# Improving Feeder Cattle Basis Forecasts

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## INTRODUCTION

Effective use of futures markets for price risk management requires that users be able to forecast basis, defined as cash price minus nearby futures price. However, forecasting feeder cattle basis has long been difficult because of the myriad factors that can influence basis. Factors that affect cash feeder cattle prices, by definition, impact feeder cattle basis, and previous studies provide strong evidence that a wide variety of factors affect cash feeder cattle prices. These include lot characteristics (location, season, sex, weight, lot size, and condition) and market conditions, as measured by feeder cattle futures prices (Schroeder et al., Sartwelle et al.). Input and output prices (measured by corn and live cattle futures) also have been demonstrated to have a significant impact on cash prices paid for feeder cattle (Dhuyvetter and Schroeder).

The primary objective of this research is to develop an improved approach to forecasting feeder cattle basis, drawing upon knowledge of the various factors that influence cash feeder cattle prices. Specifically, hedonic feeder cattle basis models that explicitly incorporate specific lot characteristics and market conditions are estimated. Out-of-sample testing is used to compare the predictive power of these hedonic models to a multi-year average, likely the most widely used approach to forecasting feeder cattle basis.

The outcome of this research has important implications for cattle producers. Through a research partnership with the Risk Management Agency (RMA) of the U.S. Department of Agriculture (USDA), a team of economists from Custom Ag Solutions and Kansas State University have developed a web-based feeder cattle basis forecasting tool (available online at BeefBasis.com) using the models described in this paper. The goal of this partnership is to improve the ability of cattle producers to make decisions that are influenced by basis risk. As a result of the applied nature of this research project, practical criteria are important in choosing appropriate forecasting techniques and models.

## PREVIOUS LITERATURE

Demand for feeder cattle is a derived demand for an input into a production process whereby light-weight feeder steers and heifers are transformed into slaughter-weight cattle. Relying on this foundation, Buccola developed a theoretical model that examined the influence of breakeven prices on feeder cattle price differentials. Buccola concluded that a dynamic analysis of feeder cattle price differentials was more useful than static analysis, and this result had a significant impact on subsequent research. For example, Marsh examined the monthly price premiums and discounts between steer calves and yearlings and concluded that expected changes in fed slaughter cattle prices and feedlot cost of gain were important determinants of price differentials.

Several groups of researchers in the mid-1980s and early 1990s took a different approach to explaining prices paid for feeder cattle by examining transaction prices of individual cattle lots[1] at auction. Faminow and Gum examined feeder cattle prices at Arizona auctions, Schroeder et al. examined prices at Kansas auctions, and Turner et al. researched prices paid at Georgia tele-

[1] The terms “lot” and “pen” are used interchangeably herein to indicate groups of cattle that are sold together in a single transaction.

auctions. Although the researchers' conclusions were not identical, several key factors were identified as having a significant impact on feeder cattle prices. Those factors include sex, weight, lot size, health, muscling, frame size, condition, fill, breed, presence of horns, location, time of sale, and market conditions, which were captured by including feeder cattle futures prices in the models. Squared values of weight and lot size typically were included in the empirical models to capture nonlinear impacts of these two factors on feeder cattle prices. In addition, Schroeder et al. concluded that several factors' impacts varied seasonally. In a follow-up study using Kansas data collected in 1992-1993, Sartwelle et al. concluded that nearly all of the variables identified by Schroeder et al. still had significant impacts on cattle prices. However, the researchers also found that many parameter estimates had changed, compared to the mid-1980s, leading to the conclusion that models need to be re-estimated periodically.

Video auctions became an important market outlet in the 1980s and 1990s. Bailey and Peterson determined that the impacts of market factors (such as lot characteristics, market information, and merchandising strategies) on cattle prices essentially were identical at video and conventional auctions. Perhaps because of differences between market participants in video versus conventional auctions, the researchers noted that lot size premiums varied between the two types of auctions, concluding that optimal lot size was larger at video auctions than at traditional auctions.

Prices paid for feeder cattle are expected to be sensitive to changes in both input and output prices because the demand for feeder cattle is a derived demand. As a result, corn price variability and the impact it has on feeder cattle prices were examined in research conducted by Anderson and Trapp and also by Dhuyvetter and Schroeder. Both groups of researchers concluded that corn prices had a significant impact on cash prices paid for feeder cattle. In particular, Dhuyvetter and Schroeder concluded that live cattle futures prices, corn prices, and recent cattle feeding margins all had important impacts on feeder cattle prices. Their empirical results were consistent with economic theory as live cattle futures prices could be viewed as a proxy for expected slaughter cattle prices while corn prices were a proxy for expected cost of gain, both of which would be expected to impact the derived demand for feeder cattle.

The extant literature provides strong evidence that numerous factors affect feeder cattle cash prices. Sex, weight, lot size, frame size, corn prices, and live cattle futures prices all have been demonstrated to have a significant impact on cash prices paid for feeder cattle. In particular, more recent research modeled weight as a continuous variable and added weight squared to capture non-linearity, which improved models' ability to explain cash price variability (Schroeder et al., Sartwelle et al., Turner et al., Dhuyvetter and Schroeder). Additionally, researchers concluded that market conditions can be captured by incorporating feeder cattle futures prices in their models, theorizing that feeder cattle futures prices would capture the effects of movement in expected output and input prices (Schroeder et al.).

Despite strong evidence that many factors affect feeder cattle cash prices, scant attention has been paid to incorporating this information into feeder cattle basis forecasting models. Instead, simple numerical techniques commonly have been used to forecast feeder cattle basis. For example, multi-year averages of feeder cattle basis often are used to forecast basis for the upcoming year. Recognizing that feeder cattle prices vary significantly by sex, weight, and time of year, averages usually are calculated separately for steers and heifers and by weight group (typically in 100-pound increments). To capture seasonal basis variation, basis often is computed by month or week and averaged over a specified number of years. The most recent multi-year average for the appropriate week or month is then used as a forecast for the upcoming period. Following this approach, Tonsor, Dhuyvetter, and Mintert examined a variety of simple historical basis averages for out-of-sample forecast accuracy and concluded that three-year averages generally provided superior forecasts to a naïve forecast and other multi-year averages. An example of this historical-average-based forecasting approach can be found on Kansas State University's AgManager.info web site.[2] The multi-year average approach to forecasting basis captures some of the variation in cash prices, and hence basis variation, but it does so in a limited way, leaving a significant portion of basis variation unexplained. Reasons for this are many, but it can best be explained by the failure to incorporate information from the wide variety of economic variables known to affect feeder cattle prices in the forecasts.

A review of the literature suggests that development of improved feeder cattle basis forecasting techniques requires the use of econometric-based forecasting models. For example, through use of such models, Parcell, Schroeder, and Dhuyvetter demonstrated that factors such as corn prices and choice-select spreads are important determinants of fed cattle basis. Further, these models should incorporate as many key variables known to impact cash prices as possible, and they will require detailed cash sale data for individual lots of cattle over several years. Many previous studies on feeder cattle price variation have relied on specialized data collection and, as a result, have sometimes included variables that are not widely available. Our research relies on transaction level feeder cattle pricing data collected and made available by USDA's Agricultural Marketing Service, which contain many of the most important variables that impact feeder cattle prices. Data for each cash market transaction include the sex, weight, lot size, frame size, muscling, and sale date. Cash market transaction data were augmented with fed cattle, corn, and feeder cattle futures settlement prices. Estimating basis models using this rich data set has the potential to greatly improve feeder cattle basis forecast accuracy.

## METHODS

Three distinct models are used to predict nearby feeder cattle basis. Nearby feeder cattle basis is defined as

$$BASIS_{it} = CashPrice_{it} - FC_t \,,$$

where $i$ indexes pens of cattle, $t$ indexes time, *CashPrice* is the local cash price for feeder cattle, and *FC* is the nearby feeder cattle futures price.

The first model, referred to as *MEAN*, uses an average of historical basis for the most recent three years to forecast basis next year. In a formal model framework, the *MEAN* forecast of *BASIS* for cattle in a given *location* to be sold in year $T$+1 is defined as

(1) *MEAN* $$E\left[BASIS_{sex,wt50,month,location,T+1}\right] = \frac{1}{3}\sum_{t=T-2}^{T} BASIS_{sex,wt50,month,location,t} \,,$$

[2] http://www.agmanager.info/livestock/marketing/graphs/cattlebasis.asp

where *sex* is steers, heifers or bulls, *wt50* is weight class in 50 lb increments, and *month* is the sale month. For example, basis for 450-500 lb steers in March 2003 is forecast by averaging the basis for 450-500 lb steers during March 2000, March 2001, and March 2002.

Hedonic regression basis models incorporate information about individual lot characteristics and current market conditions. Because feeder cattle cash prices, hence basis, are derived from the fed cattle market and cost of gain, two different basis models were constructed, including either feeder cattle futures prices directly or indirectly via live cattle and corn futures prices. Both of these model renditions are theoretically justified, making final model selection an empirical issue. Conceptually, the forecasts of feeder cattle basis for the feeder cattle futures model (*FCModel*) and the live cattle and corn futures model (*LCCNModel*), respectively, are,

(2) *FCModel* $$E_{w-h}\left[BASIS_{it}\right] = f\left(E_{w-h}\left[FC_{it}\right], E_{w-h}\left[LOTCHAR_{it}\right]\right)$$

(3) *LCCNModel* $$E_{w-h}\left[BASIS_{it}\right] = f\left(E_{w-h}\left[LC_{it}\right], E_{w-h}\left[CN_{it}\right], E_{w-h}\left[LOTCHAR_{it}\right]\right),$$

where *FC* is a feeder cattle futures price, *LC* is a live cattle futures price, *CN* is a corn futures price, and *LOTCHAR* refers to the characteristics (e.g., location, season, sex, weight, lot size, condition) of a particular set of cattle in pen *i* at time *t*. *E* refers to expectation of future prices and lot characteristics taken *h* weeks prior to week *w* when the lot is sold (or purchased) and actual basis is observed.

Although futures contract prices at the time of sale are not known in advance, forecasts of these prices (i.e., today's prices of deferred futures contracts) are readily available. Thus, a current price for the feeder cattle futures contract that will be nearby when cattle are marketed is used in *FCModel* (2). Similarly, in *LCCNModel* (3) a current price for the corn contract that will be nearby at the time cattle are sold or purchased is used to measure corn price expectations. Live cattle price expectation is taken as the current price for the live cattle contract that will be nearby when the cattle are expected to weigh 750 lb.[3]

Estimating these hedonic models requires several additional variables to capture lot characteristics and seasonality. The following two empirical models are estimated to generate nearby feeder cattle basis predictions using the variables discussed above:

[3] Slaughter price expectations for feeder cattle are reflected in deferred live cattle futures contracts. In the absence of practical considerations, the nearby live cattle contract when cattle are ready for slaughter (approximately 1,250 lb) would be used for this variable. However, at the time that basis forecasts for light-weight cattle are generated, deferred contracts are often thinly traded or unavailable. The choice of the nearby live cattle contract at the time cattle are expected to weigh 750 lb was a concession to data availability and practical application of the forecasting models. Nearby price is used for cattle weighing more than 750 lb at sale date. The date when light-weight feeder cattle are expected to weigh 750 lb is calculated assuming a 1.5 lb/day rate of gain for cattle weighing less than 500 lb and a 2 lb/day gain for cattle weighing more than 500 lb.

(4) *FCModel*

$$\begin{aligned}BASIS_{it}^{FC} &= \beta_0 + \beta_1 Wt_i + \beta_2 Wt_i^2 + \beta_3 Lotsize_i + \beta_4 Lotsize_i^2 + \beta_5 Lotsize_i Wt_i + \beta_6 Lotsize_i^2 Wt_i \\ &+ \beta_7 Hfr_i + \beta_8 Hfr_i Wt_i + \beta_9 Hfr_i Wt_i^2 + \beta_{10} FC_t + \beta_{11} FC_t Wt_i + \beta_{12} FC_t Wt_i^2 + \beta_{13} Diesel_t \\ &+ \beta_f Frame_{fi} + \beta_g Grade_{gi} + \beta_c ContractChange_{ct} + \beta_c ContractChange_{ct} Wt_i \\ &+ \beta_c ContractChange_{ct} Wt_i^2 + \beta_m Month_m + \beta_m Month_m Wt_i + \beta_m Month_m Wt_i^2 + \beta_l Location_i + \varepsilon_{it}\end{aligned}$$

and

(5) *LCCNModel*

$$\begin{aligned}BASIS_{it}^{LCCN} &= \beta_0 + \beta_1 Wt_i + \beta_2 Wt_i^2 + \beta_3 Lotsize_i + \beta_4 Lotsize_i^2 + \beta_5 Lotsize_i Wt_i + \beta_6 Lotsize_i^2 Wt_i \\ &+ \beta_7 Hfr_i + \beta_8 Hfr_i Wt_i + \beta_9 Hfr_i Wt_i^2 + \beta_{10} LC_{it} + \beta_{11} LC_{it} Wt_i + \beta_{12} LC_{it} Wt_i^2 + \beta_{13} CN_t + \beta_{14} CN_t Wt_i \\ &+ \beta_{15} CN_t Wt_i^2 + \beta_{16} Diesel_t + \beta_f Frame_{fi} + \beta_g Grade_{gi} + \beta_c ContractChange_{ct} + \beta_c ContractChange_{ct} Wt_i \\ &+ \beta_c ContractChange_{ct} Wt_i^2 + \beta_m Month_m + \beta_m Month_m Wt_i + \beta_m Month_m Wt_i^2 + \beta_l Location_i + \varepsilon_{it}\end{aligned}$$

Table 1 lists and describes the variables used to estimate *FCModel* and *LCCNModel*. Several variables were included in the models to allow for nonlinear effects. For example, both linear and nonlinear (quadratic) terms for weight and lot size were included. This was done to allow for diminishing returns to lot size and weight. Based on previous research, cash feeder cattle price (thus basis) is expected to increase at a decreasing rate with respect to lot size. Likewise, price is expected to decrease at a decreasing rate with respect to weight. Additionally, several variables were interacted with other variables to allow for expected impacts. For example, weight and weight squared were interacted with monthly binary variables and with futures prices, to allow the impact of weight on basis to vary both seasonally and by market conditions. Likewise, the effect of weight on basis was allowed to vary by sex of the animal. While these many interaction terms make the models more complex, they are consistent with theoretical expectations and previous research.

Finally, we consider a composite forecast model which consists of an average of the basis forecasts from equations 4 and 5. Averaging two forecasts should have the effect of making this model less sensitive to extreme values of market condition variables. The composite model is,

(6) *COMPOSITEModel*

$$BASIS_{it}^{COMPOSITE} = \frac{\left(BASIS_{it}^{FC} + BASIS_{it}^{LCCN}\right)}{2}$$

## DATA

Transaction-level feeder cattle market data were collected from USDA's Agricultural Marketing Service (AMS) for auction locations in 12 states from January 1996 through April 2008. The data represent slightly over 12 years of historical cash price information for 52 sale locations, including more than four million observations (each representing an individual lot transaction).

These transaction data include variables for lot size, average weight, sex, frame, grade (class), and sale price for each individual pen of feeder cattle.

Daily settlement prices were obtained for Chicago Mercantile Exchange (CME) feeder cattle and live cattle, and Chicago Board of Trade (CBOT) corn futures from January 1996 through April 2008. Nearby feeder cattle basis is calculated for each transaction and market condition variables are created by matching relevant contract prices to each cash transaction. Contract change binary variables are created to capture the potential impact on feeder cattle basis of four changes to the feeder cattle index that occurred during the period of analysis.
The data are grouped by state for model estimation. Locations included for each state have been selected on the basis of historical data availability and geographic representation. Models are generated for 12 states[4], including a total of 52 auction locations. Binary variables are created for each auction location within the state, thus accounting for location-specific differences in basis through an intercept shift.

Frequencies of certain variables, such as frame, grade, bulls, and weight, differ greatly across state datasets. For example, six states had fewer than five percent of observations where frame did not take a value of Large or Medium-Large. This lack of variation effectively renders the frame binary variable irrelevant in models for these states. Binary variables for grades other than 1-2 also display low frequencies in some states. Similarly, TN is the only state where the number of bulls sold is high enough to justify including a *Bull* binary variable in the model. A decision rule was established to determine whether to include a binary variable in the model. Specifically, binary variables were only included if at least five percent of the feeder cattle transactions at a particular location fit into that category. If this level of representation was not met for a specific variable, then observations having that characteristic were deleted from the analysis. The data are limited to average weights from 300-900 lb in all states except FL, where the mean lot weight is less than 400 lb and the range was adjusted to 200-800 lbs. Data also were checked for other outliers, and observations with extreme basis values were excluded from analysis.[5]

Table 2 displays summary statistics for feeder cattle cash price, basis, and variables included in the basis prediction models – *MEAN*, *FCModel* and *LCCNModel* – for Kansas. The Kansas model data initially included 301,312 individual lots of cattle, however, after removing under represented lots (e.g., bulls, small frame) there were 294,678 observations remaining for model estimation. The average basis was $1.75 per hundredweight (cwt) and the average lot weight was 652 lb. The sex of the lots are distributed as 53% steers and 47% heifers. Across the entire time period, feeder cattle futures prices ranged from $47.65 to $119.57 per cwt, live cattle futures prices ranged from $54.80 to $102.92 per cwt, corn futures prices ranged from $1.75 to $6.05 per bushel, and basis varied from -$38.25 to $85.10 per cwt.

[4] Basis models have been estimated using data from FL, IA, KS, MO, MT, ND, NE, OK, SD, TN, TX, and WY. Only summary statistics and results for Kansas are reported here to save space, results for other states are available from the authors.
[5] Extreme basis values were defined as BASIS > (140 - 0.13333*Wt) or BASIS < -40. These rules resulted in 19 observations being removed from the data set (less than 0.01% of total).

## FORECAST ESTIMATION AND TESTING

A goal of this research is to determine the predictive power of hedonic regression models relative to a multi-year average basis forecasting approach and relative to one another. It is therefore important to have a method for choosing which model is "best." Model evaluation and the inclusion-of-variable decision often are based solely on in-sample statistics such as $R^2$, root mean squared error (RMSE), t-statistics or p-values of parameter estimates, etc. Relying solely on these measures for model selection can be problematic for several reasons. First, the statistical significance of an estimated marginal impact associated with some variable that has many interactions is difficult to ascertain simply by examining t-statistics or p-values. Second, models with numerous variables and many interaction terms might "fit the data" quite well over a particular historical time period, but then "blow up" when used with data from other time periods. That is, models might predict quite well in-sample, but perform poorly out-of-sample due to over-fitting the data. This can be especially problematic when numerous variables and variable interactions are used in estimated models in order to answer impact questions of model users. To avoid this potential problem, predictive accuracy of all estimated models was evaluated using an out-of-sample RMSE measure.

To conduct out-of-sample testing, designated portions of observations from the model data set are predicted using models estimated from other portions of the data. In this case, the analysis was based on 1) dropping data for a single year (the holdout data), 2) estimating the model's parameters with the remaining considered-as-available data, 3) using that estimated model to predict the dependent variable (*BASIS*) values for the holdout data conditional upon independent variable values in the holdout data, and 4) computing a suitable measure of prediction accuracy (RMSE). This process is repeated for each year of available data. RMSE measures of prediction accuracy are aggregated across various weight categories and months via a simple mean, resulting in an expected out-of-sample predictive accuracy measure for each model. This out-of-sample predictive accuracy analysis is referred to as a "delete-year" framework.

Data from 1996-1998 are used to compute three-year average *MEAN* basis forecasts by sex, weight class, and month in each state for feeder cattle transactions in 1999. Forecasts for transactions in each subsequent year from 2000 to 2007[6] also are estimated using only data from the three preceding years. RMSEs, each computed over the 1999-2007 time period, are calculated to measure accuracy of the predicted versus actual basis in each state by sex, weight class (50 lb increments), and month of sale.

Out-of-sample basis forecasts also are estimated for *FCModel*, *LCCNModel*, and *COMPOSITEModel* for the years 1999-2007. In contrast to the multi-year average *MEAN* forecast, basis predictions from the hedonic models for a subject year are estimated using data from all other years in the dataset. For example, 2001 basis values are predicted using data from 1996-2000 and 2002-2007. As with the out-of-sample work for *MEAN* forecasts, an RMSE across 1999-2007 is computed for each sex, weight class, and month.

[6] Out-of-sample analyses were based on only data through 2007 such that "full years" could be used for comparison purposes. However, final models reported here were estimated with data through April 2008.

The hedonic models estimated here are structural models, where variable values are assumed to be contemporaneously known. That is, for example, the sex of a feeder calf today determines its cash price today. Or, the nearby feeder cattle futures price today affects the basis of a feeder calf today. Equivalently, the nearby futures price 100 days from now will determine the basis 100 days from now. Contemporaneous structural models generally are thought to be reliable indicators of the quantitative impact of causal forces on some dependent variable, e.g., relative to a steer, how much is a heifer calf discounted? But, using contemporaneous structural relationships to aid predictions of variables in the future is potentially problematic in that it requires predictions of the independent variables in order to let the prediction of the dependent variable arise from the model. In short, prediction RMSEs arising from the delete-year framework described above generally will overstate the true real-time accuracy since they do not account for the additional error implied by having to predict the independent variable values in real time. Hence, understanding the real-world predictive accuracy associated with competing models requires more than a simple delete-year testing framework. It requires a characterization of predictive accuracy of the dependent variable conditional upon the predictive accuracy of the independent variables. Moreover, it needs to consider that more distant forecasts likely will be less accurate than ones closer in, which is a critical issue for the current problem, where producers presumably will be using the basis prediction tool developed here to make basis predictions from different vantage points (i.e., at different time horizons).

Essentially, in making future basis predictions, many of the variable values that are included in the model will be known or assumed known at sale time (e.g., cattle characteristics and anticipated sale time). However, futures prices on the cash sale date will not be known with certainty in advance and must be forecast. Thus, it will be important to impose on our expected accuracy tests of predictive models not only estimates of future futures prices, but also expected accuracies of such measures across different time horizons. In short, it is important to account for when these forecasts might be made (i.e., the time horizon). Thus, in addition to evaluating the models' predictive accuracies based upon the simple delete-year framework already described, model predictions also were made from a time horizon of 20 weeks prior to when the data were actually known by introducing error surrounding the futures price variables (we used expected percentage error measures derived from historical futures price data from 1982-2005). Effectively, for model selection, this "penalizes" models that include more futures price variables because each one of these variables will have a forecast error associated with it. Naturally, the forecast horizon is irrelevant for the *MEAN* model because it does not incorporate current-year futures price expectations.

## RESULTS AND DISCUSSION

Results from estimating *FCModel* and *LCCNModel* with Kansas data using ordinary least squares (OLS) regression are reported in Tables 3 and 4, respectively.[7] Default values of the binary variables are defined to avoid perfect collinearity. The default sex was steers, the default contract change was the current time period, and the default month was October. *FCModel* explained 81% of the variation in nearby feeder cattle basis transactions and *LCCNModel*

[7] Results presented in this paper are for Kansas. Results for the other twelve states are available upon request but were quite similar in their rankings of models.

explained 83%. Nearly every coefficient, with the exception of a few of the monthly binary variables, is statistically different from zero at the 0.05 level. However, given the large number of observations, this is to be expected. These models can be used to generate point-estimate basis forecasts.

It is difficult to discern the impact of continuous variables by simply looking at the coefficients because of the many interactions. Figure 1 shows the model-predicted basis for the two regression models (*FCmodel* and *LCCNModel*) and the composite model holding all variables constant except weight and live cattle futures price (live cattle futures price used is a function of weight).[8] Several important issues can be gleaned from this figure. First, basis forecasts from the two models can deviate considerably (although they converge at mean weight as expected). Second, the approach used that allows live cattle futures prices to change with feeder cattle weight results in a basis-weight relationship (i.e., price slide) that is not necessarily smooth. Given that the current market environment exhibits record high corn prices and live cattle trading at a premium to feeder cattle in some months, it is not surprising that the forecasts from the two models deviate. But the question still remains, which forecast should a producer use?

To compare accuracy among models, average out-of-sample RMSEs are computed for each forecasting method. These measures also are computed for the three regression models at both a 0-week (contemporaneous) and 20-week forecast horizons. Table 5 displays RMSEs averaged across weight categories, months, and years for Kansas steers and heifers for the alternative prediction models at both the 0- and 20-week horizons. The results summarized in Table 5 show that the three-year average model (*MEAN*), which is unaffected by forecasting horizon, has the highest (worst) average RMSE (6.0156 for steers and 5.7653 for heifers). The hedonic regression model based on live cattle and corn futures, *LCCNModel*, has the lowest (best) RMSE among all model approaches for both forecasting horizons, although it is only marginally better than the composite model (*FCLCCNModel*) when forecasts are assumed to be made 20 weeks in advance. These results suggest that predicting basis with an econometric model that captures cattle characteristics can improve forecast accuracy compared to using a historical average.

Figures 2 and 3 show the out-of-sample RMSEs for the alternative models at both time horizons by weight category for steers and heifers, respectively. As would be expected, basis prediction accuracy improves for all models as the weight of cattle approaches futures contract specifications. The results in Figures 2 and 3 demonstrate that the relationship between weight class and prediction accuracy generally is consistent across all models and forecast horizons. RMSEs for *MEAN* are consistently higher than those of regression models at all weight classes. At the lightest weight class, RMSEs from *LCCNModel* are lowest among the models. However, for heavier weight feeder cattle, the forecast accuracy of the feeder cattle and live cattle/corn models are very similar. The *LCCNModel* at 0-week horizon generally has the lowest RMSE, especially for weights less than 600 lb. However, it is important to remember that producers often need to forecast basis 3-6 months in advance and thus the 20-week horizon results are more germane. The advantage of the *LCCNModel* over the composite is much smaller at a forecast horizon of 20 weeks, suggesting a potential benefit of using the composite forecast.

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[8] Forecasts are for a medium-large frame, grade 1-2, steers, lot size of 18 head at default location (Winter Livestock Auction) on October 15, 2008. Futures prices were based on June 19, 2008 closing prices and were as follows: feeder cattle $114.40 per cwt, live cattle $110.82 to $116.75 per cwt, and corn $7.62 per bu.

Figure 4 shows how often the RMSE of one model was lower than another, for all model combinations, over the 288 (12 weight categories x 12 months x steers and heifers) scenarios considered. The *MEAN* forecast (designated simply by "M" in the figure) had a lower RMSE than regression-based predictions less than five percent of the time. Consistent with Table 5 and Figures 2 and 3, basis predictions from *LCCNModel* yielded lower RMSE's than the composite forecast over half (62%) of the time at the 0-week horizon. However, at the 20-week horizon, the composite forecast had a lower RMSE slightly over half (53%) of the time. Thus, even though the RMSE from *LCCNModel* was lower on average, it was not the lowest the majority of the time. This provides some additional support for using a composite forecast.

## SUMMARY AND CONCLUSIONS

The primary objective of this research is to improve on current methods of forecasting feeder cattle basis. Two hedonic regression models and a composite average forecast model have been developed and tested. If these regression-based models cannot out-predict these simple averages, then producers will be better off continuing to use the simple multi-year average forecast technique. On the other hand, if any of the estimated models can outperform the simple averages, based on out-of-sample RMSEs, then producers would be better off forecasting basis using a regression-based econometric model compared to historical averages.

Our results provide strong evidence that models developed using hedonic regression techniques and including market condition and lot variables predict basis more accurately than a simple three-year average. Though especially true for light-weight feeder cattle, this result holds true across all weight classes.

The best choice among the two regression models and the composite model is somewhat less clear. The model incorporating feeder cattle futures price as an explanatory variable has the highest out-of-sample RMSE among the three models. Furthermore, our results suggest that the relative accuracy of the *FCModel* declines as feeder cattle weight declines. This result is not surprising. The corn price variable in the *LCCNModel* directly accounts for changes in feed cost, while a single feeder cattle price used in the *FCmodel* could reflect any number of different combinations of live cattle and corn prices. Feed cost impacts obviously are more important for lighter cattle because of their greater future feed requirements. On average, the *LCCNModel* has the lowest RMSE at a 0-week forecasting horizon. However the relative accuracy of this model and the composite model are very close at the 20 week forecast horizon. Since most producers interested in using feeder cattle futures or option to manage price risk are interested in forecasting basis several weeks or months into the future, results from the 20 week forecast horizon are likely more relevant for most potential users of these forecast models.

The results of this research provide practical results that producers can use to forecast and better understand feeder cattle basis. Improved ability to forecast basis and understanding of the factors that affect basis will help producers manage their market risks.

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**Table 1. Variables Included in Basis Model Estimation**

| Variable | Definition/description |
|---|---|
| *Wt* | Average weight (lb/head) of animals in pen; allows basis forecasts to vary by weight nonlinearly (using its squared term) and also interacted with other variables. |
| *Lotsize* | Lot size is the number of head being sold or purchased and allows basis forecasts to vary nonlinearly by lot size. |
| *Hfr* | Binary variable equal to 1 if the cattle are heifers and 0 otherwise. Basis forecasts differ for steers, heifers, and bull calves. |
| *Diesel* | Diesel fuel price forecast from the Energy Information Administration (EIA) for the month in which cattle are to be sold. |
| *Frame* | Binary variable to allow basis forecasts to vary by frame size, where frame size is defined as one of two categories (*Med-Large/Large* and *Other*). |
| *Grade* | Binary variables to allow basis forecasts to vary by grade (or class) of cattle, where class is defined as one of three categories (*Grade1*, *Grade12*, *GradeOther*). |
| *ContractChange* | Feeder cattle futures contract change variables are included to account for four changes in contract specifications over time. Model-predictions are based on current contract specifications. |
| *Month* | A set of binary variables for month (*m*=Jan, Feb,…, Oct (default), Nov, Dec) included to account for seasonality. |
| *Location* | A set of binary variables corresponding to individual auction locations within a state. |
| *FC* | Futures price ($/cwt) of nearby feeder cattle contract at the time cattle are sold or purchased (*FCModel* only). |
| *LC* | Futures price ($/cwt) of live cattle contract that will be the nearby contract when feeder cattle are expected to weigh 750 lb or more (*LCCNModel* only). |
| *CN* | Futures price ($/bushel) of nearby corn contract at the time cattle are sold or purchased (*LCCNModel* only). |

**Table 2. Summary Statistics of Feeder Cattle Cash Price and Variables Used in Basis Models for Kansas, January 1996 to April 2008**

| Variable | N | Mean | Standard Deviation | Minimum | Maximum |
|---|---|---|---|---|---|
| Continuous Variables | | | | | |
| *Feeder cattle price, $/cwt* | 294,678 | 87.56 | 19.68 | 28.50 | 199.00 |
| *Basis, $/cwt* | 294,678 | 1.75 | 9.59 | -38.25 | 85.10 |
| *Lot size, head* | 294,678 | 17.76 | 18.72 | 1.00 | 335.00 |
| *Weight (Wt), lbs/head* | 294,678 | 652.43 | 139.58 | 300.00 | 900.00 |
| *FC, $/cwt* | 294,678 | 85.81 | 16.02 | 47.65 | 119.57 |
| *LC, $/cwt* | 294,678 | 74.73 | 10.47 | 54.80 | 102.92 |
| *CN, $/bu* | 294,678 | 2.64 | 0.77 | 1.75 | 6.05 |
| *Diesel price, cents/gallon* | 294,678 | 164.82 | 67.21 | 96.00 | 408.00 |
| Binary Variables | | | | | |
| *Steer (Str)* | 294,678 | 0.53 | 0.50 | 0.00 | 1.00 |
| *Heifer (Hfr)* | 294,678 | 0.47 | 0.50 | 0.00 | 1.00 |
| *Grade1* | 294,678 | 0.74 | 0.44 | 0.00 | 1.00 |
| *Grade12* | 294,678 | 0.18 | 0.38 | 0.00 | 1.00 |
| *GradeOther* | 294,678 | 0.09 | 0.28 | 0.00 | 1.00 |
| *ContractChange1* | 294,678 | 0.34 | 0.47 | 0.00 | 1.00 |
| *ContractChange2* | 294,678 | 0.09 | 0.29 | 0.00 | 1.00 |
| *ContractChange3* | 294,678 | 0.19 | 0.39 | 0.00 | 1.00 |
| *Jan* | 294,678 | 0.11 | 0.32 | 0.00 | 1.00 |
| *Feb* | 294,678 | 0.09 | 0.29 | 0.00 | 1.00 |
| *Mar* | 294,678 | 0.12 | 0.33 | 0.00 | 1.00 |
| *Apr* | 294,678 | 0.11 | 0.31 | 0.00 | 1.00 |
| *May* | 294,678 | 0.07 | 0.25 | 0.00 | 1.00 |
| *Jun* | 294,678 | 0.03 | 0.16 | 0.00 | 1.00 |
| *Jul* | 294,678 | 0.05 | 0.22 | 0.00 | 1.00 |
| *Aug* | 294,678 | 0.07 | 0.26 | 0.00 | 1.00 |
| *Sep* | 294,678 | 0.06 | 0.24 | 0.00 | 1.00 |
| *Oct* | 294,678 | 0.11 | 0.31 | 0.00 | 1.00 |
| *Nov* | 294,678 | 0.11 | 0.31 | 0.00 | 1.00 |
| *Dec* | 294,678 | 0.06 | 0.24 | 0.00 | 1.00 |
| *Location1* | 294,678 | 0.24 | 0.42 | 0.00 | 1.00 |
| *Location2* | 294,678 | 0.34 | 0.48 | 0.00 | 1.00 |
| *Location3* | 294,678 | 0.42 | 0.49 | 0.00 | 1.00 |

**Table 3. Regression Results for *FCModel* (feeder cattle futures) – Kansas**

| Variable[1] | Parameter Estimate | Standard Error | t Value | Pr > \|t\| |
|---|---|---|---|---|
| *Intercept* | -51.95165 | 1.73949 | -29.87 | 0.00010 |
| *Wt* | 0.07288 | 0.00567 | 12.86 | 0.00010 |
| *$Wt^2$* | -1.1E-05 | 4.5E-06 | -2.53 | 0.01150 |
| *Lotsize* | 0.08906 | 0.00613 | 14.52 | 0.00010 |
| *$Lotsize^2$* | 0.00029 | 0.00009 | 3.40 | 0.00070 |
| *LotsizeWt* | -8.1E-05 | 8.3E-06 | -9.79 | 0.00010 |
| *$Lotsize^2Wt$* | -5.2E-07 | 1.1E-07 | -4.61 | 0.00010 |
| *Hfr* | -32.46196 | 0.29468 | -110.16 | 0.00010 |
| *HfrWt* | 0.06100 | 0.00097 | 63.20 | 0.00010 |
| *$HfrWt^2$* | -3.4E-05 | 7.7E-07 | -43.82 | 0.00010 |
| *FC* | 1.30683 | 0.02233 | 58.52 | 0.00010 |
| *FCWt* | -0.00270 | 0.00007 | -37.05 | 0.00010 |
| *$FCWt^2$* | 1.2E-06 | 5.7E-08 | 21.15 | 0.00010 |
| *Diesel* | -0.03032 | 0.00036 | -85.19 | 0.00010 |
| *Grade1* | 7.44196 | 0.02892 | 257.34 | 0.00010 |
| *Grade12* | 2.78600 | 0.03215 | 86.65 | 0.00010 |
| *ContractChange1* | 17.71162 | 0.46903 | 37.76 | 0.00010 |
| *ContractChange2* | 28.23270 | 0.94561 | 29.86 | 0.00010 |
| *ContractChange3* | 11.67478 | 0.92222 | 12.66 | 0.00010 |
| *ContractChange1Wt* | -0.04068 | 0.00153 | -26.60 | 0.00010 |
| *ContractChange2Wt* | -0.06616 | 0.00305 | -21.67 | 0.00010 |
| *ContractChange3Wt* | -0.02040 | 0.00299 | -6.82 | 0.00010 |
| *$ContractChange1Wt^2$* | 2.7E-05 | 1.2E-06 | 21.98 | 0.00010 |
| *$ContractChange2Wt^2$* | 4.9E-05 | 2.4E-06 | 20.42 | 0.00010 |
| *$ContractChange3Wt^2$* | 1.8E-05 | 2.4E-06 | 7.73 | 0.00010 |
| *Jan* | 7.59365 | 0.63412 | 11.98 | 0.00010 |
| *Feb* | 10.49286 | 0.67150 | 15.63 | 0.00010 |
| *Mar* | 10.73945 | 0.63514 | 16.91 | 0.00010 |
| *Apr* | 0.31243 | 0.61517 | 0.51 | 0.61150 |
| *May* | 0.31109 | 0.73293 | 0.42 | 0.67120 |
| *Jun* | 1.69625 | 1.00929 | 1.68 | 0.09280 |
| *Jul* | -3.69761 | 0.80242 | -4.61 | 0.00010 |
| *Aug* | -12.27950 | 0.67575 | -18.17 | 0.00010 |
| *Sep* | -15.45587 | 0.70348 | -21.97 | 0.00010 |
| *Nov* | 10.62124 | 0.60722 | 17.49 | 0.00010 |
| *Dec* | 8.73871 | 0.70830 | 12.34 | 0.00010 |
| *JanWt* | -0.00121 | 0.00207 | -0.58 | 0.55880 |
| *FebWt* | 0.00653 | 0.00219 | 2.98 | 0.00290 |
| *MarWt* | 0.01889 | 0.00207 | 9.12 | 0.00010 |
| *AprWt* | 0.05118 | 0.00203 | 25.21 | 0.00010 |
| *MayWt* | 0.03907 | 0.00237 | 16.51 | 0.00010 |
| *JunWt* | 0.01735 | 0.00323 | 5.37 | 0.00010 |

**Table 3. Regression Results for *FCModel* (feeder cattle futures) – Kansas (*cont.*)**

| Variable[1] | Parameter Estimate | Standard Error | t Value | Pr > \|t\| |
|---|---|---|---|---|
| *JulWt* | 0.03074 | 0.00258 | 11.91 | 0.00010 |
| *AugWt* | 0.05386 | 0.00221 | 24.37 | 0.00010 |
| *SepWt* | 0.05577 | 0.00231 | 24.14 | 0.00010 |
| *NovWt* | -0.02907 | 0.00203 | -14.31 | 0.00010 |
| *DecWt* | -0.01922 | 0.00234 | -8.21 | 0.00010 |
| $JanWt^2$ | -1.1E-05 | 1.6E-06 | -6.41 | 0.00010 |
| $FebWt^2$ | -2.5E-05 | 1.7E-06 | -14.63 | 0.00010 |
| $MarWt^2$ | -4.2E-05 | 1.6E-06 | -25.54 | 0.00010 |
| $AprWt^2$ | -6.5E-05 | 1.6E-06 | -39.89 | 0.00010 |
| $MayWt^2$ | -4.9E-05 | 1.9E-06 | -26.40 | 0.00010 |
| $JunWt^2$ | -2.3E-05 | 2.5E-06 | -9.12 | 0.00010 |
| $JulWt^2$ | -3.0E-05 | 2.0E-06 | -14.91 | 0.00010 |
| $AugWt^2$ | -4.6E-05 | 1.8E-06 | -26.18 | 0.00010 |
| $SepWt^2$ | -4.4E-05 | 1.8E-06 | -24.15 | 0.00010 |
| $NovWt^2$ | 2.0E-05 | 1.7E-06 | 12.02 | 0.00010 |
| $DecWt^2$ | 1.2E-05 | 1.9E-06 | 6.36 | 0.00010 |
| *Location2* | 0.44681 | 0.02092 | 21.36 | 0.00010 |
| *Location3* | 1.31224 | 0.02110 | 62.20 | 0.00010 |
| | | | | |
| $R^2$ | 0.8133 | | | |
| RMSE | 4.1432 | | | |
| Number of observations | 294,678 | | | |

[1] See Table 1 for variable definitions.

**Table 4. Regression Results for *LCCNModel* (live cattle and corn futures) – Kansas**

| Variable[1] | Parameter Estimate | Standard Error | t Value | Pr > \|t\| |
|---|---|---|---|---|
| *Intercept* | 14.45082 | 2.33716 | 6.18 | 0.00010 |
| *Wt* | 0.02106 | 0.00737 | 2.86 | 0.00430 |
| $Wt^2$ | -0.00007 | 0.00001 | -12.05 | 0.00010 |
| *Lotsize* | 0.11094 | 0.00583 | 19.02 | 0.00010 |
| $Lotsize^2$ | 0.00010 | 0.00008 | 1.17 | 0.24100 |
| *LotsizeWt* | -0.00011 | 0.00001 | -13.89 | 0.00010 |
| $Lotsize^2Wt$ | 0.00000 | 0.00000 | -2.55 | 0.01070 |
| *Hfr* | -32.61119 | 0.28013 | -116.42 | 0.00010 |
| *HfrWt* | 0.06138 | 0.00092 | 66.90 | 0.00010 |
| $HfrWt^2$ | -0.00003 | 0.00000 | -46.39 | 0.00010 |
| *LC* | 1.17350 | 0.03438 | 34.14 | 0.00010 |
| *LCWt* | -0.00380 | 0.00011 | -35.11 | 0.00010 |
| $LCWt^2$ | 3.0E-06 | 8.3E-08 | 35.61 | 0.00010 |
| *CN* | -19.94421 | 0.21602 | -92.32 | 0.00010 |
| *CNWt* | 0.04134 | 0.00070 | 59.16 | 0.00010 |
| $CNWt^2$ | -2.0E-05 | 5.5E-07 | -35.74 | 0.00010 |
| *Diesel* | -0.00753 | 0.00039 | -19.15 | 0.00010 |
| *Grade1* | 7.47890 | 0.02749 | 272.07 | 0.00010 |
| *Grade12* | 2.88258 | 0.03057 | 94.31 | 0.00010 |
| *ContractChange1* | 20.16190 | 0.40983 | 49.20 | 0.00010 |
| *ContractChange2* | 43.44220 | 0.82514 | 52.65 | 0.00010 |
| *ContractChange3* | 40.64982 | 0.90027 | 45.15 | 0.00010 |
| *ContractChange1Wt* | -0.03857 | 0.00134 | -28.81 | 0.00010 |
| *ContractChange2Wt* | -0.07824 | 0.00264 | -29.61 | 0.00010 |
| *ContractChange3Wt* | -0.05672 | 0.00285 | -19.89 | 0.00010 |
| $ContractChange1Wt^2$ | 1.8E-05 | 1.1E-06 | 16.63 | 0.00010 |
| $ContractChange2Wt^2$ | 3.3E-05 | 2.1E-06 | 16.06 | 0.00010 |
| $ContractChange3Wt^2$ | 6.6E-06 | 2.2E-06 | 2.97 | 0.00300 |
| *Jan* | 7.09516 | 0.59723 | 11.88 | 0.00010 |
| *Feb* | 9.97197 | 0.62472 | 15.96 | 0.00010 |
| *Mar* | 11.74790 | 0.59182 | 19.85 | 0.00010 |
| *Apr* | 1.21116 | 0.57870 | 2.09 | 0.03640 |
| *May* | 4.01872 | 0.69863 | 5.75 | 0.00010 |
| *Jun* | 4.78928 | 0.96150 | 4.98 | 0.00010 |
| *Jul* | -6.03748 | 0.76419 | -7.90 | 0.00010 |
| *Aug* | -13.50178 | 0.64441 | -20.95 | 0.00010 |
| *Sep* | -14.18368 | 0.66950 | -21.19 | 0.00010 |
| *Nov* | 9.25840 | 0.57713 | 16.04 | 0.00010 |
| *Dec* | 7.03101 | 0.67307 | 10.45 | 0.00010 |
| *JanWt* | 0.00101 | 0.00195 | 0.52 | 0.60530 |
| *FebWt* | 0.00711 | 0.00204 | 3.49 | 0.00050 |
| *MarWt* | 0.01544 | 0.00193 | 8.00 | 0.00010 |

**Table 4. Regression Results for *LCCNModel* (live cattle and corn futures) –Kansas(*cont.*)**

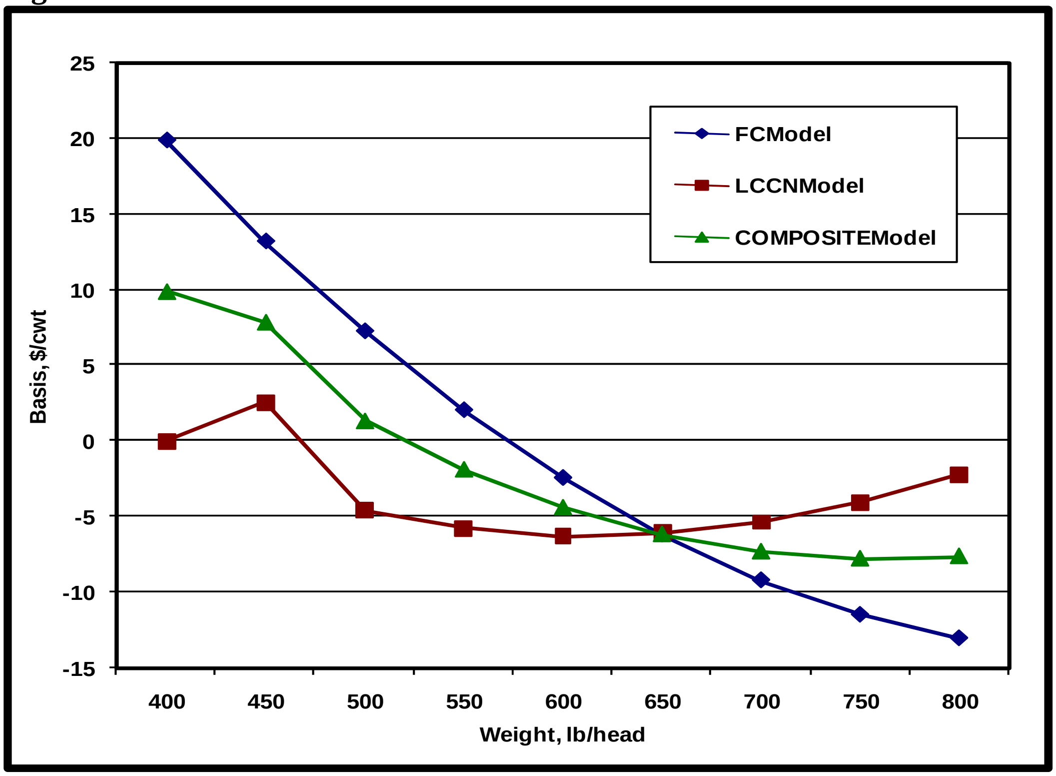
| Variable[1] | Parameter Estimate | Standard Error | t Value | Pr > \|t\| |
|---|---|---|---|---|
| *AprWt* | 0.04786 | 0.00192 | 24.97 | 0.00010 |
| *MayWt* | 0.02805 | 0.00226 | 12.39 | 0.00010 |
| *JunWt* | 0.01063 | 0.00308 | 3.45 | 0.00060 |
| *JulWt* | 0.03697 | 0.00246 | 15.03 | 0.00010 |
| *AugWt* | 0.05695 | 0.00211 | 27.01 | 0.00010 |
| *SepWt* | 0.05264 | 0.00220 | 23.95 | 0.00010 |
| *NovWt* | -0.02564 | 0.00193 | -13.28 | 0.00010 |
| *DecWt* | -0.01420 | 0.00222 | -6.38 | 0.00010 |
| $JanWt^2$ | -1.2E-05 | 1.5E-06 | -7.75 | 0.00010 |
| $FebWt^2$ | -2.4E-05 | 1.6E-06 | -15.13 | 0.00010 |
| $MarWt^2$ | -3.9E-05 | 1.5E-06 | -25.20 | 0.00010 |
| $AprWt^2$ | -6.1E-05 | 1.5E-06 | -40.14 | 0.00010 |
| $MayWt^2$ | -4.0E-05 | 1.8E-06 | -22.68 | 0.00010 |
| $JunWt^2$ | -1.9E-05 | 2.4E-06 | -7.81 | 0.00010 |
| $JulWt^2$ | -3.4E-05 | 1.9E-06 | -17.45 | 0.00010 |
| $AugWt^2$ | -4.7E-05 | 1.7E-06 | -28.30 | 0.00010 |
| $SepWt^2$ | -4.2E-05 | 1.8E-06 | -24.18 | 0.00010 |
| $NovWt^2$ | 1.8E-05 | 1.6E-06 | 11.37 | 0.00010 |
| $DecWt^2$ | 8.7E-06 | 1.8E-06 | 4.87 | 0.00010 |
| *Location2* | 0.42807 | 0.01988 | 21.53 | 0.00010 |
| *Location3* | 1.25059 | 0.02006 | 62.36 | 0.00010 |
| | | | | |
| $R^2$ | 0.8313 | | | |
| RMSE | 3.9385 | | | |
| Number of observations | 294,678 | | | |

[1] See Table 1 for variable definitions.

**Table 5. Average Out-of-Sample RMSE by Forecast Horizon, $/cwt.**

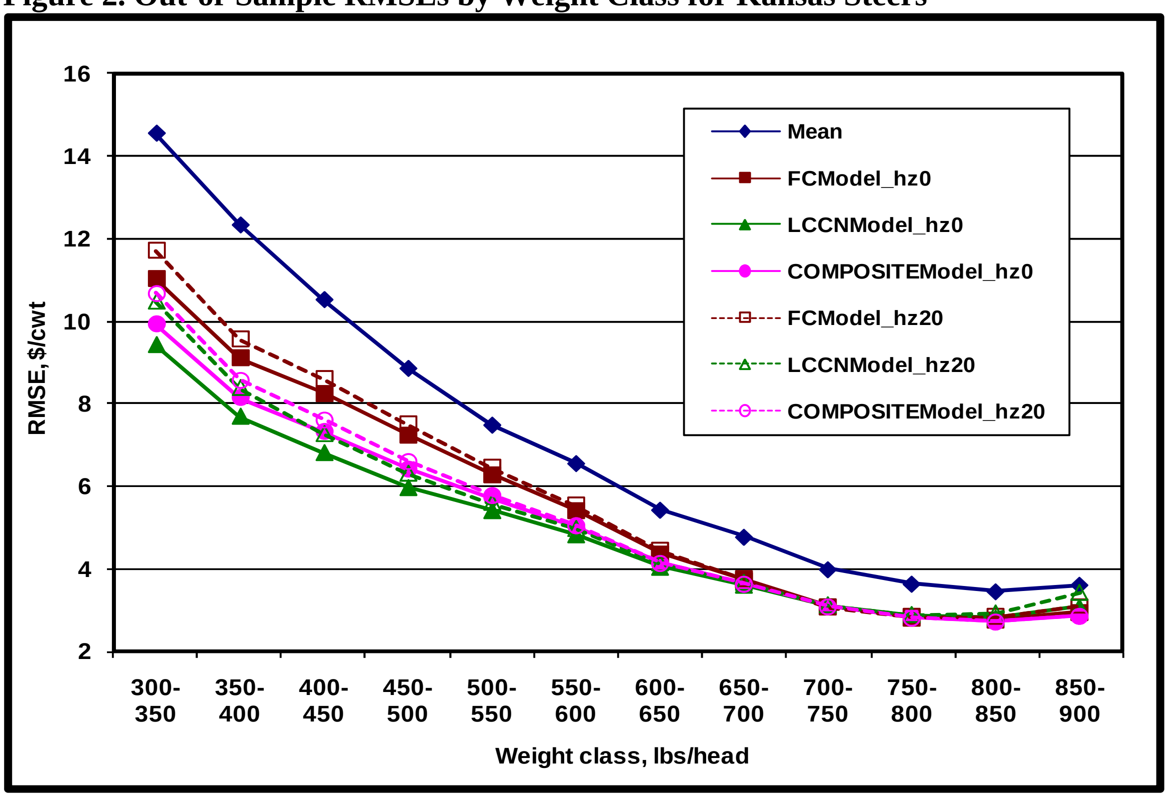
| | 0 week horizon | | 20 week horizon | |
|---|---|---|---|---|
| Basis Forecast Model | Steers | Heifers | Steers | Heifers |
| *MEAN* | 6.0156 | 5.7653 | 6.0156 | 5.7653 |
| *FCModel* | 4.7902 | 4.6782 | 4.9389 | 4.8758 |
| *LCCNModel* | 4.2940 | 3.9712 | 4.5008 | 4.2134 |
| *COMPOSITEModel* | 4.4318 | 4.2011 | 4.5347 | 4.3384 |

**Figure 1. Model-Predicted Steer Basis in Kansas***



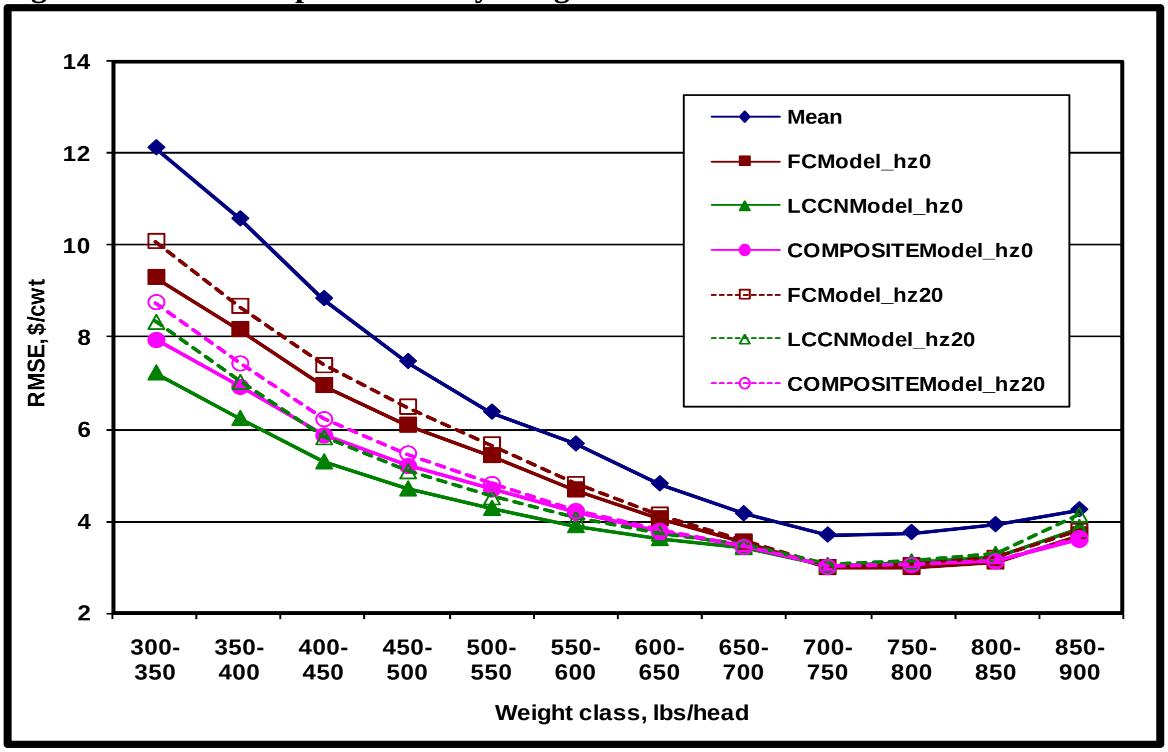

* Medium-large frame, grade 1-2, sold in lot size of 18 head in October 2008 at Winter Livestock Auction

**Figure 2. Out-of-Sample RMSEs by Weight Class for Kansas Steers***



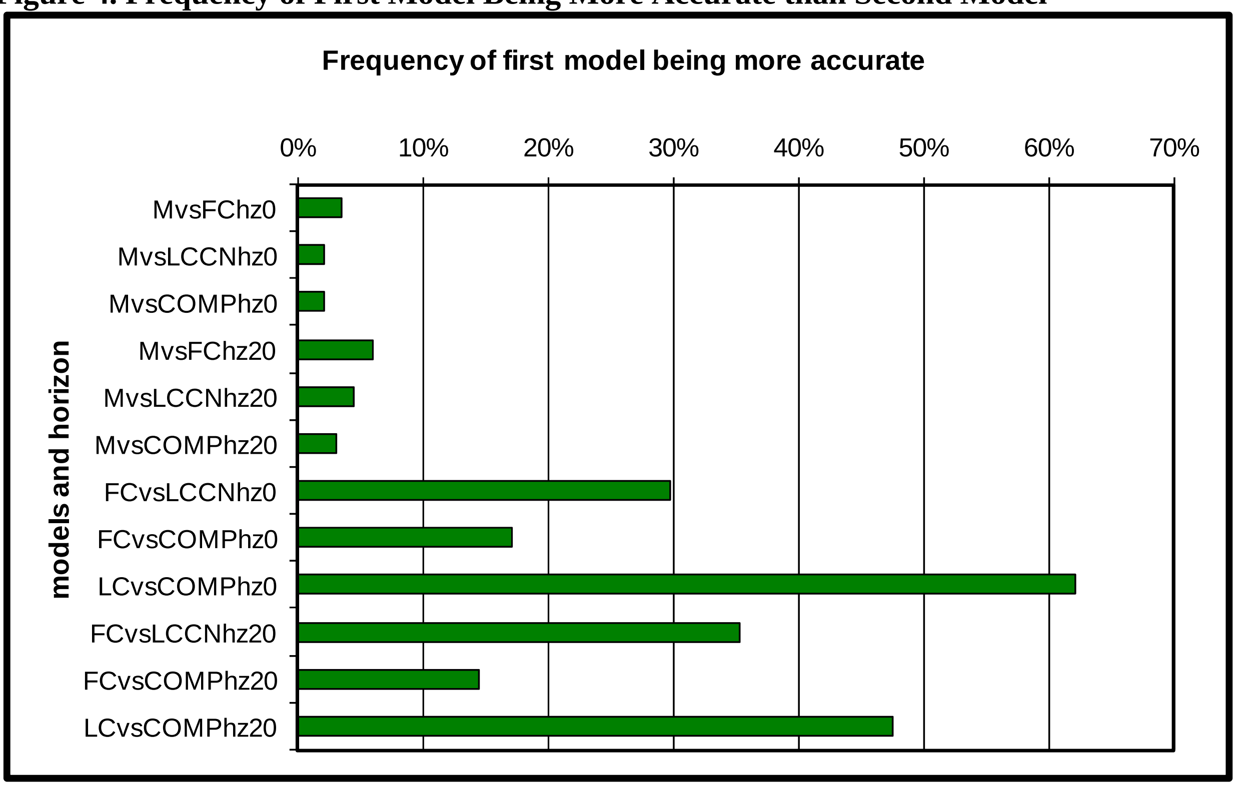

*hz = horizon (weeks)

**Figure 3. Out-of-Sample RMSEs by Weight Class for Kansas Heifers***




*hz = horizon (weeks)

**Figure 4. Frequency of First Model Being More Accurate than Second Model***




* M = MEAN; FC = Feeder cattle model; LCCN = Live cattle and corn model; COMP = Composite model; hz = horizon (weeks)