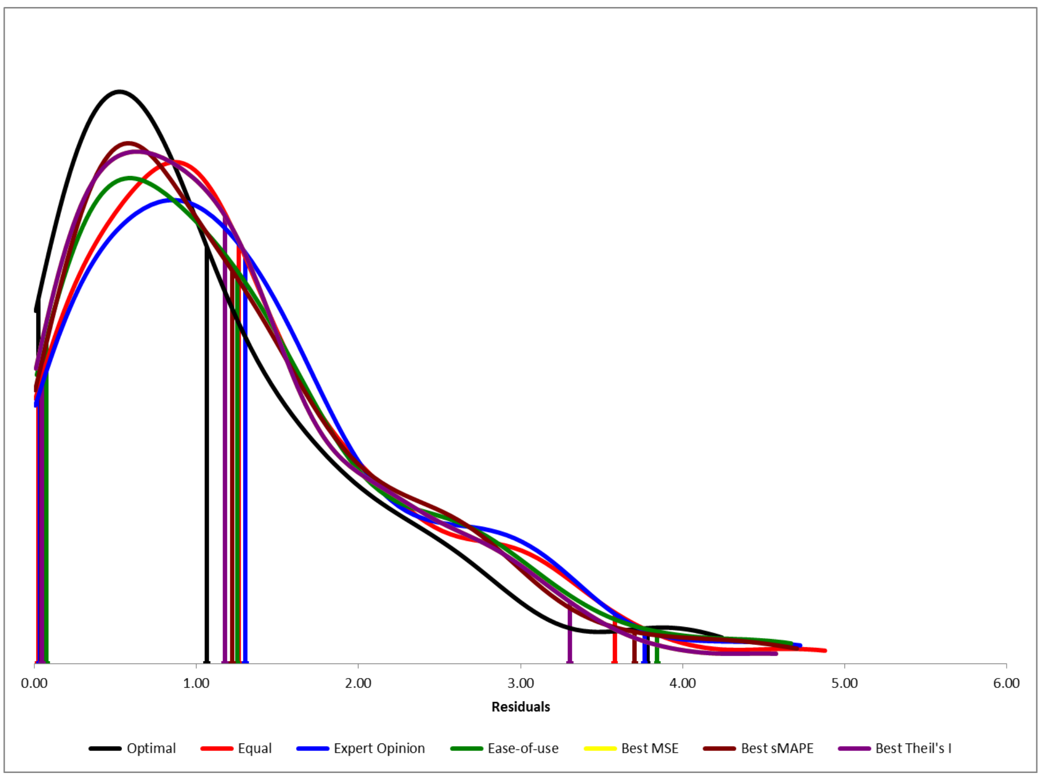

Figure 23. PDF of Western Kansas live cattle steers, composite forecasts

Appendix H

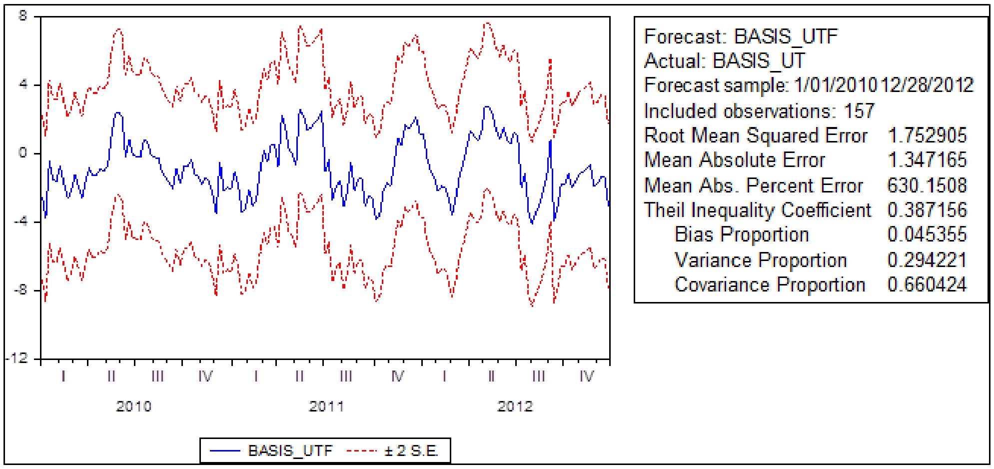

Figure 24. Lag-1 singular forecast, Utah live cattle steers

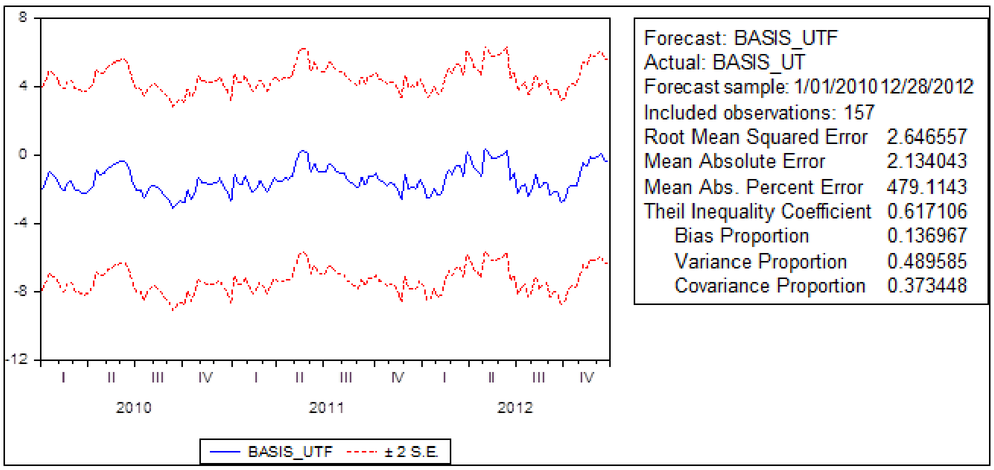

Figure 25. Lag-52 singular forecast, Utah live cattle steers

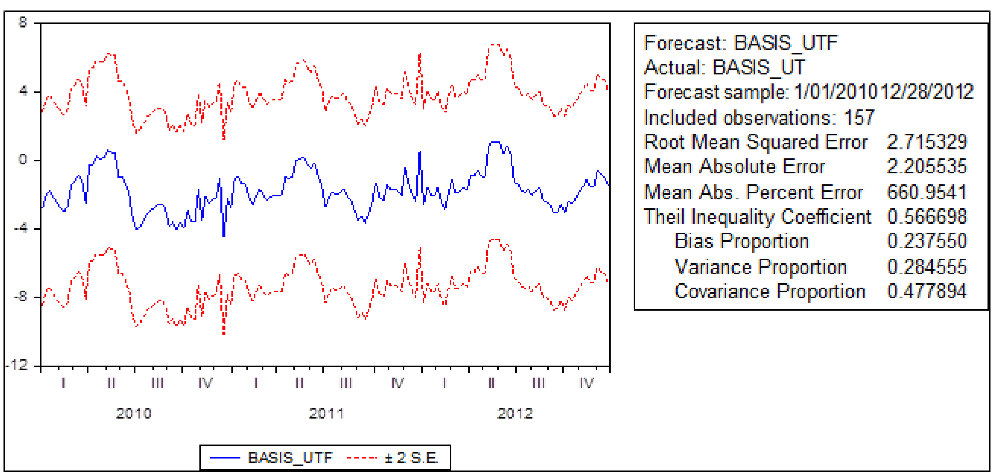

Figure 26. 3 yr. avg. singular forecast, Utah live cattle steers

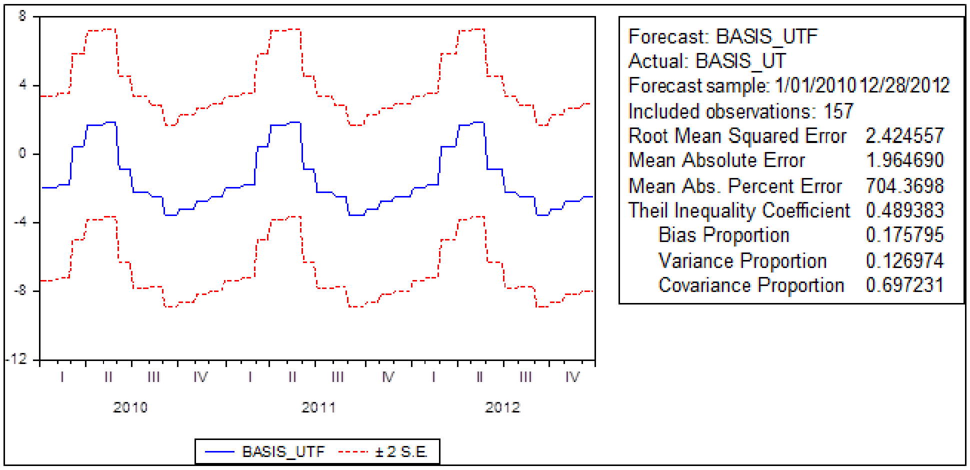

Figure 27. Seasonal singular forecast, Utah live cattle steers

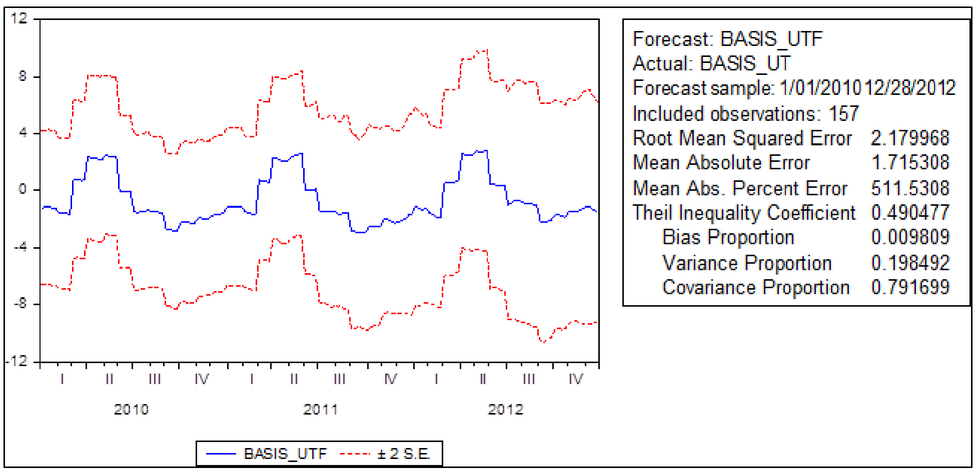

Figure 28. Interest supply singular forecast, Utah live cattle steers

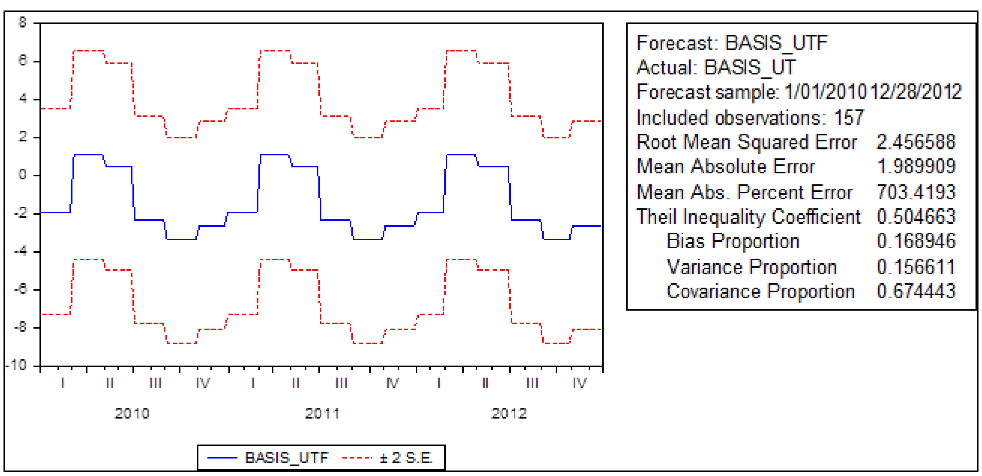

Figure 29. Contract dummies singular forecast, Utah live cattle steers

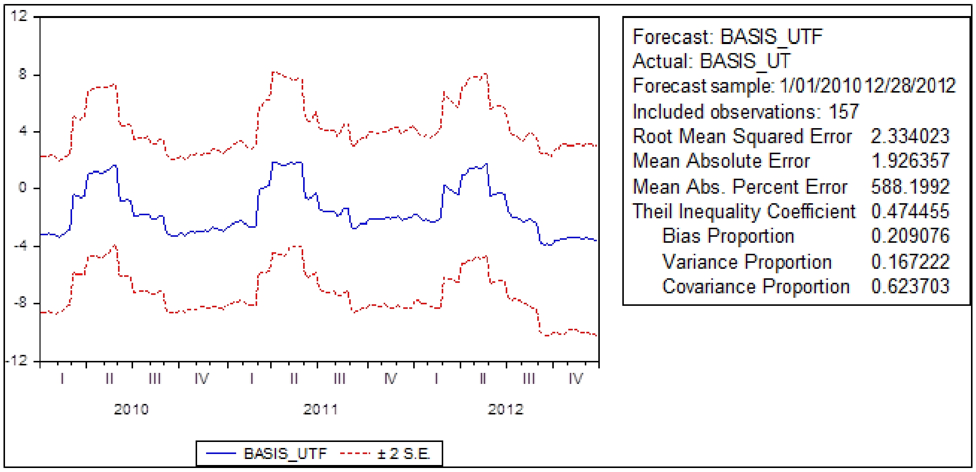

Figure 30. Meat demand singular forecast, Utah live cattle steers

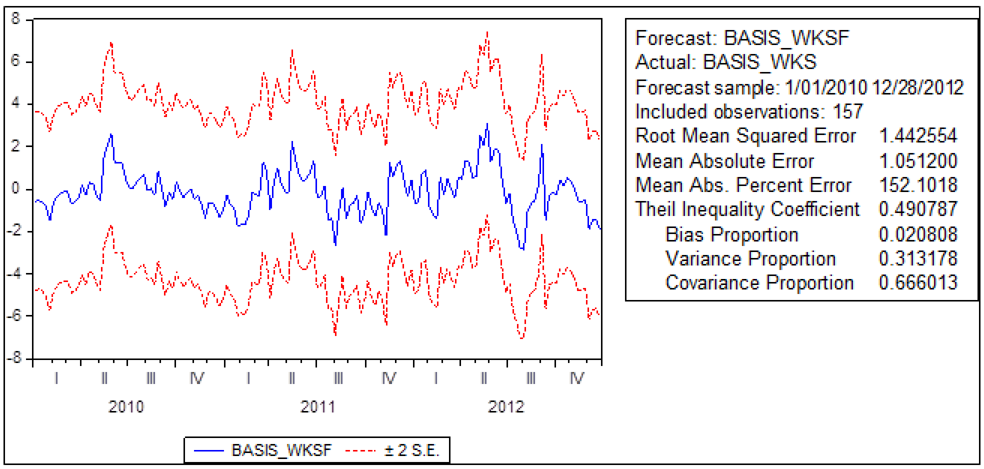

Figure 31. Lag-1 singular forecast, Western Kansas live cattle steers

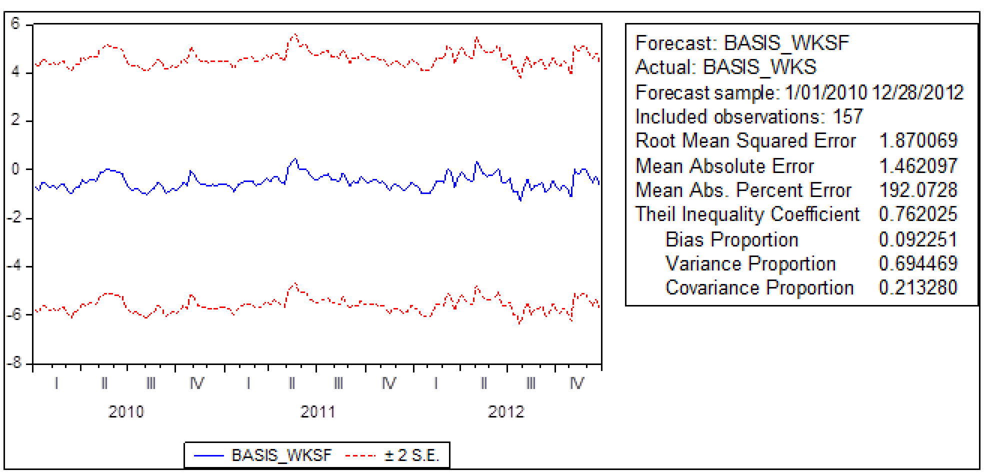

Figure 32. Lag-52 Singular forecast, Western Kansas live cattle steers

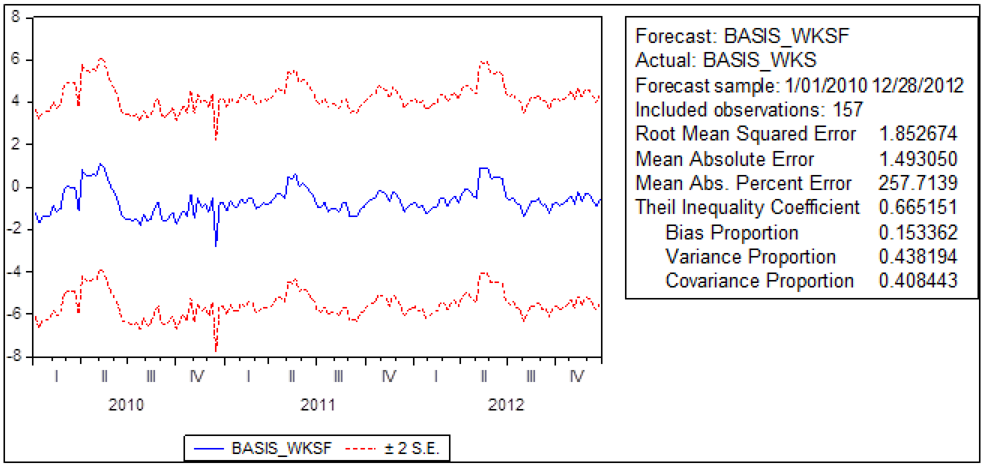

Figure 33. 3 yr. avg. Singular forecast, Western Kansas live cattle steers

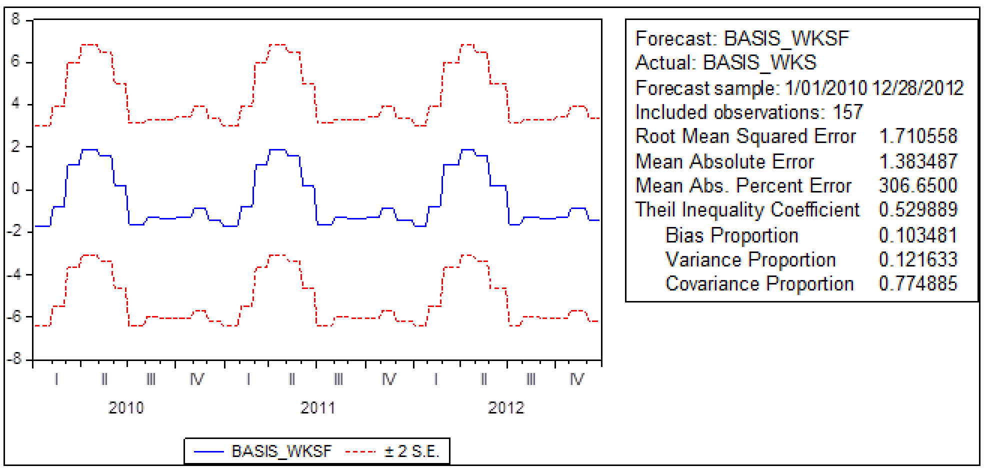

Figure 34. Seasonal singular forecast, Western Kansas live cattle steers

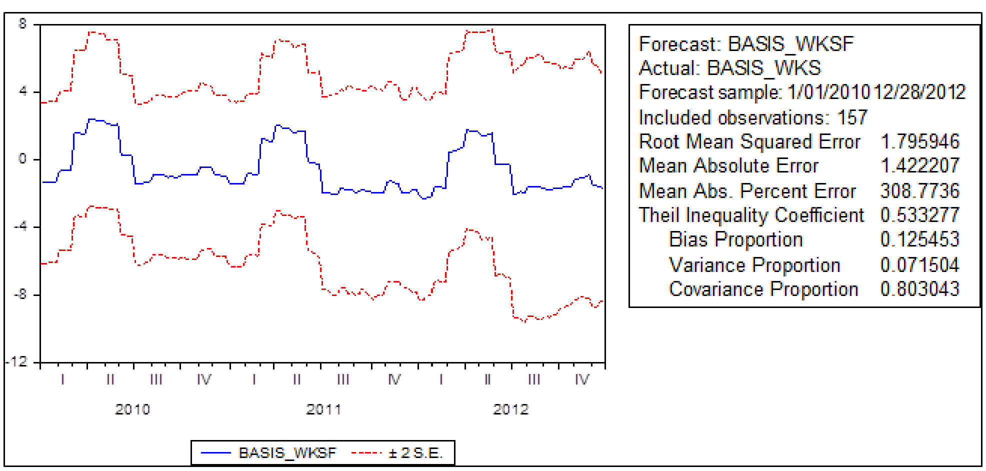

Figure 35. Interest supply singular forecast, Western Kansas live cattle steers

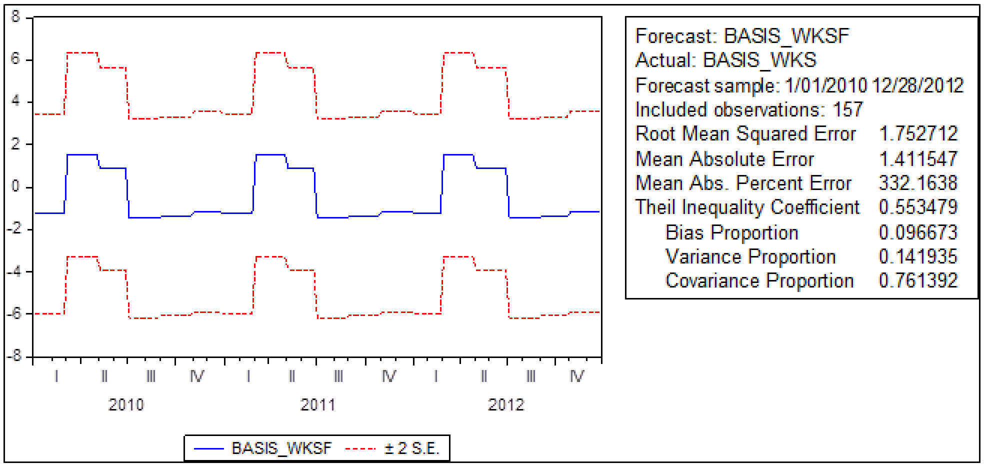

Figure 36. Contract dummies singular forecast, Western Kansas live cattle steers

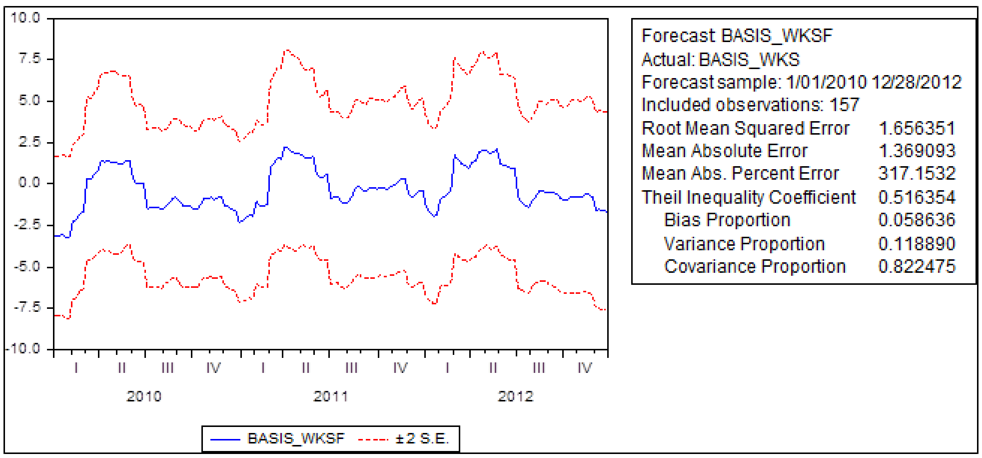

Figure 37. Meat demand singular forecast, Western Kansas live cattle steers

Appendix I

Theil's Inequality Coefficient

(56) $$U_{It} = \frac{\sqrt{\frac{1}{n}\sum_t (F_t - A_t)^2}}{\sqrt{\frac{1}{n}\sum_t (F_t)^2} + \sqrt{\frac{1}{n}\sum_t (A_t)^2}}$$

where F_t is a forecasted value in time "t" and A_t is the actual value in time "t" (Eviews 2014).

Mean Square Error

(57) $$MSE_t = \frac{1}{n}\sum_{t=1}^{n}(F_t - A_t)^2$$

where F_t is a forecasted value in time "t" and A_t is the actual value in time "t" (Armstrong and Collopy 2001).

Root Mean Square Error

(58) $$RMSE_t = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(F_t - A_t)^2}$$

where F_t is a forecasted value in time "t" and A_t is the actual value in time "t" (Armstrong and Collopy 2001).

Mean Absolute Percentage Error

(59) $$MAPE_t = 100 * \frac{1}{n}\sum_t^n \left|\frac{F_t - A_t}{A_t}\right|$$

where F_t is a forecasted value in time "t" and A_t is the actual value in time "t" (Eviews 2014).

Appendix J

One main complaint that can be levied against these findings is that they are not representative of the US live cattle market as a whole. Since Utah accounts for $\approx$ 2% of all live cattle marketed in the US each year and Western Kansas accounts for $\approx$ 20% these results may prove to be a mere anomaly. While the findings in the study demonstrate an effort to provide a proof of concept model, as suggested in the Limitations and Further Research section of this thesis, a case study extension was expand larger live cattle markets of Texas and Nebraska.

The results are laid out as follows: Part I – singular forecast results following the exact structure in the thesis; Part II – composite forecast results are displayed; Part III – the singular and composite forecasting summary; Part IV – the regression results; Part V – the forecasting graphs for Nebraska; Part VI – the forecasting graphs for Texas[44]; Part VII – PDFs for singular and composite forecasts for Nebraska and Texas; and Part VIII – Risk premium graphs for Nebraska and Texas, singular and composite.

[44] It should be noted that while the Tables, Figures, and Charts are provided, no formal written interpretation is offered to the reader.

Part I

Table 43. Singular Forecast Accuracy for Nebraska Live Cattle Steers Basis

Forecast	**Forecast Error** RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Lag-1	1.61	1.21	2.60	265.8	1,027.8	0.67	0.426	0.69
Lag-52	2.51	2.00	6.32	297.7	467.5	1.10	0.738	1.08
3-yr. avg.	2.64	2.05	6.97	329.4	922.8	1.13	0.742	1.14
Seasonal	2.47	1.97	6.11	478.5	371.7	1.08	0.574	1.06
Interest Supply	2.46	1.92	6.03	428.7	363.2	1.05	0.575	1.06
CD	2.51	2.02	6.31	499.5	486.4	1.11	0.594	1.08
Meat Demand	2.02	1.67	4.09	314.8	1,692.0	0.92	0.473	0.86

Table 44. Singular Forecast Accuracy for Texas Live Cattle Steers Basis

Forecast	**Forecast Error** RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Lag-1	1.43	1.05	2.06	268.5	1,679.1	0.78	0.492	0.79
Lag-52	1.85	1.45	3.44	222.8	1,196.1	1.08	0.823	1.02
3-yr. avg.	1.83	1.50	3.34	269.1	2,593.8	1.11	0.715	1.01
Seasonal	1.78	1.46	3.17	475.6	515.9	1.09	0.573	0.98
Interest Supply	1.68	1.38	2.82	384.1	577.0	1.02	0.543	0.92
CD	1.81	1.48	3.26	473.6	452.1	1.10	0.590	0.99
Meat Demand	1.72	1.45	2.95	288.6	296.6	1.08	0.554	0.94

Table 45. Singular Forecast Rankings for Nebraska Live Cattle Steers Basis

Singular Forecast	Forecast Error							
	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Lag-1	1	1	1	1	6	1	1	1
Lag-52	2	2	2	3	7	2	2	2
3-yr. avg.	3	3	3	5	1	3	4	3
Seasonal	4	4	4	6	2	4	3	4
Interest Supply	5	6	5	7	4	6	5	5
CD	6	5	6	2	3	5	6	6
Meat Demand	7	7	7	4	5	7	7	7

Table 46. Singular Forecast Rankings for Texas Live Cattle Steers Basis

Singular Forecast	Forecast Error							
	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Lag-1	1	1	1	2	6	1	1	1
Lag-52	2	2	2	5	4	2	2	2
3-yr. avg.	3	3	3	4	1	3	3	3
Seasonal	4	5	4	7	3	5	4	4
Interest Supply	5	6	5	6	2	6	5	5
CD	6	7	6	3	7	7	6	6
Meat Demand	7	4	7	1	5	4	7	7

Table 47. Spearman Rank of Nebraska Live Cattle Steers Forecast Errors

Forecast Error	Forecast Error							
	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
RMSE	1.00	0.96	1.00	0.32	(0.29)	0.96	0.96	1.00
MAD		1.00	0.96	0.50	(0.25)	1.00	0.93	0.96
MSE			1.00	0.32	(0.29)	0.96	0.96	1.00
MAPE				1.00	(0.50)	0.50	0.29	0.32
sMAPE					1.00	(0.25)	(0.32)	(0.29)
RAE						1.00	0.93	0.96
Theil's I							1.00	0.96
Theils U2								1.00

Table 48. Spearman Rank of Texas Live Cattle Steers Forecast Errors

Forecast Error	Forecast Error							
	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
RMSE	1.00	0.79	1.00	(0.18)	0.14	0.79	1.00	1.00
MAD		1.00	0.79	0.29	0.04	1.00	0.79	0.79
MSE			1.00	(0.18)	0.14	0.79	1.00	1.00
MAPE				1.00	(0.61)	0.29	(0.18)	(0.18)
sMAPE					1.00	0.04	0.14	0.14
RAE						1.00	0.79	0.79
Theil's I							1.00	1.00
Theils U2								1.00

Table 49. Stochastic Dominance Forecast Rank Preference

	Nebraska		Texas	
Singular Forecast	Risk Adverse[a]	Risk Loving[b]	Risk Adverse[c]	Risk Loving[d]
Lag-1	1	1	1	1
Lag-52	3	6	7	2
3-yr. avg.	7	4	5	6
Seasonal	4	5	4	5
Interest Supply	6	3	3	3
CD	5	7	6	4
Meat Demand	2	2	2	7

[a] Risk loving is equal to an RAC of -1.4
[b] Risk Adverse is equal to an RAC of 1.4
[c] Risk loving is equal to an RAC of -1.00
[d] Risk Adverse is equal to an RAC of 1.00

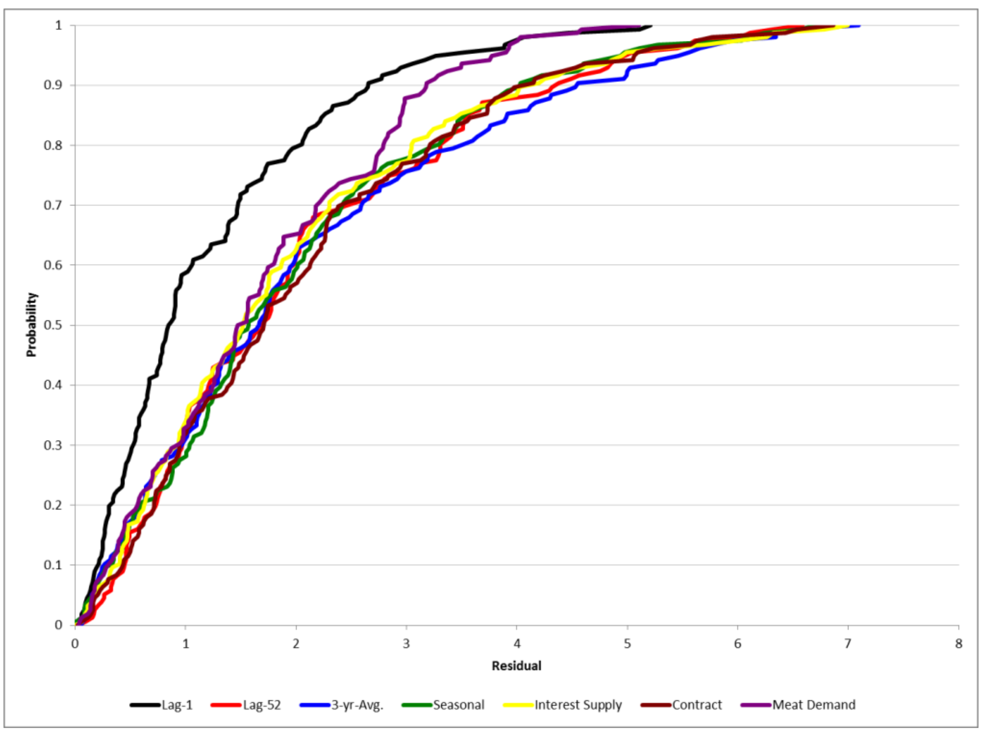

Figure 38. CDF comparison of singular forecasts for Nebraska live cattle steers

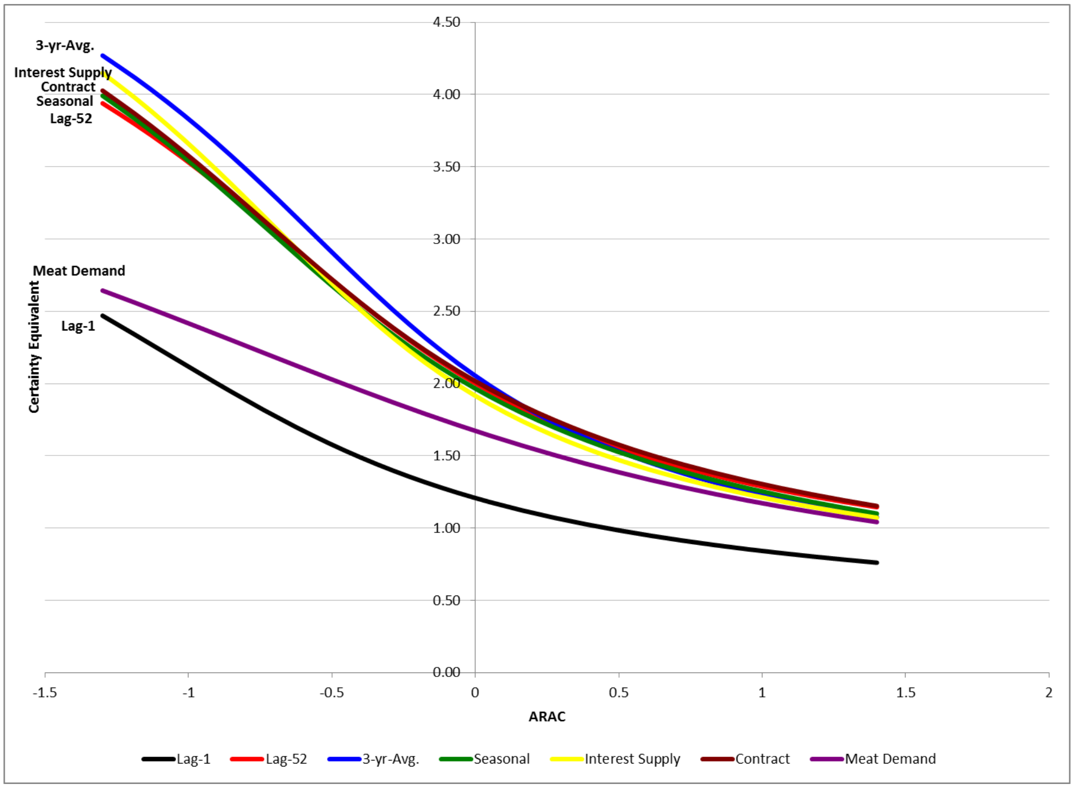

Figure 39. Stochastic efficiency of singular forecasts for Nebraska live cattle steers

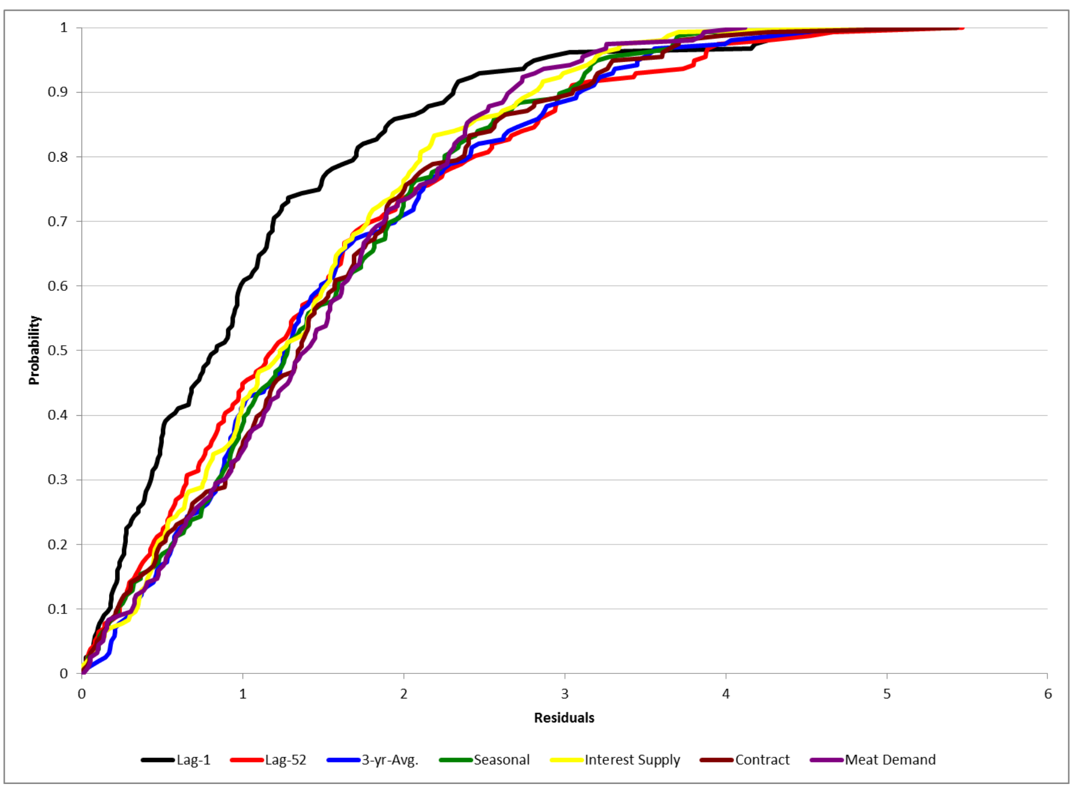

Figure 40. CDF comparison of singular forecasts for Texas live cattle steers

Table 50. Stochastic Efficiency Ranks for Singular Forecasts: Risk Preference for Nebraska Live Cattle Steers

Forecast	Risk Preference						
	Very Risk[a] Loving	Risk[b] Loving	Semi-Risk[c] Loving	Risk[d] Neutral	Semi-Risk[e] Adverse	Risk[f] Adverse	Very Risk[g] Adverse
Lag-1	1	1	1	1	1	1	1
Lag-52	3	4	5	5	6	6	6
3-yr. avg.	7	7	7	7	5	4	4
Seasonal	4	3	4	4	4	5	5
Interest Supply	6	6	3	3	3	3	3
CD	5	5	6	6	7	7	7
Meat Demand	2	2	2	2	2	2	2

[a] Very risk loving is equal to -1.30
[b] Risk loving is equal to -0.85
[c] Semi risk loving is equal to -0.40
[d] Risk neutral is equal to 0
[e] Semi risk adverse is equal to 0.40
[f] Risk adverse is equal to 0.85
[g] Very risk adverse is equal to 1.30

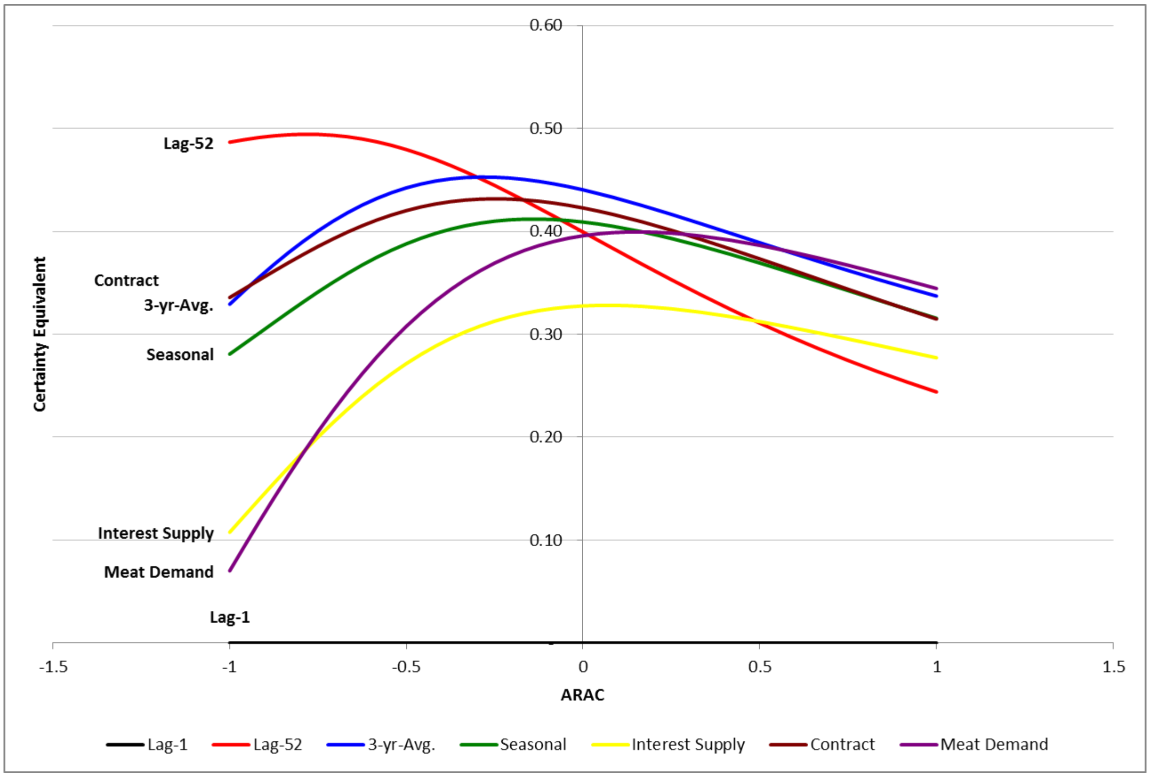

Figure 41. Stochastic efficiency of singular forecasts for Texas live cattle steers

Table 51. Stochastic Efficiency Ranks for Singular Forecasts: Risk Preference for Texas Live Cattle Steer

Forecast	Risk Preference						
	Very Risk[a] Loving	Risk[b] Loving	Semi-Risk[c] Loving	Risk[d] Neutral	Semi-Risk[e] Adverse	Risk[f] Adverse	Very Risk[g] Adverse
Lag-1	1	1	1	1	1	1	1
Lag-52	7	7	7	4	3	2	2
3-yr. avg.	3	2	2	2	2	3	3
Seasonal	6	5	5	6	5	5	4
Interest Supply	4	4	4	5	4	4	5
CD	5	6	6	7	7	6	6
Meat Demand	2	3	3	3	6	7	7

a. Very risk loving is equal to -1.00
b. Risk loving is equal to –0.66
c. Semi risk loving is equal to -0.33
d. Risk neutral is equal to 0.00
e. Semi risk adverse is equal to 0.33
f. Risk adverse is equal to 0.66
g. Very risk adverse is equal to 1.00

Table 52. Risk Premiums (Difference in Certainty Equivalent) for Singular Forecasts, Nebraska Live Cattle Steers

Forecast	Risk[a] Neutral	Moderately[b] Risk Adverse	Risk[c] Adverse	Very Risk[d] Adverse
Lag-1	-	-	-	-
Lag-52	1.47	1.36	1.07	0.76
3-yr. avg.	1.80	1.63	1.23	0.81
Seasonal	1.52	1.35	1.02	0.73
Interest Supply	1.68	1.44	1.02	0.68
CD	1.56	1.38	1.07	0.78
Meat Demand	0.17	0.36	0.46	0.46

[a] Risk Neutral is equal to an RAC of 0.00
[b] Moderately Risk Adverse is equal to an RAC of 0.40
[c] Risk Adverse is equal to an RAC of 0.85
[d] Very Risk Adverse is equal to an RAC of 1.30

Table 53. Risk Premiums (Difference in Certainty Equivalent) for Singular Forecasts, Texas Live Cattle Steers

Forecast	Risk[a] Neutral	Moderately[b] Risk Averse	Risk[c] Adverse	Very Risk[d] Adverse
Lag-1	-	-	-	-
Lag-52	0.49	0.49	0.46	0.40
3-yr. avg.	0.33	0.42	0.45	0.44
Seasonal	0.28	0.36	0.41	0.41
Interest Supply	0.11	0.23	0.30	0.33
CD	0.34	0.40	0.43	0.42
Meat Demand	0.07	0.24	0.35	0.40

[a] Risk Neutral is equal to an RAC of 0.0
[b] Moderately Risk Adverse is equal to an RAC of 0.33
[c] Risk Adverse is equal to an RAC of 0.66
[d] Very Risk Adverse is equal to an RAC of 1.00

Part II

Table 54. Composite Forecast Accuracy for Nebraska Live Cattle Steers Basis

	Forecast Error							
Forecast	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Optimal	1.57	1.18	2.45	233.4	231.4	0.65	0.402	0.67
Equal	2.13	1.66	4.52	304.3	344.9	0.91	0.578	0.92
Expert Opinion	2.20	1.70	4.85	272.7	2,337.0	0.94	0.622	0.95
Ease-of-use	2.15	1.66	4.63	267.7	510.5	0.91	0.623	0.93
Best MSE	1.82	1.42	3.33	247.0	510.9	0.78	0.476	0.79
Best sMAPE	2.37	1.86	5.61	375.6	875.9	1.02	0.613	1.02
Best Theil's I	1.83	1.44	3.35	261.7	431.8	0.79	0.476	0.79

Table 55. Composite Forecast Accuracy for Texas Live Cattle Steers Basis

Forecast	Forecast Error							
	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Optimal	1.40	1.07	1.95	272.1	292.5	0.79	0.435	0.77
Equal	1.60	1.29	2.55	312.2	4,718.8	0.96	0.597	0.88
Expert Opinion	1.64	1.32	2.69	280.0	630.6	0.98	0.638	0.90
Ease-of-use	1.60	1.27	2.57	277.6	527.7	0.94	0.643	0.88
Best MSE	1.48	1.20	2.19	287.5	462.7	0.89	0.520	0.81
Best sMAPE	1.72	1.44	2.96	404.6	382.0	1.07	0.571	0.95
Best Theil's I	1.48	1.20	2.19	287.5	462.7	0.89	0.520	0.81

Table 56. Composite Forecast Rankings for Nebraska Live Cattle Steers Basis

Composite Forecast	Forecast Error							
	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Optimal	1	1	1	1	1	1	1	1
Equal	2	2	2	2	5	2	2	2
Expert Opinion	3	3	3	3	3	3	3	3
Ease-of-use	4	5	4	6	2	5	4	4
Best MSE	5	4	5	4	4	4	7	5
Best sMAPE	6	6	6	5	7	6	6	6
Best Theil's I	7	7	7	7	6	7	5	7

Table 57. Composite Forecast Rankings for Texas Live Cattle Steers Basis

Composite Forecast	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
	Forecast Error							
Optimal	1	1	1	1	1	1	1	1
Equal	2	2	2	4	3	2	2	2
Expert Opinion	3	3	3	5	4	3	3	3
Ease-of-use	4	5	4	6	7	5	5	4
Best MSE	5	4	5	2	5	4	7	5
Best sMAPE	6	6	6	3	6	6	6	6
Best Theil's I	7	7	7	7	2	7	4	7

Table 58. Spearman Rank of Nebraska Live Cattle Steers Forecast Errors

Forecast Error	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
	Forecast Error							
RMSE	1	0.96	1.00	0.89	0.71	0.96	0.86	1.00
MAD		1	0.96	0.96	0.64	1.00	0.75	0.96
MSE			1	0.89	0.71	0.96	0.86	1.00
MAPE				1	0.46	0.96	0.68	0.89
sMAPE					1	0.64	0.57	0.71
RAE						1	0.75	0.96
Theil's I							1	0.86
Theils U2								1

Table 59. Spearman Rank of Texas Live Cattle Steers Forecast Errors

Forecast Error	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
RMSE	1	0.96	1.00	0.46	0.36	0.96	0.75	1.00
MAD		1	0.96	0.61	0.43	1.00	0.68	0.96
MSE			1	0.46	0.36	0.96	0.75	1.00
MAPE				1	0.18	0.61	0.07	0.46
sMAPE					1	0.43	0.75	0.36
RAE						1	0.68	0.96
Theil's I							1	0.75
Theils U2								1

Table 60. Stochastic Dominance Ranks: Risk Preference for Live Cattle

Composite Forecast	Nebraska		Texas	
	Risk Loving[a]	Risk Adverse[b]	Risk Loving[c]	Risk Adverse[d]
Optimal	1	1	1	1
Equal	4	6	4	5
Expert Opinion	5	4	6	4
Ease-of-use	6	5	5	6
Best MSE	3	2	3	3
Best sMAPE	7	7	7	7
Best Theil's I	2	3	2	2

[a] Risk Loving is equal to an RAC of -1.25
[b] Risk Adverse is equal to an RAC of 1.25
[c] Risk Loving is equal to an RAC of -0.90
[d] Risk Adverse is equal to an RAC of 0.90

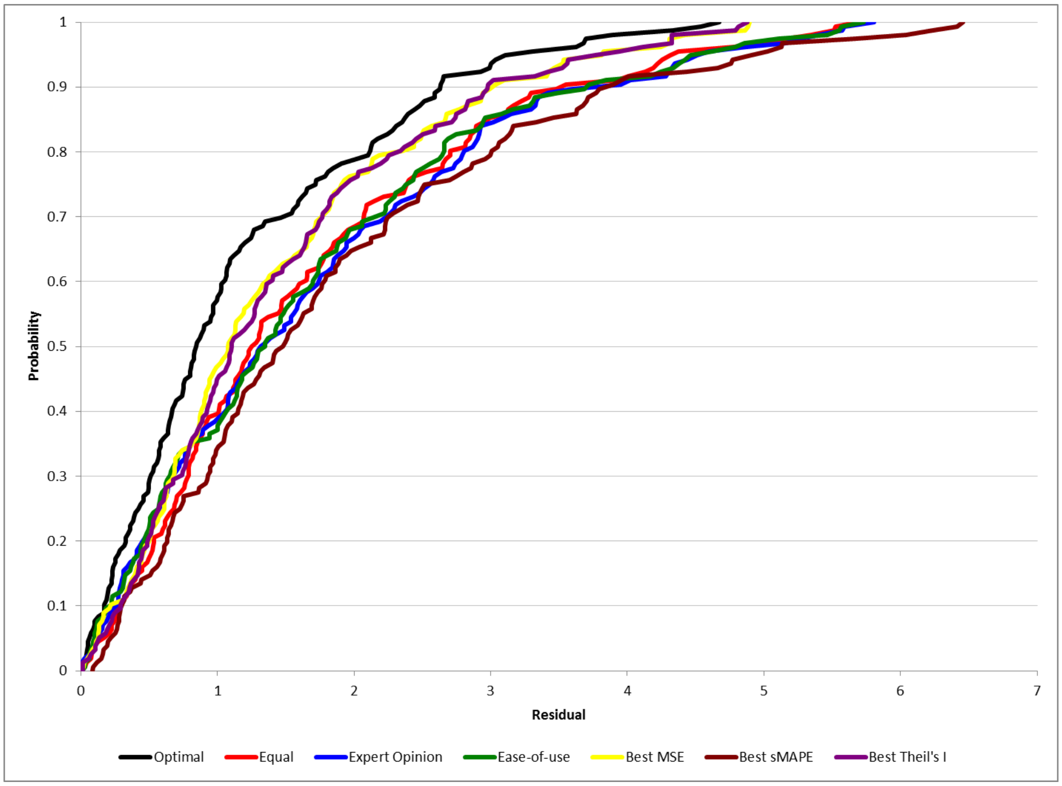

Figure 42. CDF comparison of composite forecast errors for Nebraska live steers

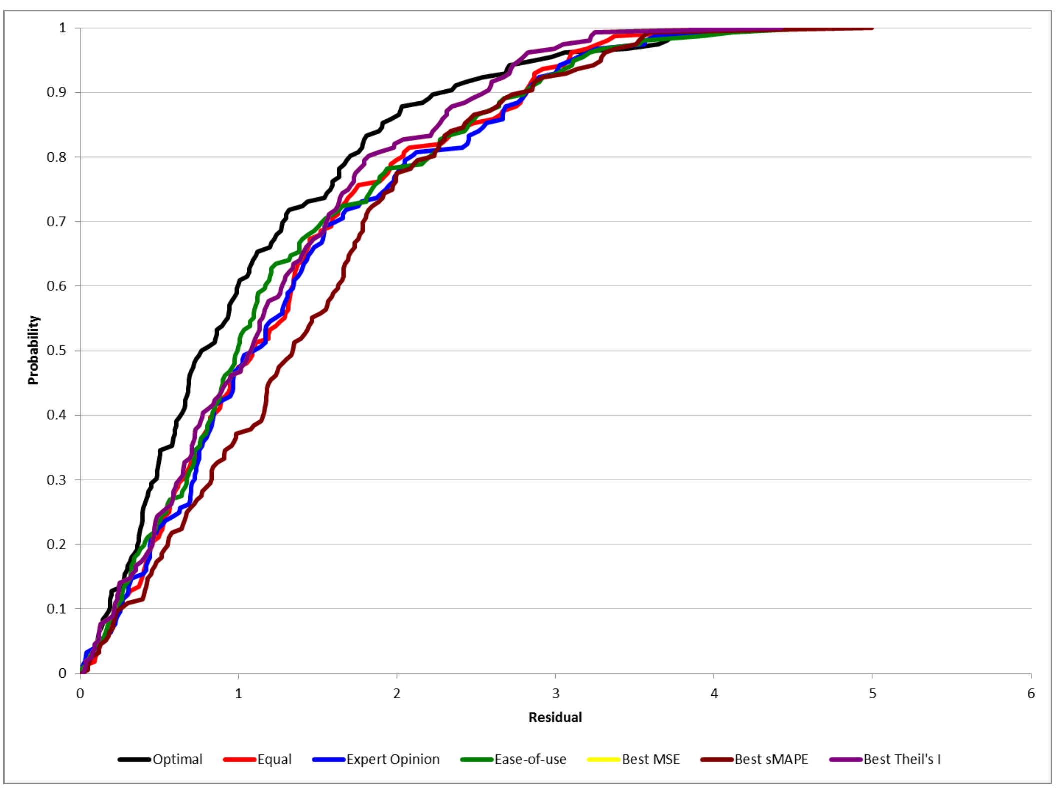

Figure 43. CDF comparison of composite forecast errors for Texas live steers

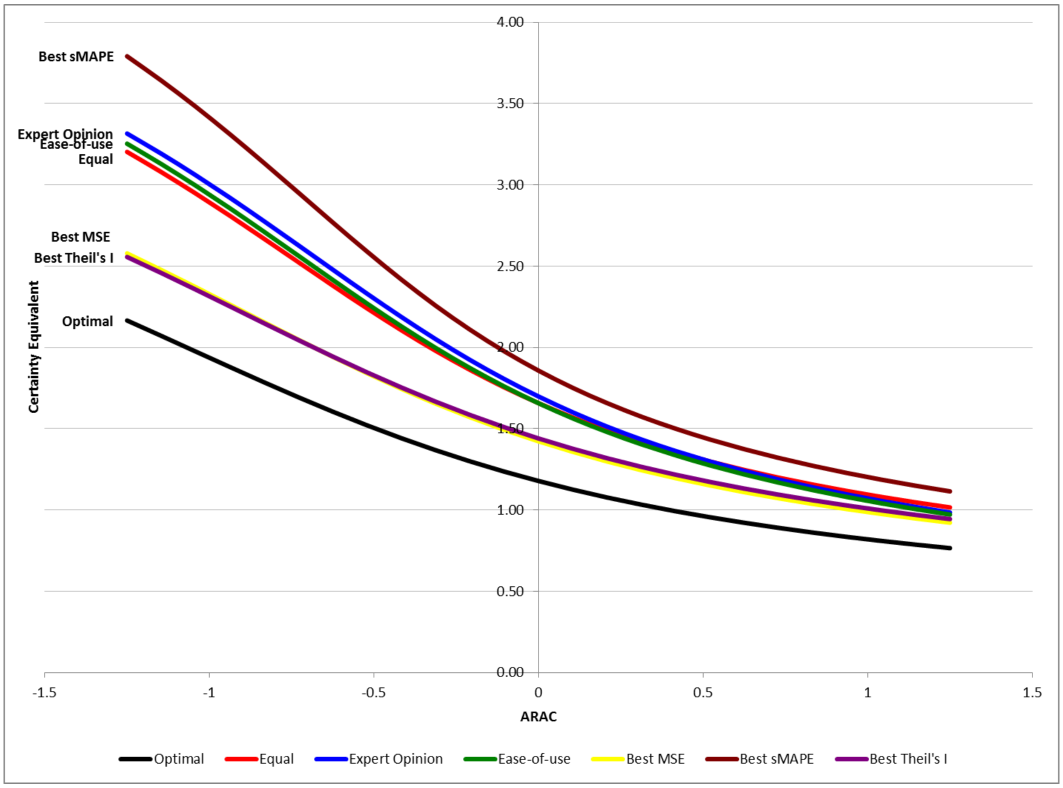

Figure 44. Stochastic efficiency of composite forecasts for Nebraska live cattle steers

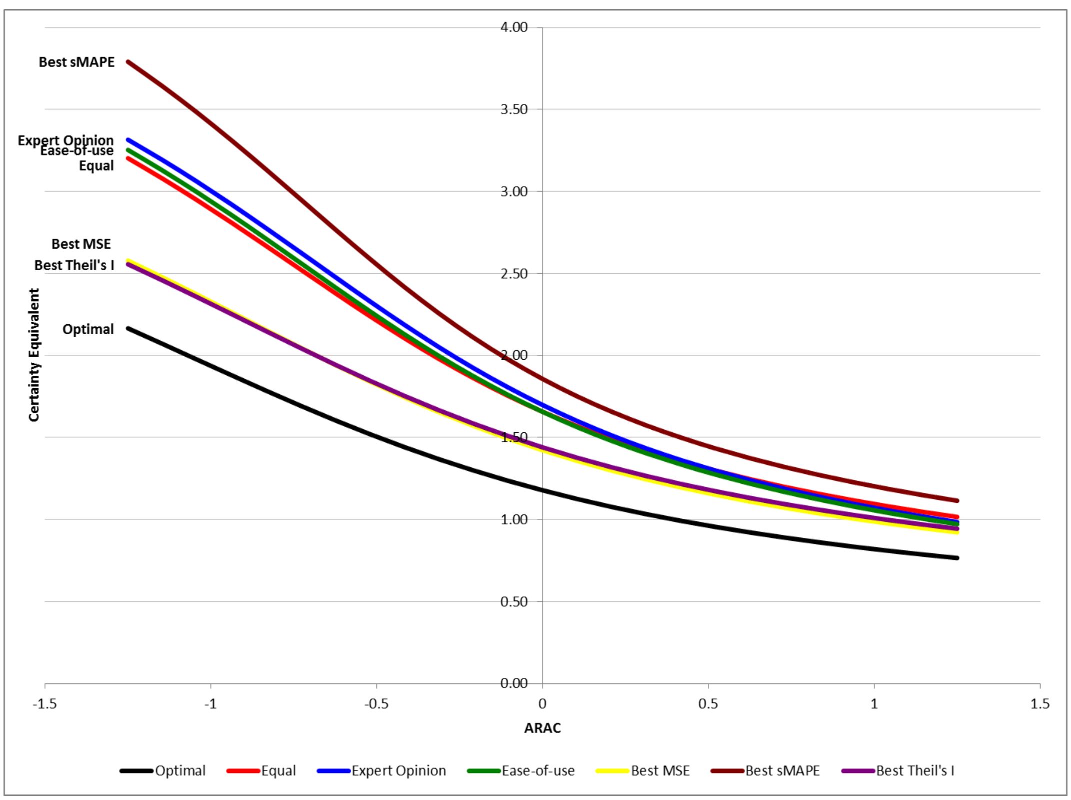

Figure 45. Stochastic efficiency of composite forecasts for Texas live cattle steers

Table 61. Stochastic Efficiency Ranks for Composite Forecasts: Risk Preference for Nebraska Live Cattle Steers

Composite Forecast	Risk Preference						
	Very Risk[a] Loving	Risk[b] Loving	Semi-Risk[c] Loving	Risk[d] Neutral	Semi-Risk[e] Adverse	Risk[f] Adverse	Very Risk[g] Adverse
Optimal	1	1	1	1	1	1	1
Equal	4	4	4	5	5	6	6
Expert Opinion	6	6	6	6	6	5	5
Ease-of-use	5	5	5	4	4	4	4
Best MSE	3	3	2	2	2	2	2
Best sMAPE	7	7	7	7	7	7	7
Best Theil's I	2	2	3	3	3	3	3

[a.] Very risk loving is equal to -1.25
[b.] Risk loving is equal to -0.83
[c.] Semi risk loving is equal to -0.41
[d.] Risk neutral is equal to 0.00
[e.] Semi risk adverse is equal to 0.41
[f.] Risk adverse is equal to 0.83
[g.] Very risk adverse is equal to 1.25

Table 62. Risk Premiums (Improvement in Residuals) for Composite, Nebraska Live Cattle Steers

Composite Forecast	Risk[a] Neutral	Moderately[b] Risk Adverse	Risk[c] Adverse	Very Risk[d] Adverse
Optimal	-	-	-	-
Equal	1.04	0.88	0.66	0.48
Expert Opinion	1.15	0.99	0.75	0.52
Ease-of-use	1.09	0.93	0.69	0.48
Best MSE	0.41	0.37	0.30	0.24
Best sMAPE	1.63	1.35	0.98	0.68
Best Theil's I	0.39	0.36	0.31	0.26

[a] Risk Neutral is equal to an RAC of 0.0
[b] Moderately Risk Adverse is equal to an RAC of 0.41
[c] Risk Adverse is equal to an RAC of 0.83
[d] Very Risk Adverse is equal to an RAC of 1.25

Table 63. Stochastic Efficiency Ranks for Composite Forecasts: Risk Preference for Texas Live Cattle Steers

Composite Forecast	Risk Preference: Very Risk[a] Loving	Risk[b] Loving	Semi-Risk[c] Loving	Risk[d] Neutral	Semi-Risk[e] Adverse	Risk[f] Adverse	Very Risk[g] Adverse
Optimal	3	1	1	1	1	1	1
Equal	4	4	5	5	5	5	5
Expert Opinion	6	6	6	6	6	6	6
Ease-of-use	5	5	4	4	4	4	4
Best MSE	1	2	2	2	2	2	2
Best sMAPE	7	7	7	7	7	7	7
Best Theil's I	2	3	3	3	3	3	3

[a.] Very risk loving is equal to -1.00
[b.] Risk loving is equal to -0.66
[c.] Semi risk loving is equal to -0.33
[d.] Risk neutral is equal to 0.00
[e.] Semi risk adverse is equal to 0.33
[f.] Risk adverse is equal to 0.66
[g.] Very risk adverse is equal to 1.00

Table 64. Risk Premiums (Improvement in Residuals) for Composite, Texas Live Cattle Steers

Composite Forecast	Risk[a] Neutral	Moderately[b] Risk Adverse	Risk[c] Adverse	Very Risk[e] Adverse
Optimal	-	-	-	-
Equal	0.19	0.22	0.23	0.23
Expert Opinion	0.24	0.27	0.27	0.26
Ease-of-use	0.23	0.24	0.22	0.20
Best MSE	-	0.07	0.11	0.14
Best sMAPE	0.33	0.36	0.38	0.37
Best Theil's I	-	0.07	0.11	0.14

[a] Risk Neutral is equal to an RAC of 0.0
[b] Moderately Risk Adverse is equal to an RAC of 0.33
[c] Risk Adverse is equal to an RAC of 0.66
[d] Very Risk Adverse is equal to an RAC of 1.00

Table 65. Forecast Risk Summary for Singular Forecasts

Forecast Evaluation	**Nebraska**		**Texas**	
	Best	Worse	Best	Worse
Forecast Error	Lag-1, Lag-52	Meat Demand, Contract Dummy	Lag-1, Lag-52	Meat Demand, Contract Dummy
Stochastic Dominance	Lag-1, Meat Demand	Contract Dummy, 3 yr. avg.	Lag-1	3 yr. avg.
Stochastic Efficiency	Lag-1, Meat Demand	3 yr. avg., Lag-52	Lag-1, 3 yr. avg.	Seasonal, Contract Dummy
Recommendations (Yes/No)	Lag-1, Meat Demand	Contract Dummy, 3 yr. avg.	Lag-1	Contract Dummy

Table 66. Forecast Risk Summary for Composite Forecasts

Forecast Evaluation	**Nebraska**		**Texas**	
	Best	Worse	Best	Worse
Forecast Error	Optimal, Equal	Best sMAPE, Best Theil's I	Optimal, Equal	Best sMAPE, Best Theil's I
Stochastic Dominance	Optimal, Best Theil's I	Best sMAPE, Ease-of-use	Optimal, Best Theil's I	Best sMAPE, Ease-of-use
Stochastic Efficiency	Optimal, Best Theil's I	Best sMAPE, Expert Opinion	Best MSE, Optimal	Ease-of-use, Expert Opinion
Recommendations (Yes/No)	Optimal, Best Theil's I	Best sMAPE	Optimal	Ease-of-use

Table 67. Live Cattle Lag-1 Regression Results, 2004-2009

Variables	Nebraska C	S.E.	T-stat	Prob.	Texas C	S.E.	T-stat	Prob.
Intercept	(0.35)	0.17	(2.12)	0.03	(0.13)	0.13	(1.03)	0.30
Lag-1	0.63	0.07	9.55	-	0.61	0.07	8.38	-
No. of obs.	313				313			
Adjusted R^2	41				0.37			
F-stat	215.58				185.65			

Table 68. Live Cattle Lag-52 Regression Results, 2004-2009

Variables	Nebraska C	S.E.	T-stat	Prob.	Texas C	S.E.	T-stat	Prob.
Intercept	(0.92)	0.31	(2.97)	0.00	(0.35)	0.26	(1.32)	0.19
Lag-52	0.22	0.07	3.09	0.00	0.18	0.07	2.66	0.01
No. of obs.	313				313			
Adjusted R^2	0.07				0.04			
F-stat	24.52				12.99			

Table 69. Live Cattle 3-yr. avg. Regression Results, 2004-2009

Variables	Nebraska				Texas			
	C	S.E.	T-stat	Prob.	C	S.E.	T-stat	Prob.
Intercept	(0.90)	0.31	(2.90)	0.00	(0.31)	0.25	(1.22)	0.22
3-yr. avg.	0.18	0.09	1.95	0.05	0.45	0.11	4.07	0.00
No. of obs.	313				313			
Adjusted R^2	0.05				0.10			
F-stat	17.21				37.33			

Table 70. Live Cattle Contract Dummy Regression Results, 2004-2009

Variables	Nebraska				Texas			
	C	S.E.	T-stat	Prob.	C	S.E.	T-stat	Prob.
Intercept	1.79	0.67	2.67	0.01	1.51	0.63	2.40	0.02
Contract-February	(4.20)	0.87	(4.84)	-	(2.55)	0.78	(3.29)	0.00
Contract-June	(1.16)	0.86	(1.35)	0.18	(0.42)	0.75	(0.55)	0.58
Contract-August	(3.47)	0.76	(4.55)	-	(2.91)	0.74	(3.93)	0.00
Contract-October	(4.14)	0.76	(5.45)	-	(2.86)	0.72	(3.99)	0.00
Contract-December	(3.71)	0.88	(4.21)	-	(2.36)	0.87	(2.72)	0.01
No. of obs.	313				313			
Adjusted R^2	0.28				0.20			
F-stat	25.61				16.57			

Table 71. Live Cattle Seasonal Regression Results, 2004-2009

	Nebraska				Texas			
Variables	C	S.E.	T-stat	Prob.	C	S.E.	T-stat	Prob.
Intercept	1.30	0.78	1.67	0.10	1.10	0.70	1.56	0.12
January	(4.20)	1.01	(4.15)	-	(2.46)	0.90	(2.73)	0.01
February	(3.20)	0.99	(3.24)	0.00	(1.81)	0.90	(2.01)	0.05
April	0.98	0.99	0.99	0.32	0.82	0.98	0.84	0.40
May	0.36	1.13	0.32	0.75	0.59	1.09	0.54	0.59
June	(1.70)	1.15	(1.48)	0.14	(0.60)	1.00	(0.60)	0.55
July	(3.27)	0.97	(3.36)	0.00	(2.51)	0.96	(2.63)	0.01
August	(2.69)	0.85	(3.17)	0.00	(2.49)	0.77	(3.24)	0.00
September	(3.66)	0.93	(3.93)	0.00	(2.60)	0.80	(3.26)	0.00
October	(3.65)	0.99	(3.70)	0.00	(2.30)	0.93	(2.46)	0.01
November	(2.93)	1.08	(2.71)	0.01	(1.86)	1.08	(1.71)	0.09
December	(3.49)	1.04	(3.36)	0.00	(2.03)	0.95	(2.15)	0.03
No. of obs.	313				313			
Adjusted R^2	0.30				0.20			
F-stat	13.27				8.13			

Table 72. Live Cattle Interest Supply Regression Results, 2004-2009

Variables	**Nebraska**				**Texas**			
	C	S.E.	T-stat	Prob.	C	S.E.	T-stat	Prob.
Intercept	2.22	4.31	0.51	0.61	2.60	4.34	0.60	0.55
January	(4.48)	1.06	(4.25)	-	(2.43)	1.11	(2.20)	0.03
February	(3.54)	1.05	(3.37)	0.00	(2.01)	1.05	(1.92)	0.06
April	1.18	1.19	0.99	0.32	1.10	1.20	0.92	0.36
May	0.75	1.37	0.55	0.58	1.04	1.33	0.78	0.43
June	(1.73)	1.26	(1.37)	0.17	(0.49)	1.26	(0.39)	0.70
July	(2.97)	1.30	(2.27)	0.02	(2.30)	1.35	(1.70)	0.09
August	(2.29)	1.19	(1.93)	0.06	(2.27)	1.18	(1.92)	0.06
September	(3.32)	1.26	(2.64)	0.01	(2.39)	1.18	(2.02)	0.04
October	(3.30)	1.30	(2.54)	0.01	(2.07)	1.23	(1.68)	0.09
November	(2.57)	1.35	(1.91)	0.06	(1.61)	1.29	(1.25)	0.21
December	(3.18)	1.17	(2.73)	0.01	(1.89)	1.12	(1.69)	0.09
Boxed Beef: Lag-26	(0.00)	0.03	(0.09)	0.93	(0.01)	0.02	(0.47)	0.64
Feeder: Lag-26	0.01	0.05	0.23	0.82	0.01	0.05	0.27	0.78
Corn: Lag-26	(0.24)	0.21	(1.17)	0.24	(0.08)	0.19	(0.43)	0.67
Interest: Lag-26	(0.22)	0.20	(1.11)	0.27	(0.20)	0.20	(1.02)	0.31
No. of obs.	287				287			
Adjusted R^2	0.33				0.21			
F-stat	10.44				6.18			

Table 73. Live Cattle Meat Demand Regression Results, 2004-2009

	Nebraska				**Texas**			
Variables	C	S.E.	T-stat	Prob.	C	S.E.	T-stat	Prob.
Intercept	10.24	10.83	0.94	0.35	7.55	10.98	0.69	0.49
January	(4.89)	1.00	(4.91)	-	(2.71)	1.06	(2.54)	0.01
February	(3.47)	1.00	(3.46)	0.00	(1.96)	1.01	(1.93)	0.05
April	0.90	1.02	0.88	0.38	0.75	1.05	0.72	0.47
May	0.59	1.21	0.49	0.62	0.79	1.16	0.68	0.50
June	(0.94)	1.12	(0.84)	0.40	(0.05)	1.00	(0.05)	0.96
July	(2.13)	1.12	(1.90)	0.06	(1.74)	1.18	(1.47)	0.14
August	(1.62)	1.01	(1.60)	0.11	(1.75)	1.00	(1.76)	0.08
September	(2.67)	1.07	(2.50)	0.01	(1.95)	0.96	(2.03)	0.04
October	(2.79)	1.00	(2.81)	0.01	(1.77)	0.99	(1.80)	0.07
November	(2.45)	0.99	(2.47)	0.01	(1.61)	1.08	(1.49)	0.14
December	(3.15)	1.05	(3.01)	0.00	(1.85)	1.03	(1.79)	0.07
Boxed Beef	0.07	0.03	2.30	0.02	0.05	0.03	1.65	0.10
Hog	(0.01)	0.03	(0.37)	0.72	(0.02)	0.03	(0.62)	0.54
Broiler	(0.12)	0.06	(1.97)	0.05	(0.08)	0.06	(1.22)	0.23
ELA	(0.08)	0.05	(1.55)	0.12	(0.05)	0.05	(1.05)	0.29
No. of obs.	313				313			
Adjusted R^2	0.37				0.22			
F-stat	12.50				6.63			

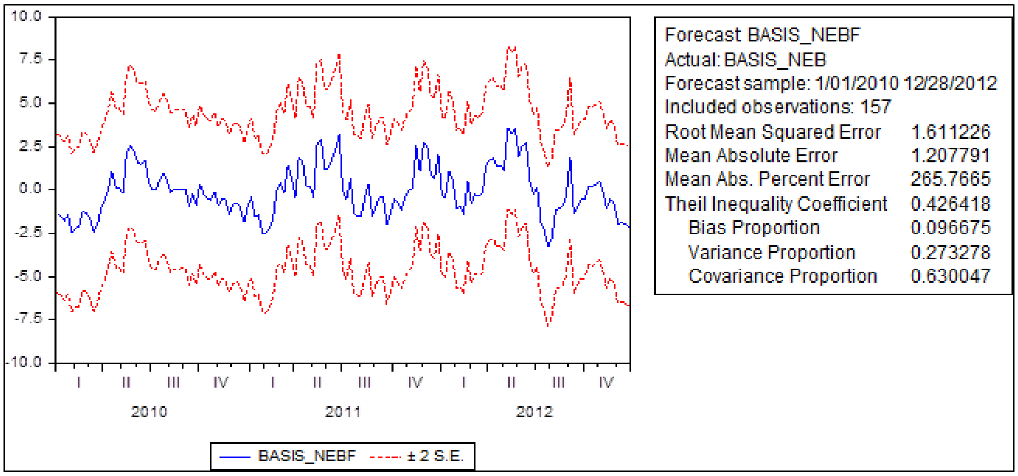

Figure 46. Lag-1 Singular forecast, Nebraska live cattle steers

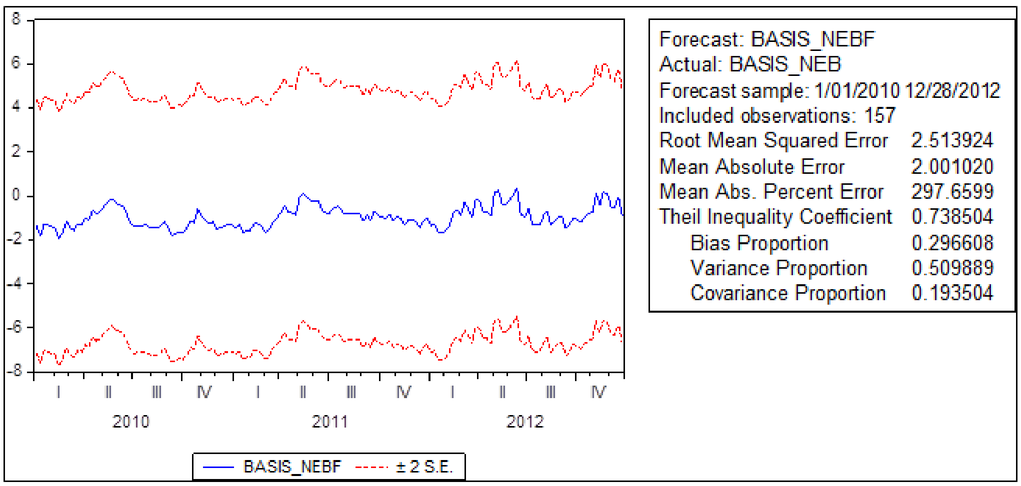

Figure 47. Lag-52 Singular forecast, Nebraska live cattle steers

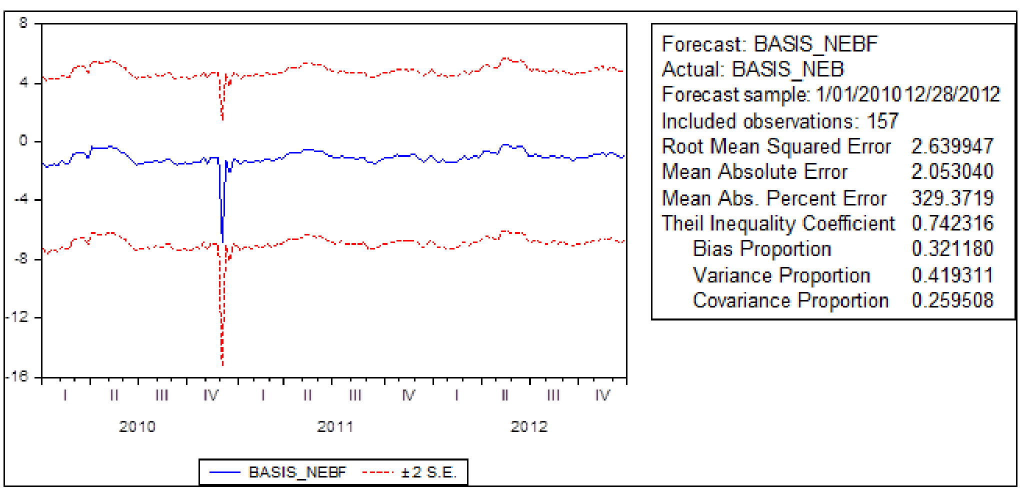

Figure 48. 3 yr. avg. Singular forecast, Nebraska live cattle steers

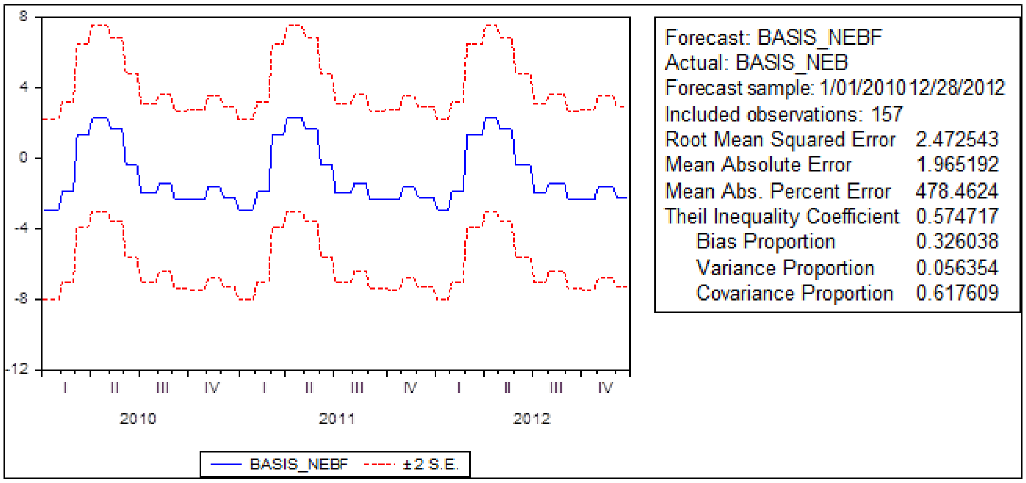

Figure 49. Seasonal singular forecast, Nebraska live cattle steers

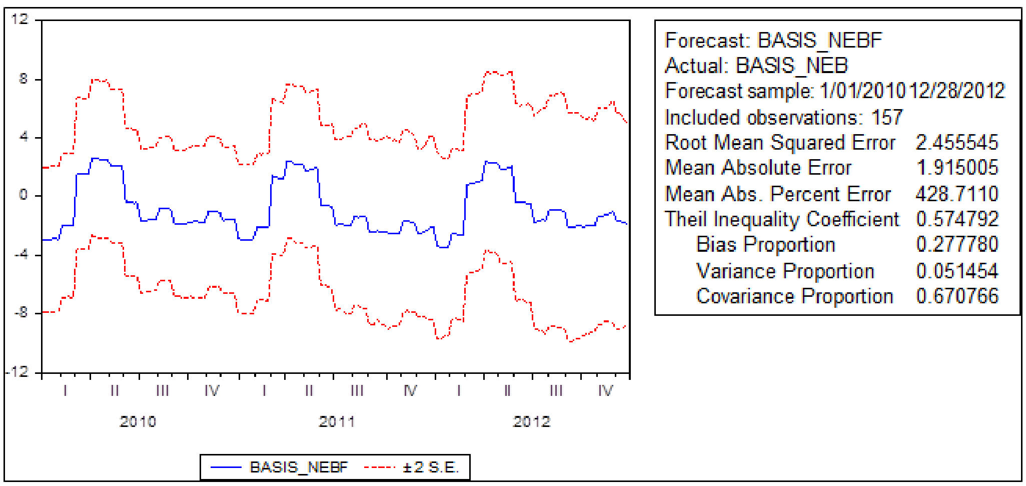

Figure 50. Interest supply singular forecast, Nebraska live cattle steers

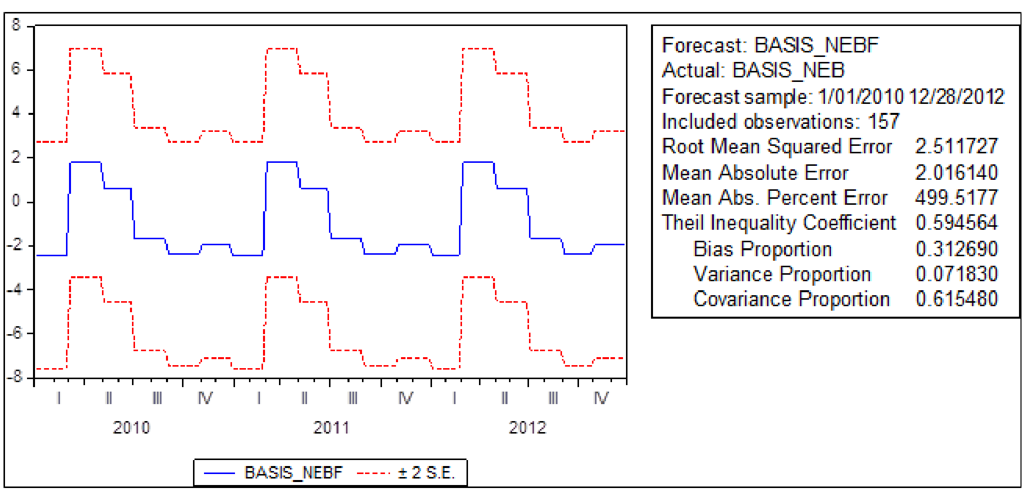

Figure 51. Contract dummies singular forecast, Nebraska live cattle steers

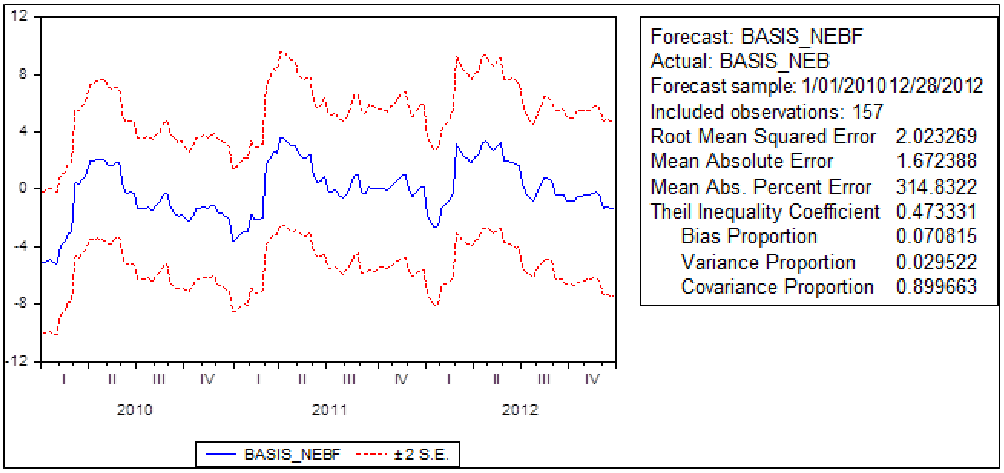

Figure 52. Meat demand singular forecast, Nebraska live cattle steers

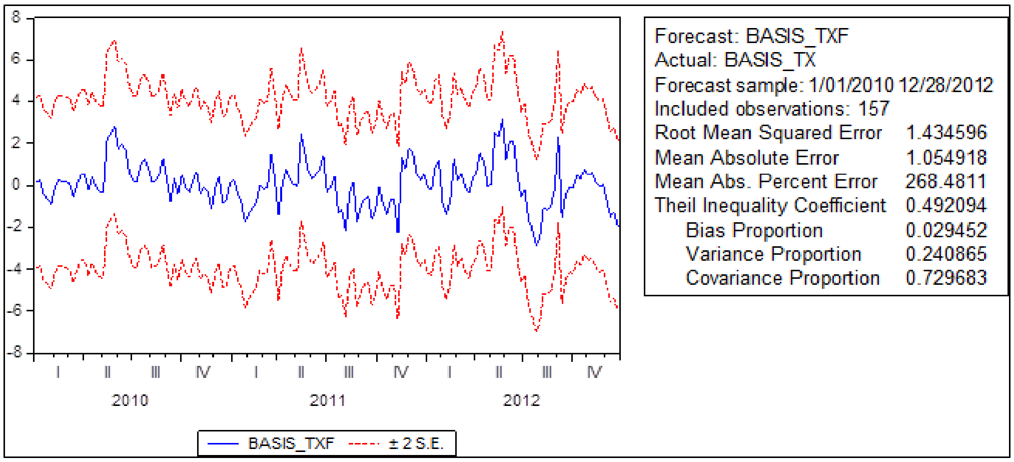

Figure 53. Lag-1 Singular forecast, Western Kansas live cattle steers

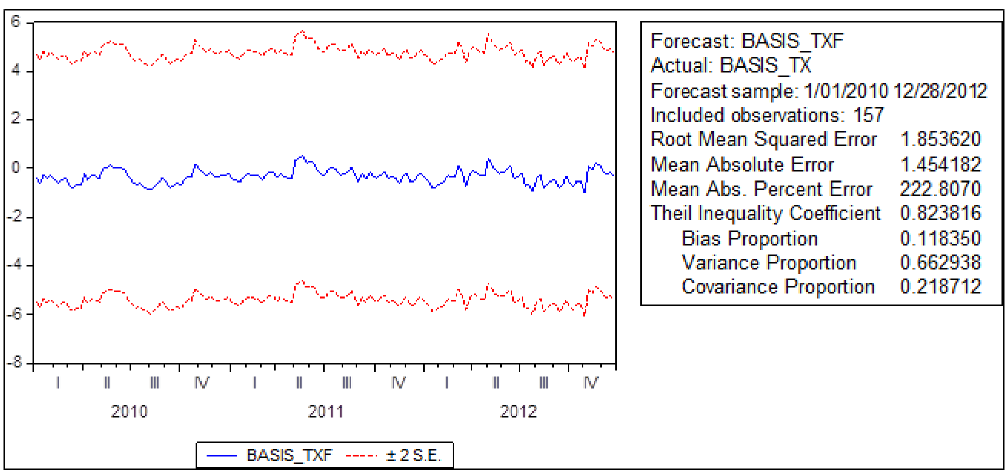

Figure 54. Lag-52 Singular forecast, Western Kansas live cattle steers

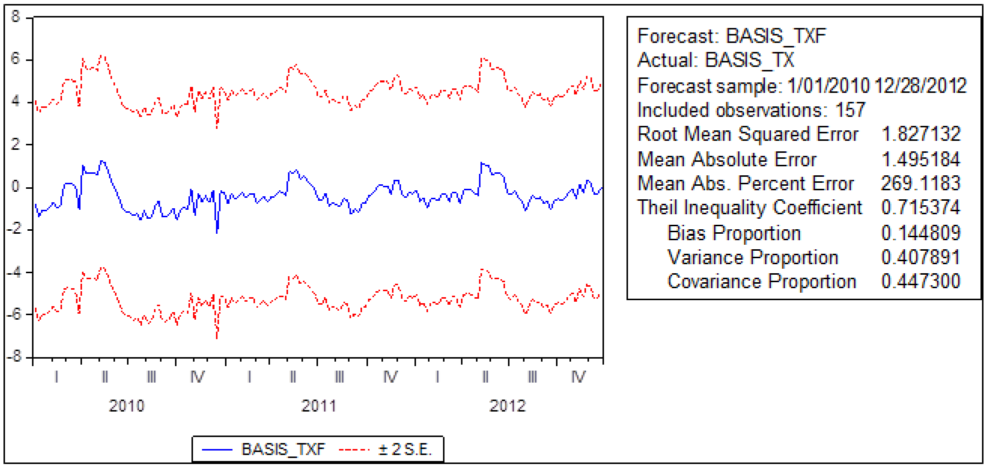

Figure 55. 3 yr. avg. Singular forecast, Western Kansas live cattle steers

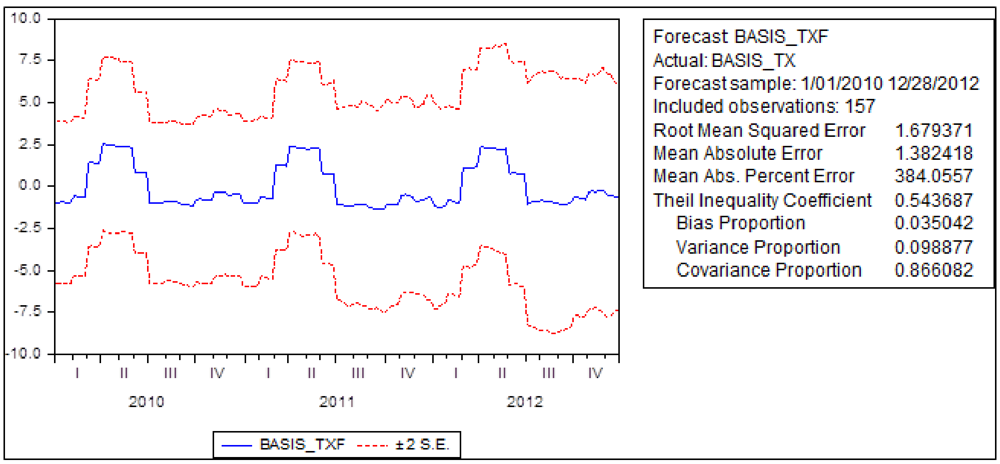

Figure 56. Interest supply singular forecast, Western Kansas live cattle steers

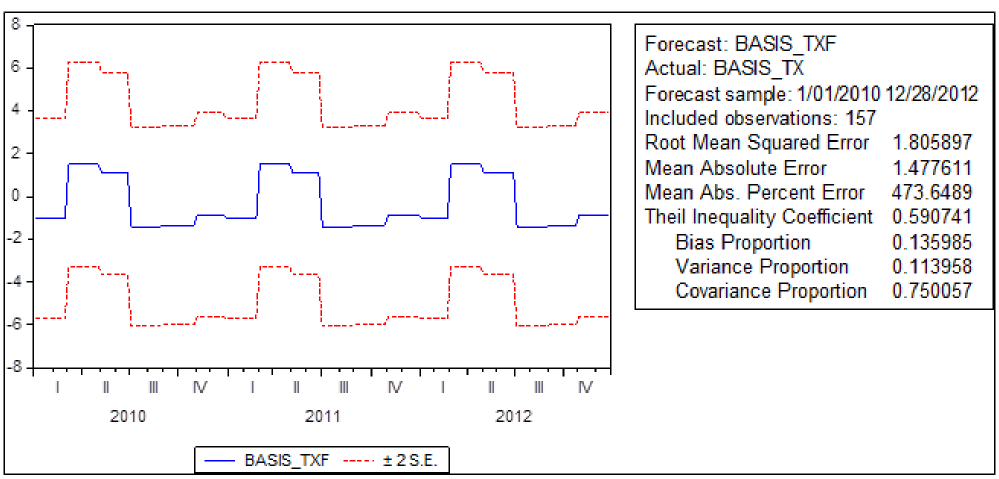

Figure 57. Contract dummies singular forecast, Western Kansas live cattle steers.

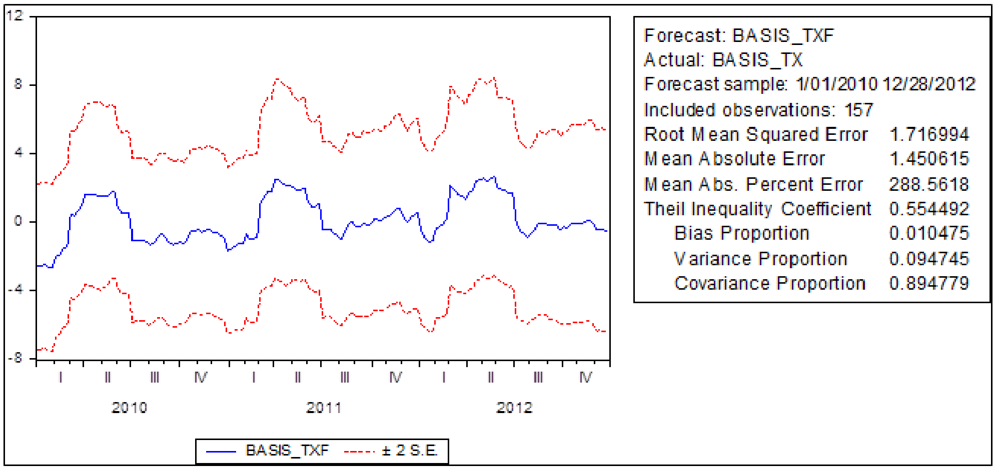

Figure 58. Meat demand singular forecast, Western Kansas live cattle steers

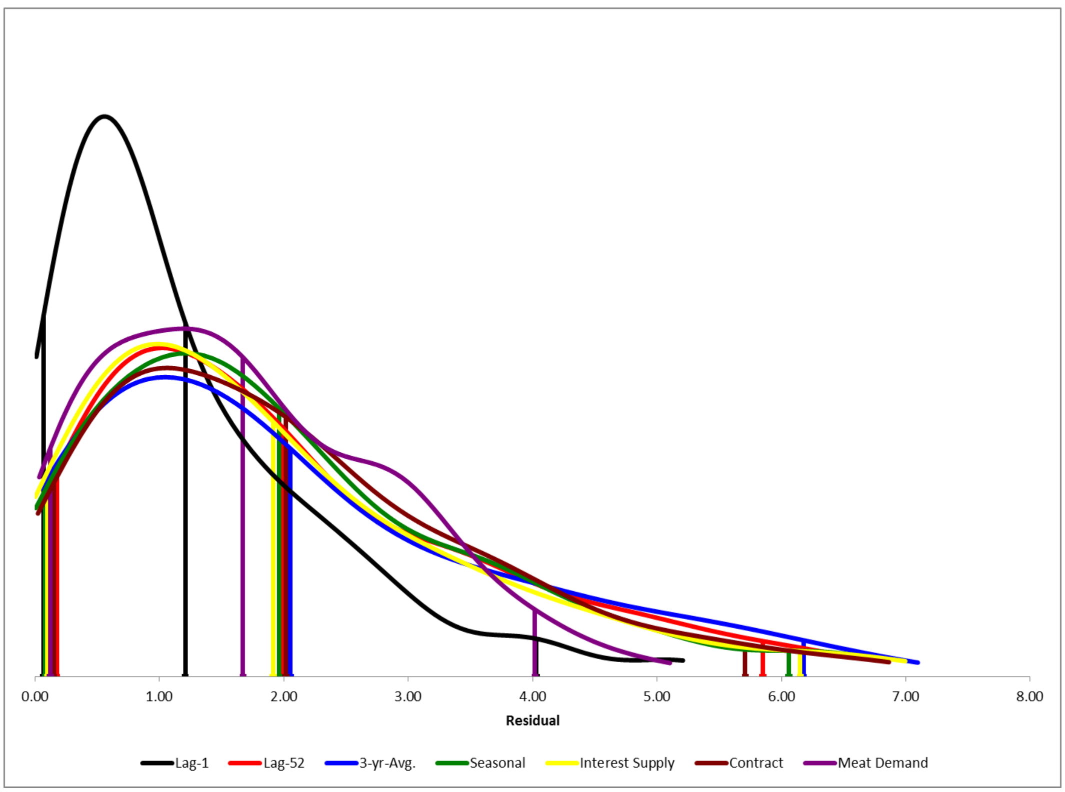

Figure 59. PDF of Nebraska live cattle steers, singular forecasts

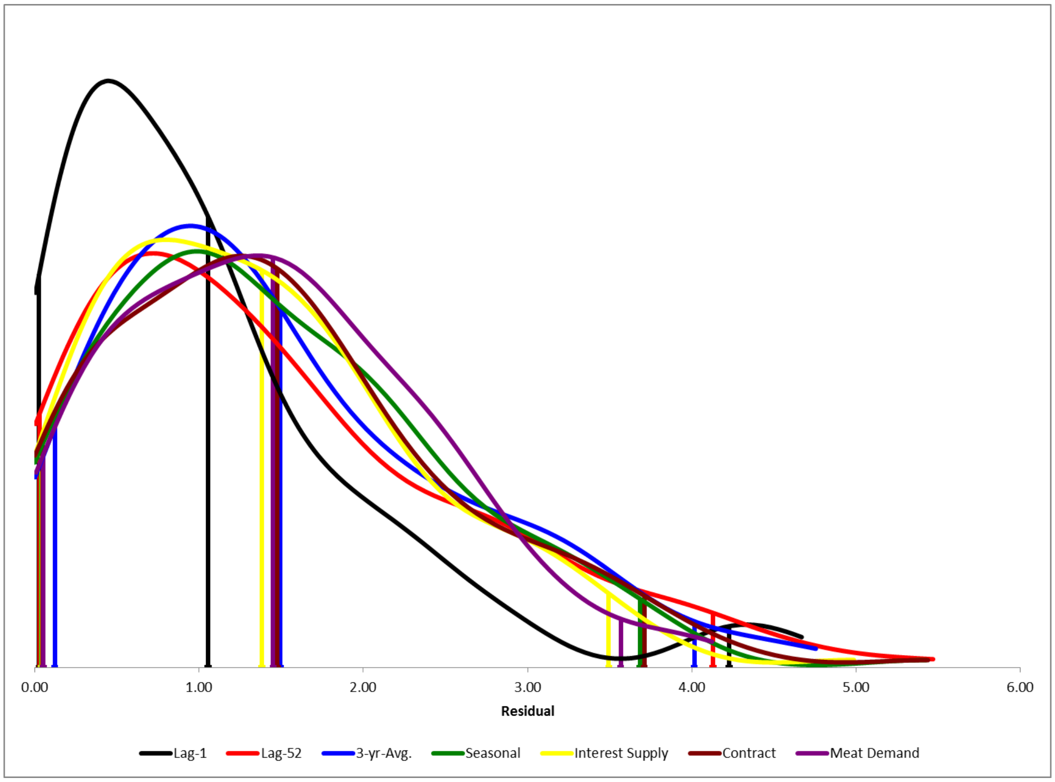

Figure 60. PDF of Texas live cattle steers, singular forecasts

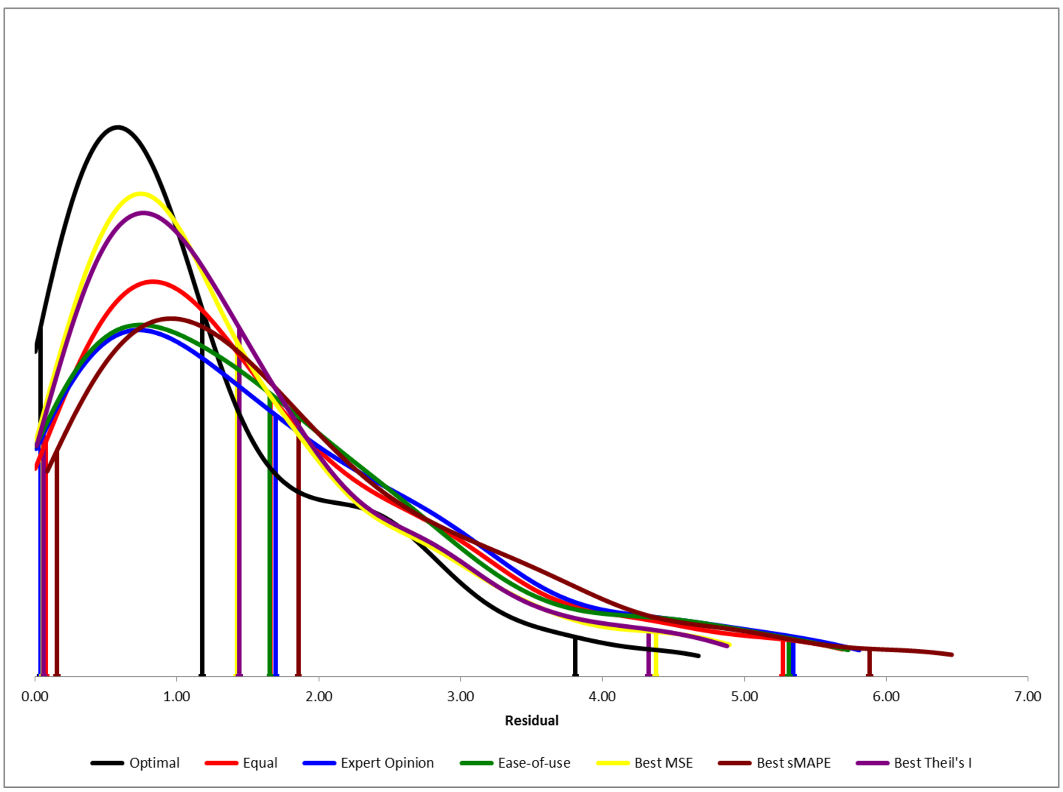

Figure 61. PDF of Nebraska live cattle steers, composite forecasts

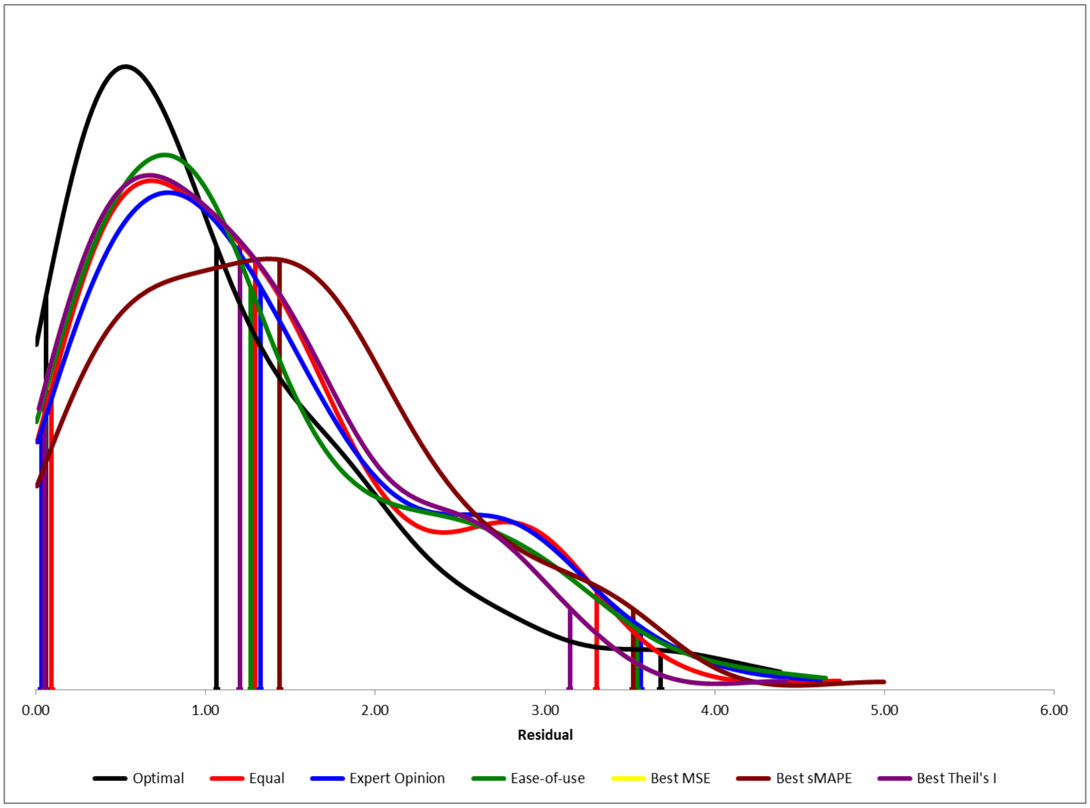

Figure 62. PDF of Texas live cattle steers, composite forecasts

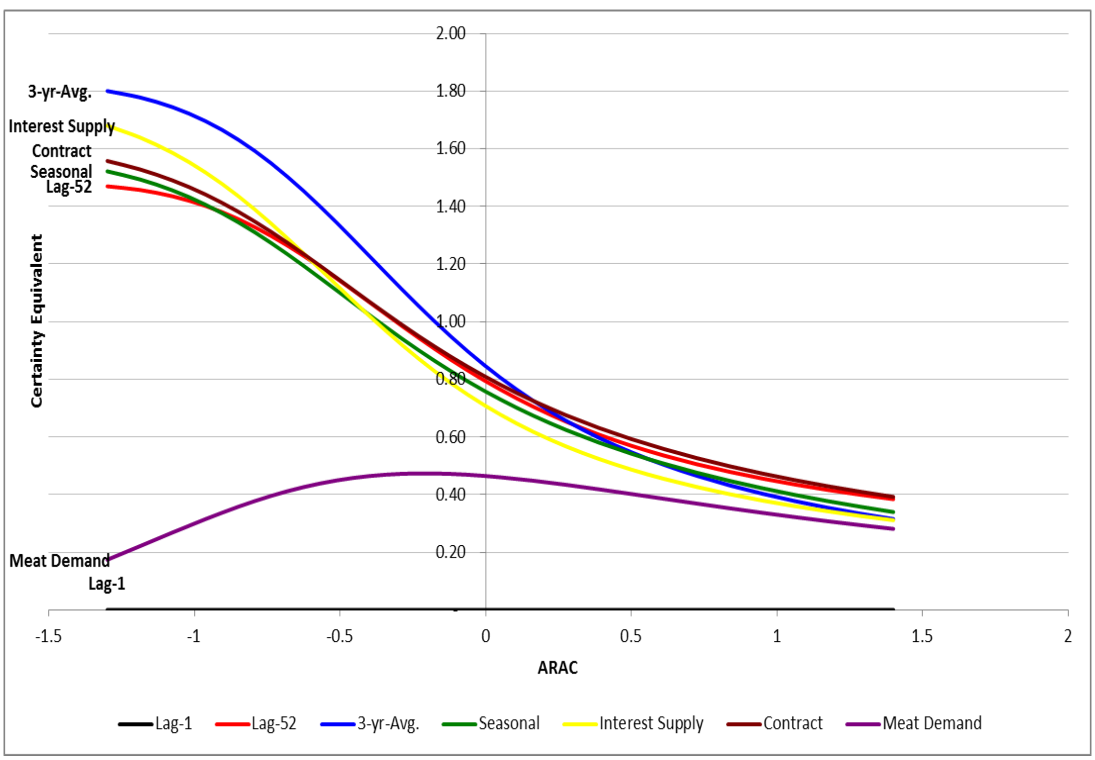

Figure 63. Risk premiums for single forecasts, Nebraska live cattle steers

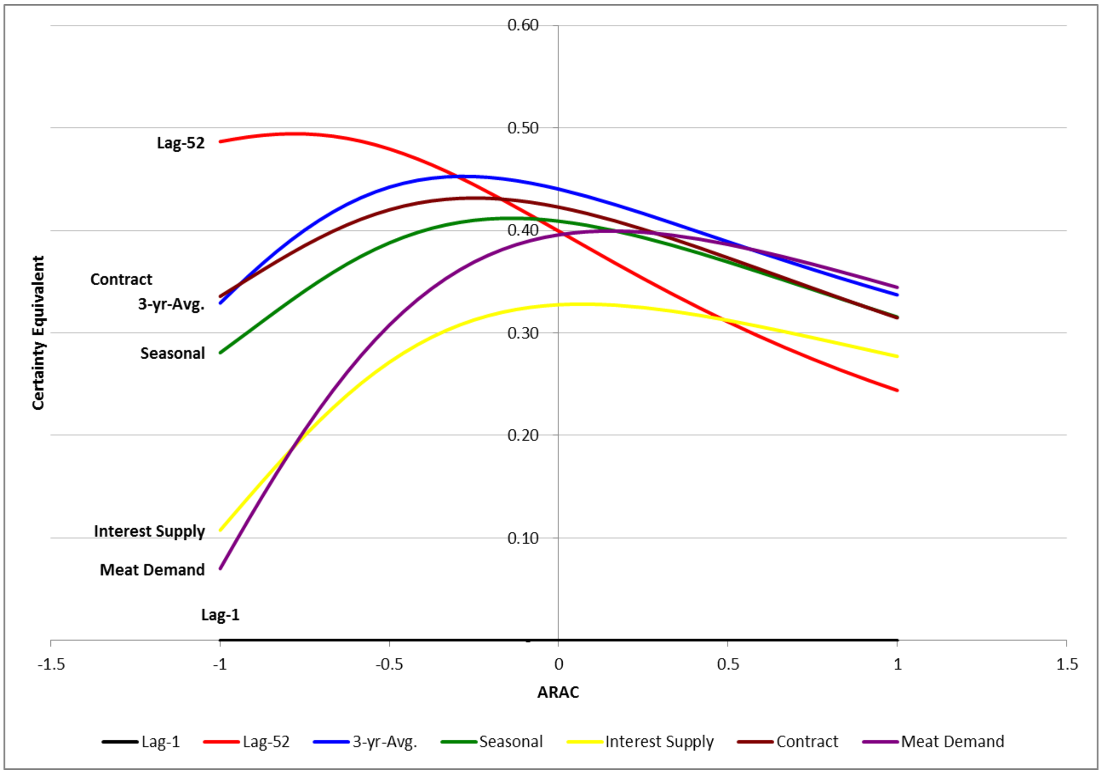

Figure 64. Risk premiums for singular forecasts, Texas live cattle steers

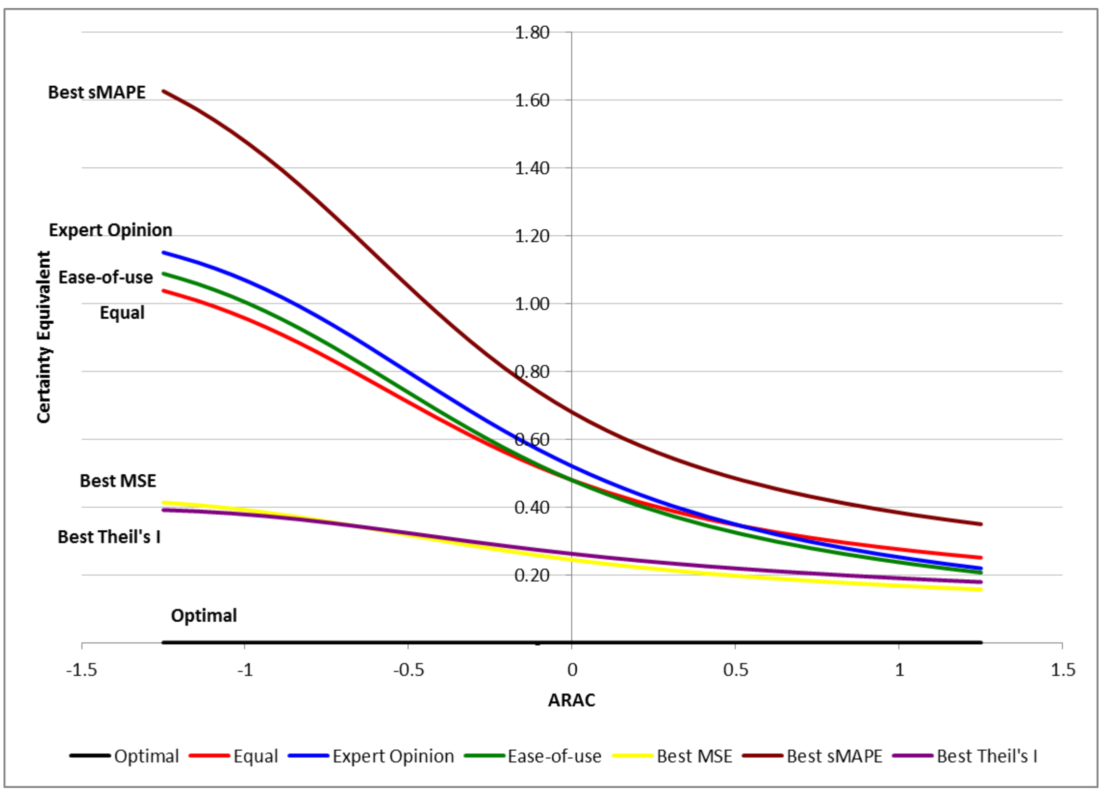

Figure 65. Risk premiums for composite forecasts, Nebraska live cattle steers

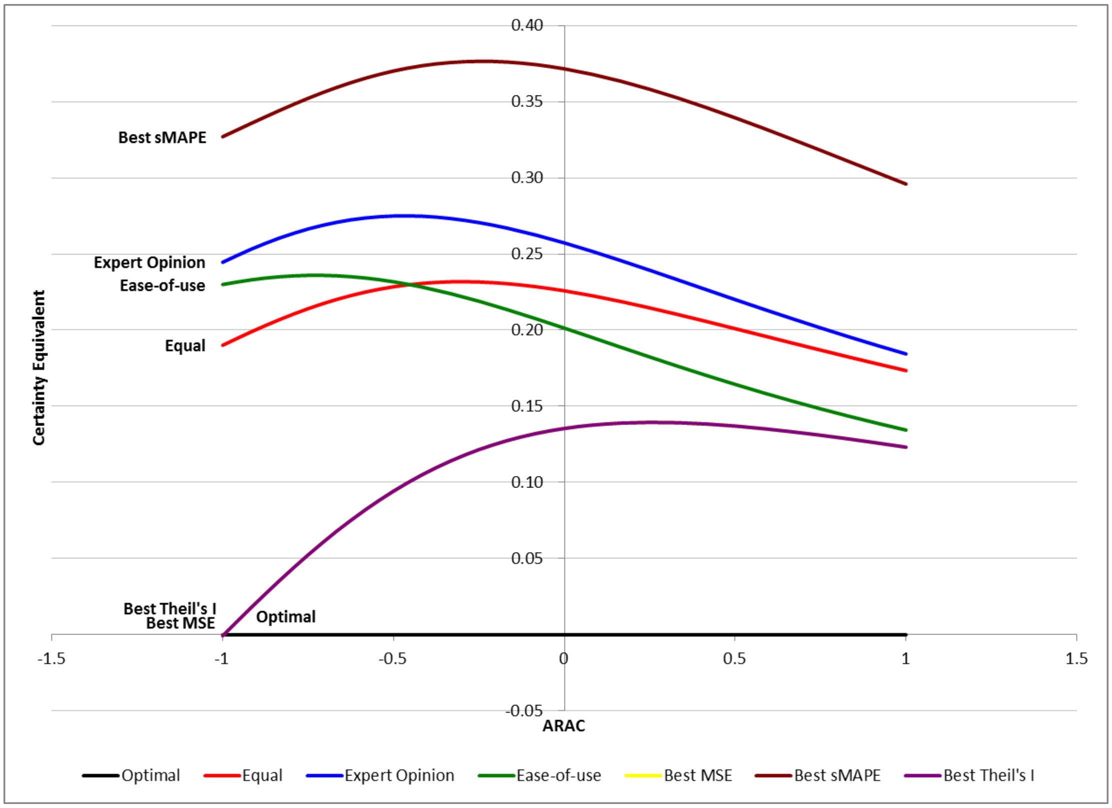

Figure 66. Risk premiums for composite forecasts, Texas live cattle steers

Appendix K

Table 74. Improvement in Utah Live Cattle Forecasting Errors

Composite Forecasts	Forecasting Error	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Optimal	**RMSE**	(0.01)	0.89	0.96	0.66	0.42	0.70	0.57	(0.01)
	MAD	(0.03)	0.75	0.83	0.58	0.34	0.61	0.55	(0.03)
	MSE	(0.03)	3.90	4.27	2.78	1.65	2.93	2.35	(0.03)
	MAPE	20.10	(131.00)	50.90	94.30	(98.60)	93.30	(21.90)	20.10
	sMAPE	(53.70)	224.30	340.10	463.00	24.30	769.40	824.80	(53.70)
	RAE	(0.01)	0.35	0.38	0.27	0.16	0.28	0.26	(0.01)
	Theil's I	(0.01)	0.22	0.17	0.09	0.09	0.11	0.08	(0.01)
	Theil's U2	(0.01)	0.33	0.36	0.24	0.15	0.26	0.21	(0.01)
Equal	**RMSE**	(0.44)	0.46	0.53	0.23	(0.01)	0.27	0.14	(0.44)
	MAD	(0.42)	0.36	0.44	0.19	(0.05)	0.22	0.16	(0.42)
	MSE	(1.74)	2.19	2.56	1.07	(0.06)	1.22	0.64	(1.74)
	MAPE	53.60	(97.50)	84.40	127.80	(65.10)	126.80	11.60	53.60
	sMAPE	(294.00)	(16.00)	99.80	222.70	(216.00)	529.10	584.50	(294.00)
	RAE	(0.19)	0.17	0.20	0.09	(0.02)	0.10	0.08	(0.19)
	Theil's I	(0.10)	0.13	0.08	(0.00)	(0.00)	0.01	(0.02)	(0.10)
	Theil's U2	(0.17)	0.17	0.20	0.08	(0.01)	0.10	0.05	(0.17)

Table 74. Cont.

Composite Forecasts	Forecasting Error	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Expert Opinion	**RMSE**	(0.57)	0.33	0.40	0.10	(0.14)	0.14	0.01	(0.57)
	MAD	(0.53)	0.25	0.33	0.08	(0.16)	0.11	0.05	(0.53)
	MSE	(2.33)	1.60	1.97	0.48	(0.65)	0.63	0.05	(2.33)
	MAPE	33.30	(117.80)	64.10	107.50	(85.40)	106.50	(8.70)	33.30
	sMAPE	(1,950.90)	(1,672.90)	(1,557.10)	(1,434.20)	(1,872.90)	(1,127.80)	(1,072.40)	(1,950.90)
	RAE	(0.25)	0.11	0.14	0.03	(0.08)	0.04	0.02	(0.25)
	Theil's I	(0.13)	0.10	0.05	(0.03)	(0.02)	(0.01)	(0.04)	(0.13)
	Theil's U2	(0.22)	0.12	0.15	0.03	(0.06)	0.05	0.00	(0.22)
Ease-of-use	**RMSE**	(0.46)	0.44	0.51	0.21	(0.03)	0.25	0.12	(0.46)
	MAD	(0.43)	0.35	0.43	0.18	(0.06)	0.21	0.15	(0.43)
	MSE	(1.84)	2.09	2.46	0.97	(0.16)	1.12	0.54	(1.84)
	MAPE	37.20	(113.90)	68.00	111.40	(81.50)	110.40	(4.80)	37.20
	sMAPE	(310.90)	(32.90)	82.90	205.80	(232.90)	512.20	567.60	(310.90)
	RAE	(0.20)	0.16	0.19	0.08	(0.03)	0.09	0.07	(0.20)
	Theil's I	(0.12)	0.11	0.06	(0.02)	(0.01)	0.00	(0.03)	(0.12)
	Theil's U2	(0.18)	0.16	0.19	0.07	(0.02)	0.09	0.04	(0.18)

Table 74. Cont.

Composite Forecasts	Forecasting Error	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Best MSE	**RMSE**	(0.17)	0.73	0.80	0.50	0.26	0.54	0.41	(0.17)
	MAD	(0.19)	0.59	0.67	0.42	0.18	0.45	0.39	(0.19)
	MSE	(0.61)	3.32	3.69	2.20	1.07	2.35	1.77	(0.61)
	MAPE	76.30	(74.80)	107.10	150.50	(42.40)	149.50	34.30	76.30
	sMAPE	(185.50)	92.50	208.30	331.20	(107.50)	637.60	693.00	(185.50)
	RAE	(0.08)	0.28	0.31	0.20	0.09	0.21	0.19	(0.08)
	Theil's I	(0.05)	0.18	0.13	0.06	0.06	0.07	0.04	(0.05)
	Theil's U2	(0.06)	0.28	0.31	0.19	0.10	0.21	0.16	(0.06)
Best sMAPE	**RMSE**	(0.26)	0.64	0.71	0.41	0.17	0.45	0.32	(0.26)
	MAD	(0.25)	0.53	0.61	0.36	0.12	0.39	0.33	(0.25)
	MSE	(0.98)	2.95	3.32	1.83	0.70	1.98	1.40	(0.98)
	MAPE	123.10	(28.00)	153.90	197.30	4.40	196.30	81.10	123.10
	sMAPE	(92.30)	185.70	301.50	424.40	(14.30)	730.80	786.20	(92.30)
	RAE	(0.11)	0.25	0.28	0.17	0.06	0.18	0.16	(0.11)
	Theil's I	(0.10)	0.13	0.08	0.00	0.00	0.02	(0.01)	(0.10)
	Theil's U2	(0.10)	0.24	0.27	0.15	0.06	0.17	0.12	(0.10)

Table 74. Cont.

Composite Forecasts	Forecasting Error	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Best Theil's I	**RMSE**	(0.27)	0.63	0.70	0.40	0.16	0.44	0.31	(0.27)
	MAD	(0.29)	0.49	0.57	0.32	0.08	0.35	0.29	(0.29)
	MSE	(0.99)	2.94	3.31	1.82	0.69	1.97	1.39	(0.99)
	MAPE	8.90	(142.20)	39.70	83.10	(109.80)	82.10	(33.10)	8.90
	sMAPE	(220.90)	57.10	172.90	295.80	(142.90)	602.20	657.60	(220.90)
	RAE	(0.13)	0.23	0.26	0.15	0.04	0.16	0.14	(0.13)
	Theil's I	(0.05)	0.18	0.13	0.05	0.05	0.07	0.04	(0.05)
	Theil's U2	(0.10)	0.24	0.27	0.15	0.06	0.17	0.12	(0.10)

Table 75. Improvement in Western Kansas Live Cattle Forecasting Errors

Composite Forecasts	Forecasting Error	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Optimal	**RMSE**	0.03	0.46	0.44	0.30	0.39	0.34	0.25	0.03
	MAD	(0.01)	0.40	0.43	0.32	0.36	0.35	0.31	(0.01)
	MSE	0.09	1.51	1.44	0.94	1.24	1.08	0.75	0.09
	MAPE	(31.20)	8.80	74.40	123.30	125.50	148.90	133.90	(31.20)
	sMAPE	(448.30)	(269.10)	(393.60)	(364.30)	(443.60)	(144.30)	(320.20)	(448.30)
	RAE	(0.01)	0.28	0.30	0.22	0.25	0.24	0.21	(0.01)
	Theil's I	0.06	0.33	0.23	0.10	0.10	0.12	0.09	0.06
	Theil's U2	0.01	0.24	0.23	0.16	0.20	0.18	0.12	0.01
Equal	**RMSE**	(0.16)	0.27	0.25	0.11	0.20	0.15	0.06	(0.16)
	MAD	(0.21)	0.20	0.23	0.12	0.16	0.15	0.11	(0.21)
	MSE	(0.48)	0.94	0.87	0.37	0.67	0.51	0.18	(0.48)
	MAPE	(91.60)	(51.60)	14.00	62.90	65.10	88.50	73.50	(91.60)
	sMAPE	(8.00)	171.20	46.70	76.00	(3.30)	296.00	120.10	(8.00)
	RAE	(0.15)	0.14	0.16	0.08	0.11	0.10	0.07	(0.15)
	Theil's I	(0.07)	0.20	0.10	(0.03)	(0.03)	(0.01)	(0.05)	(0.07)
	Theil's U2	(0.09)	0.14	0.13	0.06	0.10	0.08	0.02	(0.09)

Table 75. Cont.

Composite Forecasts	Forecasting Error	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Expert Opinion	**RMSE**	(0.20)	0.23	0.21	0.07	0.16	0.11	0.02	(0.20)
	MAD	(0.25)	0.16	0.19	0.08	0.12	0.11	0.07	(0.25)
	MSE	(0.62)	0.80	0.73	0.23	0.53	0.37	0.04	(0.62)
	MAPE	(82.80)	(42.80)	22.80	71.70	73.90	97.30	82.30	(82.80)
	sMAPE	(48.10)	131.10	6.60	35.90	(43.40)	255.90	80.00	(48.10)
	RAE	(0.18)	0.11	0.13	0.05	0.08	0.07	0.04	(0.18)
	Theil's I	(0.11)	0.16	0.06	(0.07)	(0.06)	(0.04)	(0.08)	(0.11)
	Theil's U2	(0.11)	0.12	0.11	0.04	0.08	0.06	0.00	(0.11)
Ease-of-use	**RMSE**	(0.16)	0.27	0.25	0.11	0.20	0.15	0.06	(0.16)
	MAD	(0.20)	0.21	0.24	0.13	0.17	0.16	0.12	(0.20)
	MSE	(0.49)	0.93	0.86	0.36	0.66	0.50	0.17	(0.49)
	MAPE	(50.20)	(10.20)	55.40	104.30	106.50	129.90	114.90	(50.20)
	sMAPE	(58.30)	120.90	(3.60)	25.70	(53.60)	245.70	69.80	(58.30)
	RAE	(0.14)	0.15	0.17	0.09	0.12	0.11	0.08	(0.14)
	Theil's I	(0.11)	0.16	0.06	(0.07)	(0.07)	(0.05)	(0.09)	(0.11)
	Theil's U2	(0.09)	0.14	0.13	0.06	0.10	0.08	0.02	(0.09)

Table 75. Cont.

Composite Forecasts	Forecasting Error	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Best MSE	**RMSE**	(0.05)	0.38	0.36	0.22	0.31	0.26	0.17	(0.05)
	MAD	(0.13)	0.28	0.31	0.20	0.24	0.23	0.19	(0.13)
	MSE	(0.13)	1.29	1.22	0.72	1.02	0.86	0.53	(0.13)
	MAPE	(88.80)	(48.80)	16.80	65.70	67.90	91.30	76.30	(88.80)
	sMAPE	(113.20)	66.00	(58.50)	(29.20)	(108.50)	190.80	14.90	(113.20)
	RAE	(0.09)	0.20	0.22	0.14	0.17	0.16	0.13	(0.09)
	Theil's I	(0.01)	0.26	0.16	0.03	0.03	0.05	0.01	(0.01)
	Theil's U2	(0.03)	0.20	0.19	0.12	0.16	0.14	0.08	(0.03)
Best sMAPE	**RMSE**	(0.12)	0.31	0.29	0.15	0.24	0.19	0.10	(0.12)
	MAD	(0.17)	0.24	0.27	0.16	0.20	0.19	0.15	(0.17)
	MSE	(0.34)	1.08	1.01	0.51	0.81	0.65	0.32	(0.34)
	MAPE	(65.80)	(25.80)	39.80	88.70	90.90	114.30	99.30	(65.80)
	sMAPE	(224.20)	(45.00)	(169.50)	(140.20)	(219.50)	79.80	(96.10)	(224.20)
	RAE	(0.12)	0.17	0.19	0.11	0.14	0.13	0.10	(0.12)
	Theil's I	(0.06)	0.21	0.11	(0.02)	(0.02)	0.00	(0.04)	(0.06)
	Theil's U2	(0.07)	0.16	0.15	0.08	0.12	0.10	0.04	(0.07)

Table 75. Cont.

Composite Forecasts	Forecasting Error	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Best Theil's I	**RMSE**	(0.05)	0.38	0.36	0.22	0.31	0.26	0.17	(0.05)
	MAD	(0.13)	0.28	0.31	0.20	0.24	0.23	0.19	(0.13)
	MSE	(0.13)	1.29	1.22	0.72	1.02	0.86	0.53	(0.13)
	MAPE	(88.80)	(48.80)	16.80	65.70	67.90	91.30	76.30	(88.80)
	sMAPE	(113.20)	66.00	(58.50)	(29.20)	(108.50)	190.80	14.90	(113.20)
	RAE	(0.09)	0.20	0.22	0.14	0.17	0.16	0.13	(0.09)
	Theil's I	(0.01)	0.26	0.16	0.03	0.03	0.05	0.01	(0.01)
	Theil's U2	(0.03)	0.20	0.19	0.12	0.16	0.14	0.08	(0.03)

Table 76. Improvement in Nebraska Live Cattle Forecasting Errors

Composite Forecasts	Forecasting Error	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Optimal	**RMSE**	0.04	0.94	1.07	0.90	0.89	0.94	0.45	0.04
	MAD	0.03	0.82	0.87	0.79	0.74	0.84	0.49	0.03
	MSE	0.15	3.87	4.52	3.66	3.58	3.86	1.64	0.15
	MAPE	32.40	64.30	96.00	245.10	195.30	266.10	81.40	32.40
	sMAPE	796.40	236.10	691.40	140.30	131.80	255.00	1,460.60	796.40
	RAE	0.02	0.45	0.48	0.43	0.40	0.46	0.27	0.02
	Theil's I	0.02	0.34	0.34	0.17	0.17	0.19	0.07	0.02
	Theil's U2	0.02	0.41	0.47	0.39	0.39	0.41	0.19	0.02
Equal	**RMSE**	(0.52)	0.38	0.51	0.34	0.33	0.38	(0.11)	(0.52)
	MAD	(0.45)	0.34	0.39	0.31	0.26	0.36	0.01	(0.45)
	MSE	(1.92)	1.80	2.45	1.59	1.51	1.79	(0.43)	(1.92)
	MAPE	(38.50)	(6.60)	25.10	174.20	124.40	195.20	10.50	(38.50)
	sMAPE	682.90	122.60	577.90	26.80	18.30	141.50	1,347.10	682.90
	RAE	(0.24)	0.19	0.22	0.17	0.14	0.20	0.01	(0.24)
	Theil's I	(0.15)	0.16	0.16	(0.00)	(0.00)	0.02	(0.11)	(0.15)
	Theil's U2	(0.23)	0.16	0.22	0.14	0.14	0.16	(0.06)	(0.23)

Table 76. Cont.

Composite Forecasts	Forecasting Error	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Expert Opinion	**RMSE**	(0.59)	0.31	0.44	0.27	0.26	0.31	(0.18)	(0.59)
	MAD	(0.49)	0.30	0.35	0.27	0.22	0.32	(0.03)	(0.49)
	MSE	(2.25)	1.47	2.12	1.26	1.18	1.46	(0.76)	(2.25)
	MAPE	(6.90)	25.00	56.70	205.80	156.00	226.80	42.10	(6.90)
	sMAPE	(1,309.20)	(1,869.50)	(1,414.20)	(1,965.30)	(1,973.80)	(1,850.60)	(645.00)	(1,309.20)
	RAE	(0.27)	0.16	0.19	0.14	0.11	0.17	(0.02)	(0.27)
	Theil's I	(0.20)	0.12	0.12	(0.05)	(0.05)	(0.03)	(0.15)	(0.20)
	Theil's U2	(0.26)	0.13	0.19	0.11	0.11	0.13	(0.09)	(0.26)
Ease-of-use	**RMSE**	(0.54)	0.36	0.49	0.32	0.31	0.36	(0.13)	(0.54)
	MAD	(0.45)	0.34	0.39	0.31	0.26	0.36	0.01	(0.45)
	MSE	(2.03)	1.69	2.34	1.48	1.40	1.68	(0.54)	(2.03)
	MAPE	(1.90)	30.00	61.70	210.80	161.00	231.80	47.10	(1.90)
	sMAPE	517.30	(43.00)	412.30	(138.80)	(147.30)	(24.10)	1,181.50	517.30
	RAE	(0.24)	0.19	0.22	0.17	0.14	0.20	0.01	(0.24)
	Theil's I	(0.20)	0.12	0.12	(0.05)	(0.05)	(0.03)	(0.15)	(0.20)
	Theil's U2	(0.24)	0.15	0.21	0.13	0.13	0.15	(0.07)	(0.24)

Table 76. Cont.

Composite Forecasts	Forecasting Error	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Best MSE	**RMSE**	(0.21)	0.69	0.82	0.65	0.64	0.69	0.20	(0.21)
	MAD	(0.21)	0.58	0.63	0.55	0.50	0.60	0.25	(0.21)
	MSE	(0.73)	2.99	3.64	2.78	2.70	2.98	0.76	(0.73)
	MAPE	18.80	50.70	82.40	231.50	181.70	252.50	67.80	18.80
	sMAPE	516.90	(43.40)	411.90	(139.20)	(147.70)	(24.50)	1,181.10	516.90
	RAE	(0.11)	0.32	0.35	0.30	0.27	0.33	0.14	(0.11)
	Theil's I	(0.05)	0.26	0.27	0.10	0.10	0.12	(0.00)	(0.05)
	Theil's U2	(0.10)	0.29	0.35	0.27	0.27	0.29	0.07	(0.10)
Best sMAPE	**RMSE**	(0.76)	0.14	0.27	0.10	0.09	0.14	(0.35)	(0.76)
	MAD	(0.65)	0.14	0.19	0.11	0.06	0.16	(0.19)	(0.65)
	MSE	(3.01)	0.71	1.36	0.50	0.42	0.70	(1.52)	(3.01)
	MAPE	(109.80)	(77.90)	(46.20)	102.90	53.10	123.90	(60.80)	(109.80)
	sMAPE	151.90	(408.40)	46.90	(504.20)	(512.70)	(389.50)	816.10	151.90
	RAE	(0.35)	0.08	0.11	0.06	0.03	0.09	(0.10)	(0.35)
	Theil's I	(0.19)	0.13	0.13	(0.04)	(0.04)	(0.02)	(0.14)	(0.19)
	Theil's U2	(0.33)	0.06	0.12	0.04	0.04	0.06	(0.16)	(0.33)

Table 76. Cont.

Composite Forecasts	Forecasting Error	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Best Theil's I	**RMSE**	(0.22)	0.68	0.81	0.64	0.63	0.68	0.19	(0.22)
	MAD	(0.23)	0.56	0.61	0.53	0.48	0.58	0.23	(0.23)
	MSE	(0.75)	2.97	3.62	2.76	2.68	2.96	0.74	(0.75)
	MAPE	4.10	36.00	67.70	216.80	167.00	237.80	53.10	4.10
	sMAPE	596.00	35.70	491.00	(60.10)	(68.60)	54.60	1,260.20	596.00
	RAE	(0.12)	0.31	0.34	0.29	0.26	0.32	0.13	(0.12)
	Theil's I	(0.05)	0.26	0.27	0.10	0.10	0.12	(0.00)	(0.05)
	Theil's U2	(0.10)	0.29	0.35	0.27	0.27	0.29	0.07	(0.10)

Table 77. Improvement in Texas Live Cattle Forecasting Errors

Composite Forecasts	Forecasting Error	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Optimal	**RMSE**	0.03	0.45	0.43	0.38	0.28	0.41	0.32	0.03
	MAD	(0.02)	0.38	0.43	0.39	0.31	0.41	0.38	(0.02)
	MSE	0.11	1.49	1.39	1.22	0.87	1.31	1.00	0.11
	MAPE	(3.60)	(49.30)	(3.00)	203.50	112.00	201.50	16.50	(3.60)
	sMAPE	1,386.60	903.60	2,301.30	223.40	284.50	159.60	4.10	1,386.60
	RAE	(0.01)	0.29	0.32	0.30	0.23	0.31	0.29	(0.01)
	Theil's I	0.06	0.39	0.28	0.14	0.11	0.16	0.12	0.06
	Theil's U2	0.02	0.25	0.24	0.21	0.15	0.22	0.17	0.02
Equal	**RMSE**	(0.17)	0.25	0.23	0.18	0.08	0.21	0.12	(0.17)
	MAD	(0.24)	0.16	0.21	0.17	0.09	0.19	0.16	(0.24)
	MSE	(0.49)	0.89	0.79	0.62	0.27	0.71	0.40	(0.49)
	MAPE	(43.70)	(89.40)	(43.10)	163.40	71.90	161.40	(23.60)	(43.70)
	sMAPE	(3,039.70)	(3,522.70)	(2,125.00)	(4,202.90)	(4,141.80)	(4,266.70)	(4,422.20)	(3,039.70)
	RAE	(0.18)	0.12	0.15	0.13	0.06	0.14	0.12	(0.18)
	Theil's I	(0.11)	0.23	0.12	(0.02)	(0.05)	(0.01)	(0.04)	(0.11)
	Theil's U2	(0.09)	0.14	0.13	0.10	0.04	0.11	0.06	(0.09)

Table 77. Cont.

Composite Forecasts	Forecasting Error	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Expert Opinion	**RMSE**	(0.21)	0.21	0.19	0.14	0.04	0.17	0.08	(0.21)
	MAD	(0.27)	0.13	0.18	0.14	0.06	0.16	0.13	(0.27)
	MSE	(0.63)	0.75	0.65	0.48	0.13	0.57	0.26	(0.63)
	MAPE	(11.50)	(57.20)	(10.90)	195.60	104.10	193.60	8.60	(11.50)
	sMAPE	1,048.50	565.50	1,963.20	(114.70)	(53.60)	(178.50)	(334.00)	1,048.50
	RAE	(0.20)	0.10	0.13	0.11	0.04	0.12	0.10	(0.20)
	Theil's I	(0.15)	0.19	0.08	(0.07)	(0.10)	(0.05)	(0.08)	(0.15)
	Theil's U2	(0.11)	0.12	0.11	0.08	0.02	0.09	0.04	(0.11)
Ease-of-use	**RMSE**	(0.17)	0.25	0.23	0.18	0.08	0.21	0.12	(0.17)
	MAD	(0.22)	0.18	0.23	0.19	0.11	0.21	0.18	(0.22)
	MSE	(0.51)	0.87	0.77	0.60	0.25	0.69	0.38	(0.51)
	MAPE	(9.10)	(54.80)	(8.50)	198.00	106.50	196.00	11.00	(9.10)
	sMAPE	1,151.40	668.40	2,066.10	(11.80)	49.30	(75.60)	(231.10)	1,151.40
	RAE	(0.16)	0.14	0.17	0.15	0.08	0.16	0.14	(0.16)
	Theil's I	(0.15)	0.18	0.07	(0.07)	(0.10)	(0.05)	(0.09)	(0.15)
	Theil's U2	(0.09)	0.14	0.13	0.10	0.04	0.11	0.06	(0.09)

Table 77. Cont.

Composite Forecasts	Forecasting Error	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Best MSE	**RMSE**	(0.05)	0.37	0.35	0.30	0.20	0.33	0.24	(0.05)
	MAD	(0.15)	0.25	0.30	0.26	0.18	0.28	0.25	(0.15)
	MSE	(0.13)	1.25	1.15	0.98	0.63	1.07	0.76	(0.13)
	MAPE	(19.00)	(64.70)	(18.40)	188.10	96.60	186.10	1.10	(19.00)
	sMAPE	1,216.40	733.40	2,131.10	53.20	114.30	(10.60)	(166.10)	1,216.40
	RAE	(0.11)	0.19	0.22	0.20	0.13	0.21	0.19	(0.11)
	Theil's I	(0.03)	0.30	0.20	0.05	0.02	0.07	0.03	(0.03)
	Theil's U2	(0.02)	0.21	0.20	0.17	0.11	0.18	0.13	(0.02)
Best sMAPE	**RMSE**	(0.29)	0.13	0.11	0.06	(0.04)	0.09	0.00	(0.29)
	MAD	(0.39)	0.01	0.06	0.02	(0.06)	0.04	0.01	(0.39)
	MSE	(0.90)	0.48	0.38	0.21	(0.14)	0.30	(0.01)	(0.90)
	MAPE	(136.10)	(181.80)	(135.50)	71.00	(20.50)	69.00	(116.00)	(136.10)
	sMAPE	1,297.10	814.10	2,211.80	133.90	195.00	70.10	(85.40)	1,297.10
	RAE	(0.29)	0.01	0.04	0.02	(0.05)	0.03	0.01	(0.29)
	Theil's I	(0.08)	0.25	0.14	0.00	(0.03)	0.02	(0.02)	(0.08)
	Theil's U2	(0.16)	0.07	0.06	0.03	(0.03)	0.04	(0.01)	(0.16)

Table 77. Cont.

Composite Forecasts	Forecasting Error	RMSE	MAD	MSE	MAPE	sMAPE	RAE	Theil's I	Theil's U2
Best Theil's I	**RMSE**	(0.05)	0.37	0.35	0.30	0.20	0.33	0.24	(0.05)
	MAD	(0.15)	0.25	0.30	0.26	0.18	0.28	0.25	(0.15)
	MSE	(0.13)	1.25	1.15	0.98	0.63	1.07	0.76	(0.13)
	MAPE	(19.00)	(64.70)	(18.40)	188.10	96.60	186.10	1.10	(19.00)
	sMAPE	1,216.40	733.40	2,131.10	53.20	114.30	(10.60)	(166.10)	1,216.40
	RAE	(0.11)	0.19	0.22	0.20	0.13	0.21	0.19	(0.11)
	Theil's I	(0.03)	0.30	0.20	0.05	0.02	0.07	0.03	(0.03)
	Theil's U2	(0.02)	0.21	0.20	0.17	0.11	0.18	0.13	(0.02)