STRUCTURAL CHANGES IN FED CATTLE BASIS AND THE IMPLICATIONS ON BASIS FORECASTING

by

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Abstract

The past several years has marked one of the most heightened periods of fed cattle basis volatility since the installment of live cattle futures contracts. Understanding basis, the difference between local cash price and the futures contract price, is imperative when making marketing and procurement decisions. In the face of increased volatility, the ability to produce accurate basis expectations is no simple task. The purpose of these analyses was to develop econometric models to determine the greatest influencers of fed cattle basis, to test the presence of structural changes in the determinants of fed cattle basis, and to compare out-of-sample forecasting performance.

This study analyzed in-sample econometric models using monthly data from January 2003 through September 2016, then compared the results of the competing models. Using the same time period, we then identified the presence of structural breaks in the data. Furthermore, this study analyzed the out-of-sample forecasting performance for January 2012 through September 2016. The out-of-sample results were then compared to in-sample estimations and historical average basis models.

The in-sample estimations indicated the important factors that influence fed cattle basis. The results indicate that there are multiple structural breaks present in the determinants of fed cattle basis examined during this study. We can robustly conclude that there was a market structural break present in the fourth quarter of 2013 and within the 2005-2006 time period. The results indicate that the out-of-sample regression estimations were outperformed by historical average models and did not improve our ability to accurately forecast basis. Overall, a 3 or 4 year historical average model should be preferred over econometric estimations when forecasting fed cattle basis.

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Dedication

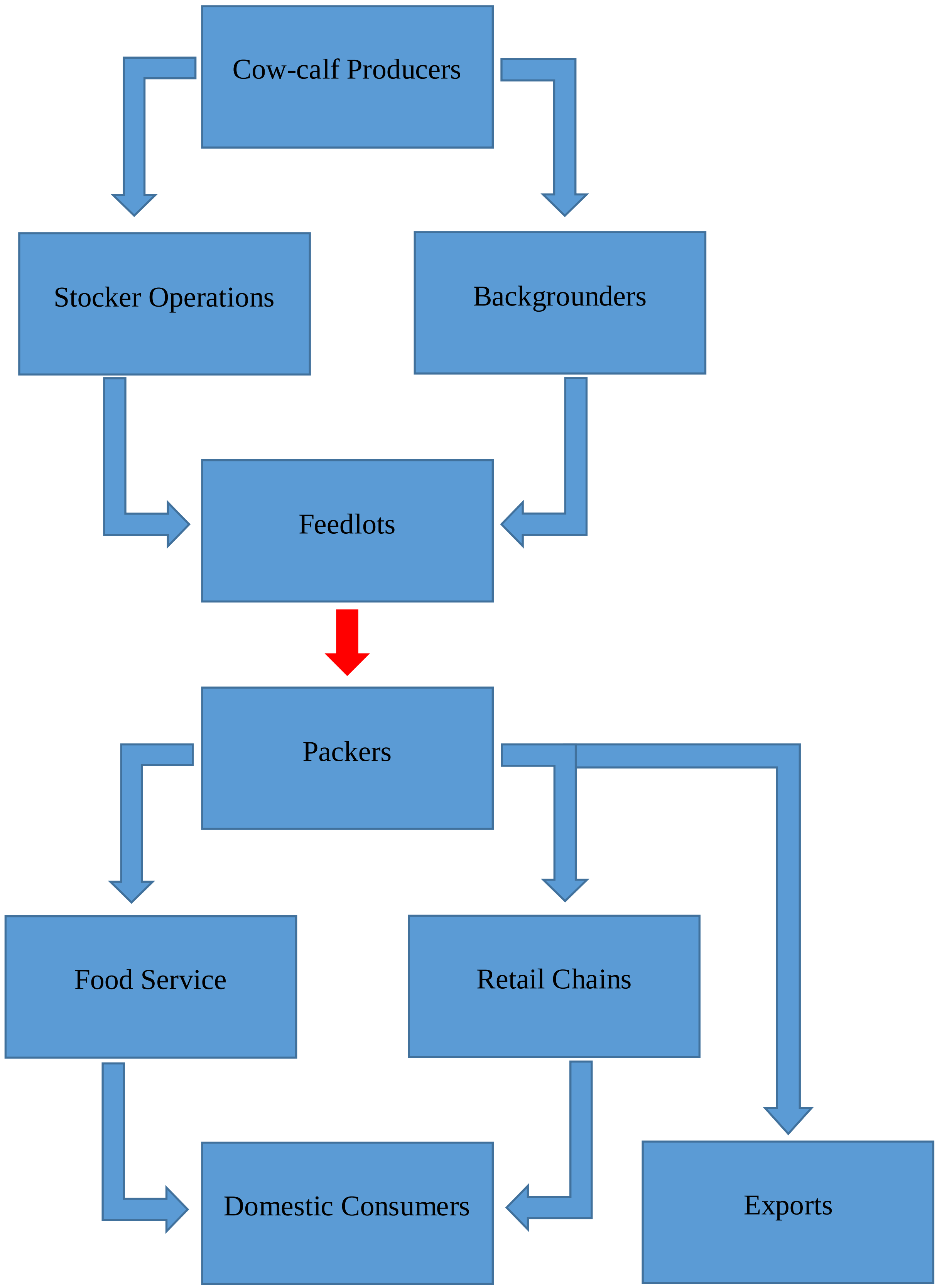
I would like to dedicate this thesis to SPC Haden James Bean.

Chapter 1 - Introduction

The agriculture industry has become accustomed to certain levels of uncertainty over the years; however, in recent years commodity markets have experienced price volatility and unpredictability that many industry participants have yet to encounter during their lifetimes. Right in the heart of this unpredictability lies the beef industry. No individual segment of the beef supply chain is experiencing the brunt of the blow associated with the recent price volatility, rather the entire supply chain, from cow-calf producers to packers, are all feeling the impact. This study will be focusing on fed cattle basis at the intersection of feedlot and packing segments of the beef supply chain which can be seen in Figure 1-1.

Basis is defined as the difference between local cash price and the futures market price. In a volatile and intricate global market, it is vital for feeders and packers to have a firm understanding of basis, especially those who utilize futures contracts as risk management tools. Beyond understanding basis, agribusiness firms are primarily concerned with forecasting basis in future months. The development of reliable basis expectations can be extremely useful when firms are making marketing or procurement decisions, but even more so during times of increased volatility. In February 2016, Philip Ellis, President of National Cattlemen's Beef Association (NCBA), and Ed Greiman, Chairman of NCBA Cattle Marketing and International Trade Committee, said this in a letter to CME Group regarding cattle market volatility: "… we continue to hear our members question their use of the cattle contracts because the volatility has made them a tool which is more of a liability than a benefit." Producers are developing sound risk management strategies, but are still facing a great risk of financial losses as a result of increased market volatility or lack of convergence. Overall, the unpredictability and erratic price

Figure 1-1 Beef Supply Chain Flowchart



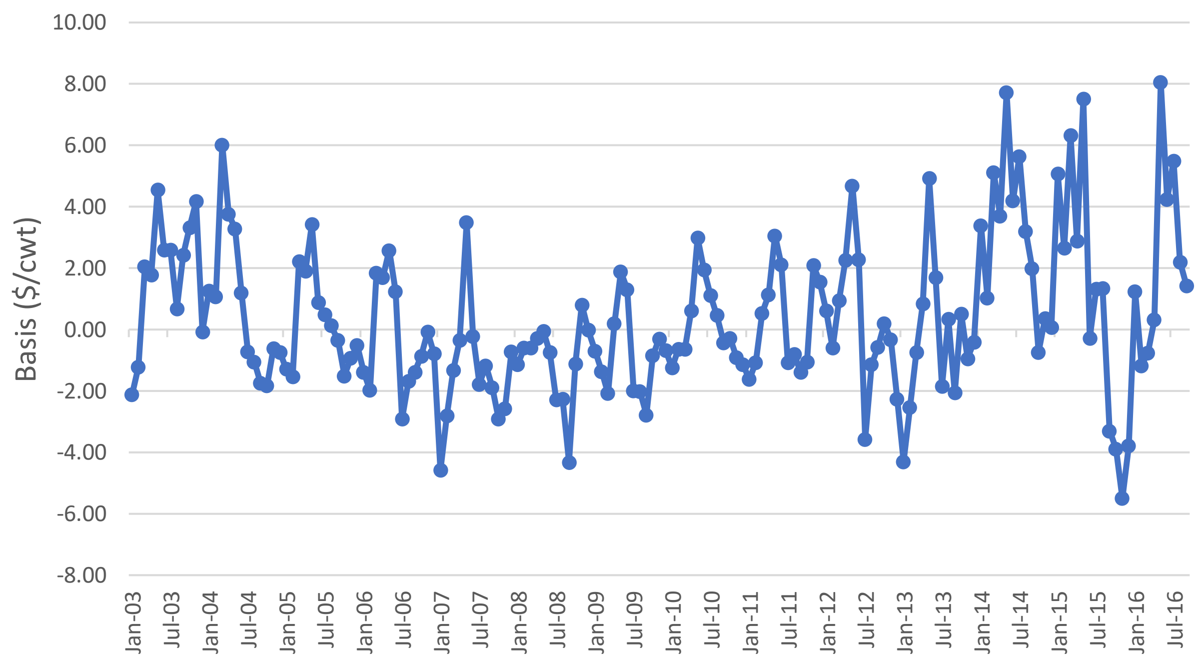
movements are leading producers to lose faith in the viability of live cattle futures contracts as an effective risk management tool.

Figure 1-1 is a flowchart displaying several segments of the beef industry. At the foundation of this supply chain are the cow-calf producers. These producers run beef cows on pasture land to produce calves that will move through the supply chain to produce beef. After approximately six months with the cow, the calves will generally be weaned and placed in either a stocker or backgrounding operation to convert forage into pounds of gain. After reaching a desired weight, which can range anywhere from 700 to 900 pounds, the stocker/backgrounder calves will enter a confined feeding operation or feedlot. In the feedlot, the yearling will be fed a grain based diet to reach a desired weight of approximately 1300 pounds. When the fed steer or heifer is ready to be marketed, they will be sold to packing plants who harvest the animals to produce boxed beef. The packer then sells the primal cuts or case ready beef, directly to food service organizations or retail chains. Another option for the packer is to export the beef as fresh/chilled beef, frozen beef, or other products such as hide and offal. The product finally reaches the end consumer through restaurants or local retail stores.

Objective:

This study will explore further the forecasting of fed cattle basis through the use of econometric models and also serve as an update to previous works conducted. Within the literature, the most recent study focusing on the econometric estimation of fed cattle basis was conducted by Parcell, Schroeder, and Dhuyvetter (2000) which is now over 15 years old. Due to the fact that the literature is rather sparse in regards to fed cattle basis forecasting as well as slightly outdated, the need for updated works is warranted. This study will focus on the comparison of 13 different econometric models to determine what variables are the most important to include as determinants of fed cattle basis. These 13 models will be tested both in-sample as well as out-of-sample. Furthermore, this study will attempt to determine the presence and timing of structural breaks that have occurred in the determinants of fed cattle basis.

Figure 1-2 National Negotiated Fed Steer Basis, January 2003 – September 2016



Source: Livestock Marketing Information Center

Figure 1-2 displays the national negotiated fed cattle basis over the past 14 years. As displayed in the graph, basis ranged between positive $6/cwt and negative $5/cwt for 2003 through 2013. For the past two to three years, there has been a notable increase in the range of fed cattle basis. This widening in the range of basis, in conjunction with very sporadic movements, warrants further exploration of the determinants of fed cattle basis.

Industry Changes:

The United States cattle and beef industry has undergone many changes over the past 40 years in their efforts to provide consumers with a source of high quality protein. Contrary to competing protein sources, the beef industry has different biological and capital constraints to consider making production management decisions. Additionally, consolidation of firms, changes in demand, and tight cattle supplies have all been contributing factors to the overall change in the structure of the beef industry.

Since the late 1970s, there has been a sizeable decrease in the size of the national cowherd. A combination of a severe decline in red meat demand over the past 30 years mixed with depressed prices throughout the 1980s and 1990s has resulted in a notable decrease in cowherd size producing a much smaller calf crop. As shown in Figure 1-3, the national cowherd peaked in size in 1975 and has continued trending downward over the past 40 years. During that time, cattle inventories have gone through several cattle cycles, but as technological advances and feeding efficiencies have improved, the outcome has resulted in fewer total animals. In 2012, much of the country experienced a severe drought that vastly impacted the entire agriculture sector. Extremely poor forage conditions and increased feed input costs added additional strain to the beef industry. As shown in Figure 1-4, 2014 marked the lowest numbers of available cattle since the 1950s which resulted in the beef industry experiencing record high prices throughout 2014 and the early months of 2015. As a result of the increase in prices, cattle producers received a positive signal and we have recently observed more heifers held back as replacements resulting in cowherd expansion into 2015 and 2016.

Figure 1-3 Total U.S. Annual Beef Cow Inventory, 1950-2016

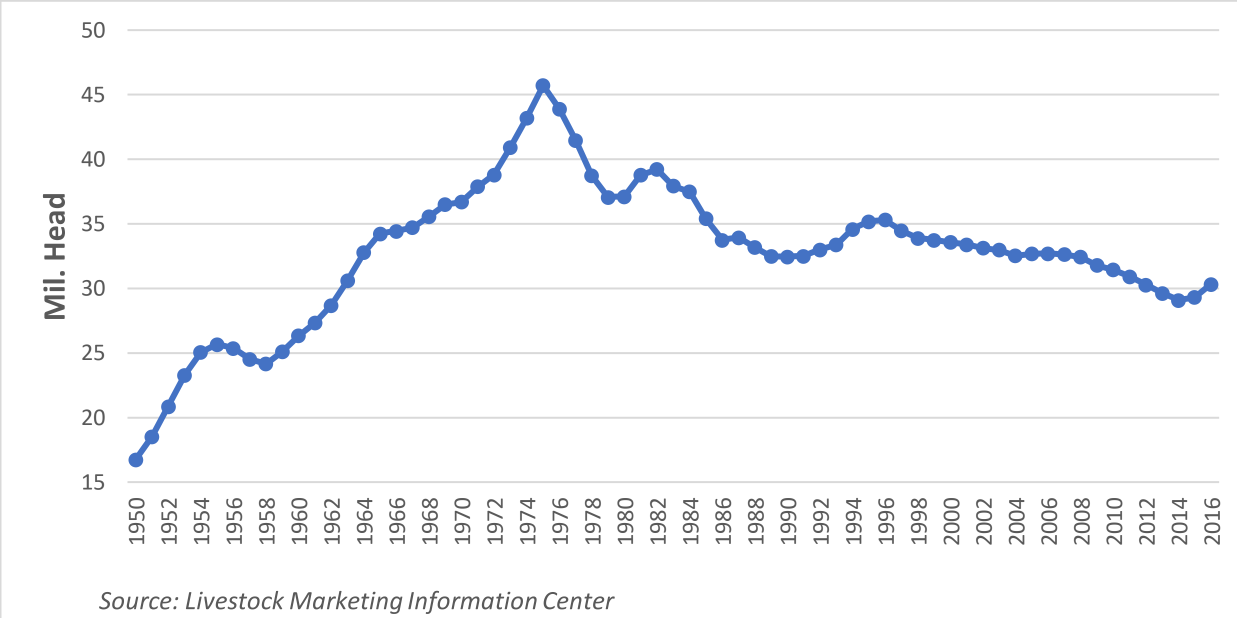
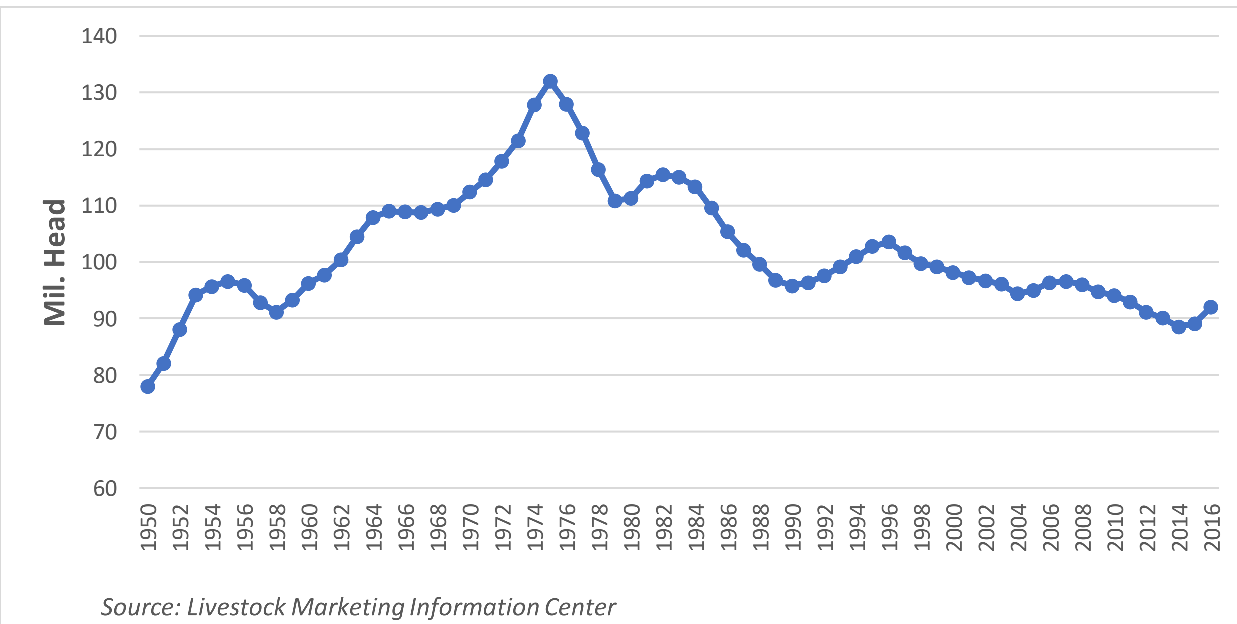
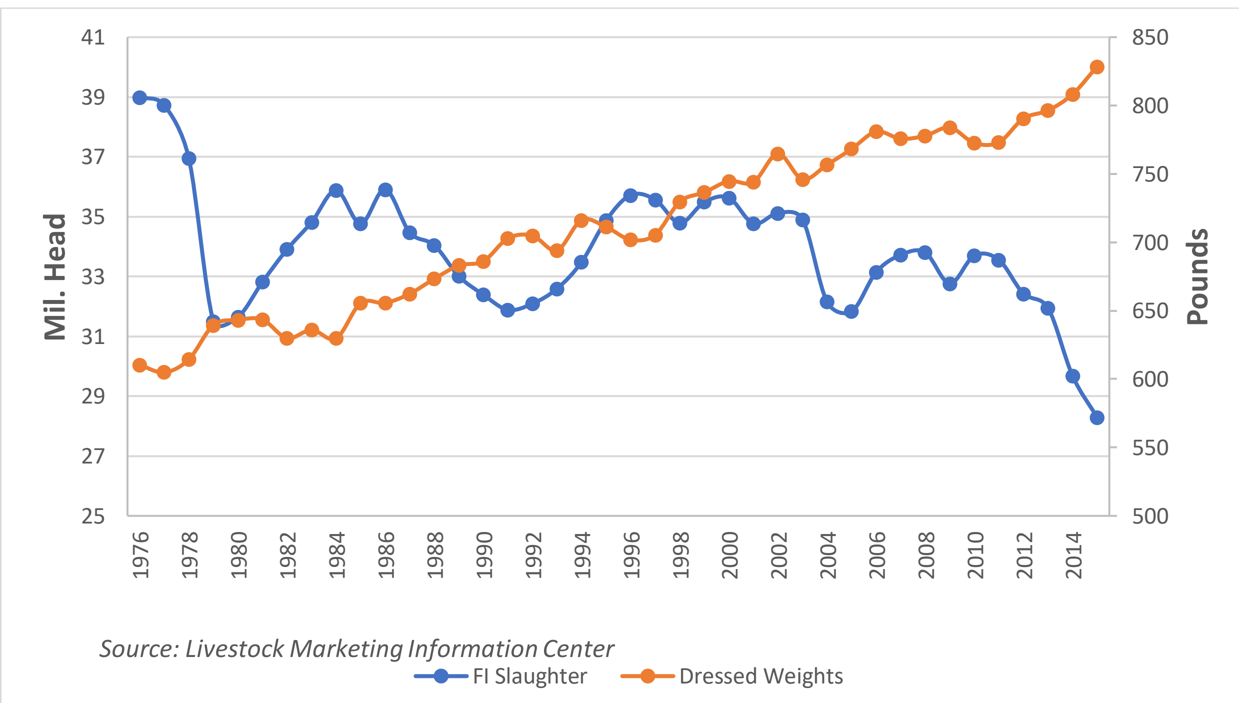


Figure 1-4 Total U.S. Annual Cattle and Calves Inventory, 1950-2016



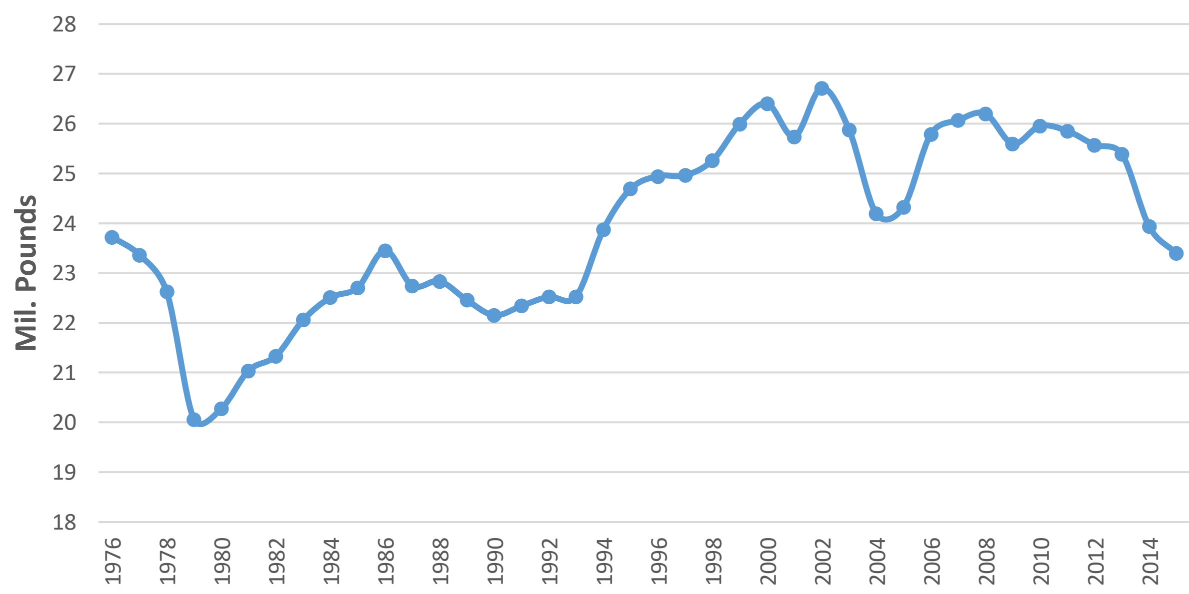
With a shorter supply of cattle, we have observed decreases in slaughter numbers over the past 30 years. As shown in Figure 1-5, federally inspected slaughter numbers have decreased over 10 million head per year from 1976 to 2015. Alternatively, dressed weights have been steadily increasing over the past 30 years which can also be seen in Figure 1-5. As a larger number of heavier feeder cattle have been placed in feed yards, the target fed weight of the animals has increased. Also, continued improvements in cattle genetics have resulted in the placement of cattle that can more efficiently convert feed into additional pounds of gain. Another factor to consider is the change in pricing of fed steers and heifers. The beef industry has shifted to more frequent use of grid pricing that pays a premium for cattle that grade better in quality and lower in yield grade. Tight supply of cattle and value of gain has lead feeders to finish animals at heavier weights, but they are also incentivized by packers to produce high quality and consistent cattle to be harvested and processed in plants.

Figure 1-5 Federally Inspected Slaughter Versus Dressed Weights, 1976-2016



In conjunction with the decrease in cattle availability in the United States, beef production and processing has become more efficient. As a result, total beef production has not decreased as drastically. Figure 1-6 shows federally inspected beef which, despite decreases in total supply of cattle, has remained relatively flat over the past 30 years.

Figure 1-6 Federally Inspected Beef Production (Mil. Pounds), 1976-2016



Source: Livestock Marketing Information Center

Overall, there have been many changes to the beef industry over time. Consolidation of firms, changes in demand, tight supplies, changes in pricing structures, placement weights, and efficiency improvements have all changed the structure of the industry. The impact of distinct industry changes have been noticeable increases in unpredictability and volatility. For feeders and packers, the ability to forecast basis has become a vitally important tool to accurately assess price risk and develop price expectations.

Organization of Thesis:

The thesis is comprised of six chapters. Chapter 2 will review articles within the literature that have focused on the uses of fed cattle basis and the different approaches for forecasting fed cattle basis. Chapter 3 will provide descriptions of the data used for these analyses and provide summary statistics of the raw data. Chapter 4 will discuss model specification as well as methods and procedures used for this research. Chapter 5 will discuss the empirical results of this study's models. Chapter 6 will discuss final conclusions and the potential improvements that could be made to this area in future research.

Chapter 2 - Review of Literature

Fed cattle basis is vital for cattle feeders and packers when making marketing or procurement decisions, respectively. Basis is the difference between local cash price and the futures market price. In order for agribusinesses to lock in margins, they should utilize risk management tools that are easily available such as hedging with futures contracts or forward contracting cattle. For many years, agricultural producers' expectations of fed cattle basis were within a consistent range and somewhat cyclical in nature, which meant their basis prediction errors were relatively close to actual basis. As displayed in chapter one, fed cattle basis experienced a change in recent years in which the range of basis widened dramatically and the volatility of fed cattle basis increased drastically as well. With a widened range and increased volatility, the ability to predict basis has become much more difficult than in the past which has motivated these research efforts.

2.1 Basis Uses

In today's markets, one of the highest risks producers face is basis risk. Due to this fact, cattle feeders and packing businesses create basis predictions when trying to make price expectations for the future. According to Tomek (1997), cash prices and futures prices should converge on the expiration date of the futures contract at the delivery point specified in the contract. If convergence does not occur as expected, then producers that apply risk management strategies will not reap the full expected benefits of protecting their agricultural commodity prices. Having a firm understanding of basis is imperative for producers making decisions across differing physical locations. Without understanding the difference between local cash and futures prices, producers' price expectations will be skewed from realized prices.

Kastens, Jones, and Schroeder (1998) demonstrated how price forecasts can be built by using futures prices to predict cash prices for several commodity classes using data beginning in 1982 through 1996. The ability to forecast cash price is incredibly useful, but one cannot solely focus on estimating cash price. This study does an excellent job demonstrating that the ability to accurately forecast basis is imperative for an analyst who is estimating cash prices in future months.

The authors developed models that ranged in level of complexity. The simplest of the models was a Naïve model using last year's observation as a prediction for this year's observation and also tested a Naïve model that averaged the past five year's observations. Next, they tested a model which included futures price plus a 5-year historical average basis as their prediction for cash price. Lastly, they developed econometric models that estimated cash price as a function of deferred futures prices.

When comparing mean absolute percentage errors (MAPE) between the different models, FUTLBAS (futures plus level basis) and FUTLPBAS (futures plus level and proportional basis) provided the greatest forecast accuracy across the examined forecast methods. On the contrary, NAÏVE5 (five-year average) was the least accurate forecast method in terms of MAPE. In regards to the six classes of cattle examined, NAÏVE5 was the least accurate in terms of MAPE for all six classes and had the highest maxMAPE for four of the six classes. MODFUT (econometric method with separate regressions for each parameter) was the least accurate in terms of maxMAPE when the MODFUT output is averaged across all commodities. This means that the econometric model can provide some benefits to MAPE when compared to the naïve models, but the model does produce forecasts that can be extremely different from the actual realized prices. It should be noted that across all commodities slaughter steer forecasts were the most accurate when MAPE and maxMAPE are averaged across all 5 forecast models. Another factor to recognize is that the explanatory power of these models is relatively low. The R-squared across models ranged from a low of 0.04 to a high of 0.19. Slaughter steers and 7-8 cwt feeder steers performed well compared to several of the commodity classes having an R-squared of 0.11 and 0.19, respectively. The authors also tested how forecast horizon effected prediction power and determined that as forecast horizon increases into the future, prediction accuracy decreases.

Riley (2013) conducted one the most recent studies to understand Extension's role to provide commodity market forecasts and how they've changed over time in light of recent increases in market volatility. The author focused his analysis on feeder cattle, live cattle, and corn markets for years ranging 1990 through 2012. The data are analyzed for differing lengths of time that were chosen by the author. After visually analyzing the data, the author chose where the forecast errors appeared to increase. For the cattle and corn contracts, the breaks were placed in 2003 and 2005, respectively. As expected, mean absolute error (MAE) of the forecasts for cattle and corn futures is smaller from 1990-2002 and 1990-2005, respectively. The basis forecasts for Oklahoma City feeder steers, fed steers, and Omaha corn, in general, had larger MAE and root mean squared error (RMSE) in recent years than in previous years. In addition, there appears to be a trend of current basis levels being more frequently statistically different from previous years.

Overall, cattle and corn futures prices are less reliable as price forecasts than in previous years primarily due to increased market volatility. The author notes that the change in market conditions should warrant economists and Extension specialists to adjust their approach towards the promotion of more practical risk management strategies rather than attempting to provide the most accurate price predictions. With increased price volatility comes increased basis volatility.

Previous research has clearly shown the importance of basis on price projections and how basis is widely used throughout the industry. As the industry faces a more volatile commodity market environment, better understanding what determines basis and how to best estimate basis is imperative for all industry participants.

2.2 Basis Forecasting Techniques

Methods for forecasting basis can be as simple or as complex as the analyst chooses. A method that has been utilized for decades by producers in every segment of the cattle business, is the historical averaging method. This particular method has been heavily researched and can be found throughout the literature. Historical averaging has received such interest and focus over the years primarily due to the easy application by the user. Producers do not consistently have the time to focus on day-to-day updates of econometric models; therefore, by using a historical average basis method, producers can easily form basis prediction estimates and focus their time on improving or maintaining high quality management practices. Historical averages are created by simply taking the basis for a specific month or week and calculating the average of the corresponding month or week over a specified number of years. This average basis value provides the user with a forecast for what they can expect basis to be for the month or week in question.

Tonsor, Dhuyvetter, and Mintert (2004) conducted an in-depth research study to better understand the methods of historical averaging basis. Firstly, they tested whether a time-to-expiration technique would improve their basis predictions when using the historical averaging method. Typically, a calendar date approach is used, but complications arise when the nearby futures contract for a certain week maybe using a different contract month than the other years included in the average. Accounting for the weeks-to-expiration helps to eliminate this problem and ensure that the same futures contract is always used when calculating basis. The authors determined that using a time-to-expiration method provided no statistically significant difference to basis forecasting when compared to the calendar date method.

Secondly, they identified the optimal number of years to include in mutli-year averages to forecast basis for fed cattle and feeder cattle. They used data ranging from 1979 to 2002 for feeder cattle and data from 1981 to 2002 for fed cattle. They conducted paired t-tests to determine the optimal number of years to include in basis predictions. For both feeder cattle and fed cattle, they varied the time periods of data that they tested to account for contract specification changes in the feeder cattle futures contract as well as testing only the most recent 5 years of data. The study determined that analysts should consider using 3-year historical averages when forecasting basis for feeder cattle and 4-year historical averages when forecasting basis for fed cattle.

Lastly, they tested whether adjusting historical averages to include current market information would improve the accuracy of the basis predictions. This question arose under the premise that if the current basis level has deviated from the historical average, then the accuracy of the prediction will be negatively affected. The authors then selected the forecast models in which current information can improve the accuracy as well as the optimal amount of information to include in fed cattle and feeder cattle basis forecasts. Tonsor, Dhuyvetter, and Mintert (2004) determined that including current information can improve the accuracy of forecasts for 4 weeks and 8 weeks in the future for live cattle. The results were similar for feeder cattle with accuracy improvements statistically significant for 4 weeks into the future, but only marginally significant for forecasts made 8 and 12 weeks into the future. Overall, the authors demonstrated that current market events can be shown, to a level of statistical significance, to improve the accuracy of basis forecasts for fed cattle.

Unlike the literature for historical averaging methods, the literature for the use of econometric models to forecast basis is quite thin. This is mostly a result of the understanding by producers that the time taken to build a complex econometric model to forecast basis makes them only marginally “better off” than if they had simply used a simpler method such as a historical average basis. Nevertheless, analysts enjoy testing different models to determine if they can provide more accurate predictions and outperform a historical average.

One of the initial studies researching fed cattle basis forecasting was conducted by Leuthold (1979). The author estimated the dependent variable, basis, as a function of number of beef cattle slaughtered, price of corn, cash price of choice fed steers, cash price of choice feeder steers, cattle on feed numbers for the 500-700, 700-900, and 900-1,100 pound weight categories, and quarterly dummy variables. Leuthold (1979) varied his forecast horizons to determine which supply factors impacted basis forecasts and whether they varied depending on the time left until expiration.

The price of corn, fed steer cash price, and feeder steer cash price were all statistically significant. Corn and feeder steers had positive coefficients. This coincides with economic intuition that as the price of inputs increases, this will discourage feedlot placements which will increase the futures price thus increasing basis. Cash price has a negative sign on the coefficient because increased cash prices decreases basis when calculating as futures price minus cash price as calculated in this study. Cattle on feed had varied results with some coefficients significant and others not significant; however, the signs were consistently negative. In regards to the 500-700 and the 700-900 cattle on feed classes, the forecasts several months out were negative and statistically significant. As more animals are placed on feed at lighter weights, the futures price will decrease due to the expected increase in future slaughter supply thus decreasing basis. This study was a pioneering effort for its time due to the still very young live cattle futures contract, but allowed plenty of room for further research in the future.

Naik and Leuthold (1988) approached basis differently than in past research efforts. The authors analyzed the relationship between cash price and futures price, i.e. basis, for both fed cattle and live hogs. They combined a risk assessment to their study and in doing so tested if there was a risk component and a speculative component within maturity basis. Maturity basis refers to the basis within the contract expiration month which, due to convergence, should be smaller in absolute terms than prior months. For one of their models, they estimated fed cattle maturity basis as a function of supply and demand shifters. The supply shifters included lagged feed price, basis, market ready cattle, pork in cold storage, cash price, and futures price. The demand shifters included per capita income, price of hogs (in the cattle estimation), and price of cattle (in the hog equation).

Based on their assessment of the correlation coefficients, the authors determined that there is both a maturity basis risk (premium) component and a speculative component within cattle and hog markets. In addition, the author's found seasonality was present in live hog basis, but did not find seasonality in fed cattle basis. In regards to the author's estimation of maturity basis, they were able to explain 47% and 57% of the variation in the expected maturity basis one month before maturity for live cattle and live hogs, respectively. As a side bar, the author makes known the presence of multicollinearity problems within the one month lagged model meaning that the model as a whole can still provide accurate predictions, but the beta coefficients cannot individually be deciphered. When the estimation time frame was increased to two months and three months into the future, the explained variation was considerably reduced. The authors attribute the higher predictability of live hog basis to the presence of seasonality within hog basis. The authors found, at a statistically significant level, that cash price influences deferred futures prices for both cattle and hogs. In the two month forecast, cash price for cattle is highly significant and negative suggesting that cash price inversely affects the futures price two months into the future. Alternatively, cash price for hogs is statistically significant with a positive coefficient suggesting that cash price and the two months deferred futures price are directly related. In the four month forecast, cash price for cattle is significant and negatively impacting the four months deferred futures price. This model had an R-squared value of .98 meaning that 98% of the variation in futures price was explained by the independent variables. Alternatively, the cash price for hogs did not impact the four months deferred futures price. The authors attribute most of this difference to the flexibility in time that cattle producers have for marketing their cattle that hog producers do not possess.

Bacon et al. (1993) analyzed whether market ready inventories, known as showlists, is a better determinant of fed price than weekly cattle slaughter. The authors are testing whether packers and feedlots more responsive to current slaughter levels or market ready cattle inventories when they are making business decisions pivoted on short-run supply.

This study utilized data from the Packer-Feeder simulation at Oklahoma State University, publicly accessible USDA data, and private data collected by Professional Cattle Consultant (PCC). The Packer-Feeder game was a semester long simulation where the participants learn, in an experiential setting, how fed cattle are marketed and what information is most relevant to fed cattle transactions from the point of view of a packing plant or a feedlot manager. The simulation was developed to provide insight on the performance and transactions of the fed cattle market.

The USDA data included the seven state cattle on feed report, slaughter numbers from the Livestock, Meat, and Wool Market News, and cash prices from the Omaha market for 1100-1300 pound slaughter steers. PCC aggregated closeout data that accounted for approximately 25% of the cattle on feed within the seven state cattle on feed report.

The experiential data and the private data resulted in a negative correlation between showlist and price that was stronger than the negative correlation between slaughter numbers and price. The signs were the same for the public data, but the slaughter levels did have a higher correlation than showlists. Overall, the hypothesis of a stronger correlation between showlist and price than slaughter levels and price seemed to be upheld by this study. The other objective of this study was to test ability to predict cash price. As a whole, the results of the econometric models were inconclusive. After using the first differences, the coefficients for both showlist and slaughter were either not significant or only marginally significant; however, the showlist coefficient did possess the correct sign and comparatively was more significant than the coefficients on slaughter. Although this a dated study, this is pertinent to these research efforts as a previous example of how market ready inventories could potentially matter when forecasting basis.

One of the most recent studies forecasting fed cattle basis was conducted by Parcell, Schroeder, and Dhuyvetter (2000) as they worked to quantify factors explaining variability in monthly fed cattle basis to better understand the factors impacting basis. They determined the optimal type and number of variables to include while building their econometric models to forecast fed cattle basis. This work estimated fed cattle basis as a function of lagged fed cattle basis, animal weight, forward contracted cattle as a percentage of total marketed cattle, corn futures prices, choice-select spread, the ratio of cattle on feed in each location to the total seven-state cattle on feed report, cold storage stocks, a binary variable for a change made to the specifications of the live cattle futures contract in 1995, and monthly binary variables for seasonality. This study used data that ranged from January 1990 to July 1997 and was comprised of publicly accessible USDA price and supply data and CME futures price data.

For the life of the data, the maximum range of basis out of the three states was $8.20/cwt for Colorado which, at the time, was considered a large range when referring to fed cattle basis. A very beneficial aspect to this study was the regional component that compared the states of Colorado, Kansas, and Texas. Since basis levels depend highly on the cash location in question and the relative delivery locations defined in the contract specifications, observing how basis is altered due to geographical changes is very important depending on the location of the agribusiness. The work found lagged live cattle basis to be statistically significant in Colorado, corn futures to be statistically significant in Colorado and Texas, Choice-Select spread to be statistically significant in all three states, the cattle-on-feed-ratio to be statistically significant in Kansas, and several of the seasonal dummy variable were also found to be statistically significant. The analysis conducted by Parcell, Schroeder, Dhuyvetter (2000) was the foundation for these research efforts to determine how basis predictability has changed over the past 15 years and whether new methods must be applied to address the volatility currently impacting the cattle industry.

2.3 Structural Change Testing

The identification of structural changes to improve forecasting accuracy has not received much attention in the past within the livestock markets literature, but recently is being recognized for the potential application of this method in commodity markets. The most commonly used structural change methods are the Chow (1960) and the Bai-Perron (2003) tests.

These tests differ in statistical approach, but both test attempt to identify changes in the determinants of an independent variable.

The Chow (1960) test examines the change in market regimes, but the analyst must select the exact data point for when the structural break occurs. After the break date is chosen, the test analyzes the data as two separate market regimes. One limitation of this approach is that the break date is an exogenous variable that is chosen subjectively by the analyst. Additionally, this test only allows for one structural break and does not test the null hypothesis of multiple structural breaks within the parameters.

The Bai-Perron (2003) test improves upon the shortcomings of the Chow test. The Bai-Perron (BP) test attempts to identify the presence of a single structural break, but will continue, in a sequential manner, to test for multiple structural breaks. The benefits of the BP test are that the break dates are endogenously identified, rather than subjectively, and the detection of multiple breaks is considered. Recently, Twine et al. (2016) conducted a study using the BP test to determine if Country of Origin Labeling (COOL) regulations had an impact on the U.S. imports of Canadian beef, feeder cattle, and fed cattle. They highlight the importance of choosing M, the maximum number of breaks tested, and v, the trimming factor. According to Bai-Perron (2003), setting the upper bound $M = 5$ is sufficient for empirical analyses. The trimming factor (v) specifies the percentage of the data that is required in each market regime. Twine et al. (2016) tested different combinations, but ultimately decided to use a trimming factor (v) of 0.15. This requires that each market regime must contain at least 15% of the observations.

Chapter 3 - Data

This research utilized both weekly and monthly price and production data. All data were accessed through the Livestock Marketing Information Center (LMIC) and is originally sourced from United States Department of Agriculture (USDA) data files or Chicago Mercantile Exchange (CME) settlement prices. The data used for in-sample econometric models and Bai-Perron structural change testing spanned from January 2003 through September 2016. The data used for out-of-sample econometric estimations spanned from January 2004 to September 2016. For the out-of-sample models, variables, other than lagged basis and monthly dummy variables, were estimated. We used lagged variables of 1-period, 12-periods, or a composite value averaging the 1-period and 12-period lags to derive estimated values consistent with a true out-of-sample exercise. As a result of the lagged estimates, these data needed to begin a minimum of 12 periods after the beginning of the data for out-of-sample comparisons to be appropriate. Table 3.1 provides a list of variables included in these analyses, a brief description of the variables, and the frequency of the raw data used.

Table 3-1 Listing and Brief Description of Variables

Variable	Units	Variable Description	Data Frequency
CASH	($/cwt)	Weekly National Average Fed Steer Cash Price	Averaged Weekly Data to Generate Monthly Average
FUTURES	($/cwt)	Weekly Live Cattle Futures Average Settlement Price	Averaged Weekly Data to Generate Monthly Average
BASIS	($/cwt)	Cash Price minus Futures Price	Averaged Weekly Data to Generate Monthly Average
WTS	(lbs)	Weekly Average Fed Steer Live Weights	Averaged Weekly Data to Generate Monthly Average
CORNFUTS	($/bu)	Weekly Corn Futures Average Settlement Price	Monthly Data
CSSPREAD	($/cwt)	Difference Between Weekly Average Choice and Select Beef Price	Averaged Weekly Data to Generate Monthly Average
MKTREADY	('000 head)	Monthly National Fed Cattle Ready for Market	Monthly Data
BFCDSTRG	(mil lbs)	Monthly National Beef Cold Storage Stocks	Monthly Data
PKCDSTRG	(mil lbs)	Monthly National Beef Pork Storage Stocks	Monthly Data
CKCDSTRG	(mil lbs)	Monthly National Chicken Cold Storage Stocks	Monthly Data
BFRET	($/cwt)	Monthly National Beef Retail Price	Monthly Data
PKRET	($/cwt)	Monthly National Pork Retail Price	Monthly Data

Table 3-1 Listing and Brief Description of Variables, Continued…

Variable	Units	Variable Description	Data Frequency
CKRET	($/cwt)	Monthly National Chicken Retail Price	Monthly Data
MONTH		Monthly Dummy Variable	

Variables:

<u>Cash Prices</u>: The cash price series is a weekly weighted average price, measured in dollars per hundred weight ($/cwt), for all fed steers marketed nationally. Simple averages across all weeks in a month were calculated to provide a monthly average price series.

<u>Futures</u>: Futures prices were calculated as simple averages of weekly live cattle futures settlement prices, measured in $/cwt. Simple averages across all weeks in a month were calculated to provide a monthly average price series.

<u>Basis</u>: Basis is defined as cash price minus live cattle futures price.

<u>Lagged Basis</u>: Lagged basis is a one-period lag of the dependent variable, basis. This variable captures price inertia of basis across months meaning it accounts for persistence and direction of how basis has moved. An additional benefit of using lagged basis is that this can help the researcher account for unobservable changes in basis. If there is a variable that is causing basis to change, but the variable is unknown to the analyst, then using lagged basis allows the analyst to account for this unobservable change without knowing the actual variable. Put more simply, if basis increased by $5/cwt last month, the analyst does not have to know specifically why basis changed, but simply accept the change as reality and account for the $5/cwt increase using lagged basis.

Weights: Weights were the weekly average live weight, in pounds, of fed steers that were marketed within that week. Simple averages across all weeks in a month were calculated to provide a monthly average price series.

Corn Futures: The data used were the monthly average corn futures settlement prices which were obtained through LMIC.

Choice-Select Spread: The data used for this series were the weekly choice and select boxed beef price series available through LMIC. The choice-select spread was calculated by taking the difference between the weekly choice and select boxed beef price.

Market Ready Cattle: The USDA releases monthly reports summarizing the number of cattle on feed, marketings, placements and weights, and other disappearance for the nation as well as individually by state. By utilizing thes data compiled by LMIC, a market ready value was generated. The weight classes for the cattle on feed report are: under 600 pounds, 600-699 pound, 700-799 pounds, and greater than 800 pounds. Assuming an average daily gain (ADG) of 3.4 pounds and a marketing weight of 1,300 pounds, the marketing window of the different weight classes can be estimated providing a market ready value for the country. This variable is often referred to as "show lists" which can be found described more in depth by Bacon et al. (1993).

Cold Storage: The USDA releases monthly reports estimating, in thousands of pounds, the red meat and poultry supplies in cold storage for the end of each month. The data were retrieved from the LMIC cold storage file. The Red Meat in Cold Storage report was used for the beef cold storage and the pork cold storage variables and the Poultry in Cold Storage report was used for the chicken cold storage variable. Aligned with the research conducted by Parcell, Schroeder, Dhuyvetter (2000), the cold storage value was divided by 1,000 to report the value in millions of pounds. This was done primarily for scaling benefits so units are similar to other variables used in the analyses.

Retail Price: The USDA Economic Research Service (ERS) releases a monthly report with the retail prices for beef, pork, chicken, and other agricultural products. These data are compiled by LMIC into their Retail Meat file. Beef and pork retail price series are used for the BFRET and PKRET variables and the broiler composite retail price series are used for the CKRET variable.

Monthly Seasonals: Using January as the default month, monthly dummy variables were created to capture seasonal patterns. This also aligns with the research conducted by Parcell, Schroeder, and Dhuyvetter (2000).

Lagged Variables: In addition to lagged basis, several lagged variables were created including: weights, market ready cattle, choice-select spread, all cold storage series, and all retail price series. Theses variables were used to generate a 1 period, a 12 period, and a composite lag series to use as estimates within the out-of-sample econometric models in these analyses.

Summary Statistics:

The summary statistics for the monthly econometric models of national fed cattle basis are provided in Table 3.2. The first observation occurs on January 2003 and runs through September 2016. The table provides the units, mean, standard deviation, minimum, and maximum values for the variables used for these analyses.

Table 3-2 Summary Statistics of Monthly Data Used to Estimate National Fed Cattle Basis, January 2003 through September 2016

Variable	Unit	Average	S.D.	Minimum	Maximum
Cash Price	($/cwt)	106.48	24.77	74.91	169.23
Live Cattle Futures Price	($/cwt)	106.11	24.14	72.31	168.87
Basis	($/cwt)	0.37	2.47	-5.50	8.05
Weights	(lbs)	1335.35	61.13	1211.18	1478.04
Corn Futures	($/bu)	4.13	1.64	1.93	8.04
Choice-Select Spread	($/cwt)	8.91	5.05	0.81	26.68
Market Ready Cattle	('000 head)	108	119	0	444
Beef Cold Storage	(mil lbs)	439.64	41.76	318.19	520.72
Pork Cold Storage	(mil lbs)	529.18	76.09	366.81	701.08
Chicken Cold Storage	(mil lbs)	703.94	76.79	534.90	925.76
Beef Retail Price	($/cwt)	471.84	81.89	339.70	641.19
Pork Retail Price	($/cwt)	321.26	45.25	258.17	421.55
Chicken Retail Price	($/cwt)	178.65	13.20	149.59	203.10

Necessary Equations:

Basis, as defined in the variable definitions, is the difference between cash price and the live cattle futures price. Error, shown below, is the difference between predicted basis and the actual basis value. All the diagnostic measures use the error terms in different manners to produce comparison between models. The following equations are necessary for understanding the comparisons made across in-sample and out-of-sample estimations.

$$\boldsymbol{Basis_t = Cash\ Price_t - \ Live\ Cattle\ Futures_t} \tag{1}$$

$$\boldsymbol{Error_t = \ Basis_t - \ \widehat{Basis}_t} \tag{2}$$

Where $Basis_t$ is the actual basis value for time t and $\widehat{Basis}_t$ is the predicted basis value for time t.

$$\boldsymbol{Mean\ Absolute\ Error\ (MAE)\ =\ \frac{1}{n}\sum_{t=1}^{n} abs(error_t)} \tag{3}$$

$$\boldsymbol{Mean\ Absolute\ Percent\ Error\ (MAPE) = \frac{1}{n}\sum_{t=1}^{n} abs\left(\frac{error_t}{Basis_t}\right)} \tag{4}$$

$$\boldsymbol{Mean\ Percent\ Error\ (MPE) = \frac{1}{n}\sum_{t=1}^{n}\left(\frac{error_t}{Basis_t}\right)} \tag{5}$$

$$\boldsymbol{Mean\ Squared\ Error\ (MSE) = \frac{1}{n}\sum_{t=1}^{n} error_t^2} \tag{6}$$

$$\boldsymbol{Root\ Mean\ Squared\ Error\ (RMSE)\ = \sqrt{\frac{1}{n}\sum_{t=1}^{n} error_t^2}} \tag{7}$$

$$\boldsymbol{Sum\ of\ Squared\ Errors\ (SSE) = \sum_{t=1}^{n} error_t^2} \tag{8}$$

Chapter 4 - Methodology

The analysis conducted for this study was performed using SAS (9.4) and Microsoft Office Excel. All in-sample and out-of-sample OLS models and Bai-Perron tests were estimated using SAS (9.4) and the results were summarized and tabulated using Microsoft Office Excel. All graphs were created using Microsoft Office Excel.

Prior to the estimation of any econometric models, the basis series was tested for the presence of a unit root using the Augmented Dickey-Fuller (ADF) test. More specifically, the ADF test examines whether or not a data series is stationary. This test helps determine if there is a trend present in the data series. The null hypothesis of the Augmented Dickey-Fuller test is that a unit root is present in the data, so a statistically significant critical value must be generated in order to reject the null hypothesis of a unit root in the series. Examples providing more depth for interpreting the Augmented Dickey-Fuller test output were provided through SAS (9.4) Support: http://support.sas.com/documentation/cdl/en/etsug/60372/HTML/default/viewer.htm#etsug_arima_sect059.htm

The Augmented Dickey-Fuller test returned a p-value that was statistically significant at less than the 0.1% level; therefore, for the national fed cattle basis series, the null hypothesis of the presence of a unit root was rejected. Additionally, by visually analyzing basis plotted over time, the series appears to possess no trends and oscillate close to zero. Without the presence of a unit root in the basis series, there was no need to use first differencing methods to adjust for autocorrelation and the determinants of basis could be tested without the fear of biased estimates.

4.1 In-Sample Estimations

As seen within the literature, estimating fed cattle basis is no easy task. As previously stated, these research efforts were guided by Parcell, Schroeder, and Dhuyvetter (2000) with several adjustments in an effort to update the methods and improve the accuracy of the models. Aligned with their research, several market fundamental variables were tested as determinants of fed cattle basis. While Parcell, Schroeder, and Dhuyvetter (2000) primarily focused on fundamentals regarding overall cattle and beef supply, these research efforts delved deeper into variables that have a larger impact from a demand perspective.

The method for testing the determinants of basis within this research was to break the variables into 4 groups: lagged basis, market fundamentals excluding retail prices, market fundamentals including retail prices, and seasonality. Model 1 through Model 10 are comprised of different variations of these 4 groups. The last model of the base regressions results in Model 11 which can be seen below in Equation 9 and is comprised of every variable tested within this study. As shown in Table 4-1, Models 1 through 10 all use a subset of the variables included in Model 11.

$$\begin{aligned} \boldsymbol{Basis_t} &= \boldsymbol{Intercept + \beta_1 Basis_{t-1} + \beta_2 Weights_t + \beta_3 Corn\ Futures_t\ +} \\ &\boldsymbol{\beta_4 Choice - Select\ Spread_t + \beta_5 Market\ Ready\ Cattle_t + \beta_6 Beef\ Cold\ Storage_t +} \\ &\boldsymbol{\beta_7 Pork\ Cold\ Storage_t + \beta_8 Chicken\ Cold\ Storage_t + \beta_9 Beef\ Retail\ Price_t +} \\ &\boldsymbol{\beta_{10} Pork\ Retail\ Price_t + \beta_{11} Chicken\ Retail\ Price_t + \beta_{12-22} Month_t} \end{aligned} \tag{9}$$

Where "*t*" is time and basis in month "*t*" is defined as the national average cash price minus the average futures settlement price. The β coefficients in these estimations can be interpreted as \$/cwt changes in basis when the respective variable is increased or decreased by one unit. The rest of this section will discuss the expected signs on the coefficients associated with each variable.

Table 4-1 Model Design Summary

	Model												
Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
Lagged Fed Cattle Basis ($/cwt)	X				X	X	X			X	X	X	X
Weight (lbs)			X	X	X	X		X	X	X	X		X
Corn Futures Price ($/bu)			X	X	X	X		X	X	X	X	X	X
Choice-Select Spread ($/cwt)			X	X	X	X		X	X	X	X	X	X
Market Ready Cattle ('000 head)			X	X	X	X		X	X	X	X	X	X
Beef Cold Storage (mil. lbs)			X	X	X	X		X	X	X	X	X	
Pork Cold Storage (mil. lbs)			X	X	X	X		X	X	X	X		X
Chicken Cold Storage (mil. lbs)			X	X	X	X		X	X	X	X		
Beef Retail ($/cwt)				X		X			X		X	X	
Pork Retail ($/cwt)				X		X			X		X		X
Chicken Retail ($/cwt)				X		X			X		X		
Monthly Dummy Variables		X					X	X	X	X	X	X	X

A one-period lag of the dependent variable basis was included to capture the inertia in basis. As stated before, no autocorrelation needed to be adjusted for, so the inclusion of a lagged basis variable was to capture the consistency of the changes and direction of basis from the previous period, but also to capture unobservable factors that the current parameters do not capture. The sign for the coefficient on lagged basis is expected to be positive because basis is expected to move in the same direction as the previous period.

The coefficient on weights is expected to have a negative impact on basis. As the average weight of fed cattle increases, this means that a larger supply of beef will be entering the supply chain. An increase in beef supply depresses the price of beef and in turn depresses the price of fed cattle potentially causing a decrease in fed cattle basis.

The nearby corn futures price serves as a proxy for feeding cost of the feedlot and is expected to have a negative sign on the coefficient. As the price of feed inputs increase, feeders may find it more profitable to reduce the number of days cattle are held on feed and more cattle will be “brought to market”, so to speak. With an increased supply of cattle available for market, we would expect cash price to decrease. In addition, if more cattle are sold in the present cash market, then less cattle will be available to market in the future causing the futures price to increase. A decrease in cash price and an increase in the futures price could result in a negative impact on basis. On the contrary, when the price of feed inputs decrease, feeders may find it more profitable to hold cattle longer on feed if their marginal cost of gain is less than the value of an additional pound of gain.

Choice-select spread is expected to have a positive impact on basis. If the choice-select spread increases meaning that beef grading choice is becoming more valuable relative to beef grading select, then this would suggest an increase in the demand for high quality beef. If high quality beef experiences an increase in demand and therein becomes more valuable, then the derived demand for fed cattle would increase as well which would increase the cash value of the animal. If this demand increase is not accounted for in the futures contract pricing, then we would observe a strengthening in fed cattle basis.

The coefficient on market ready cattle is expected to be negative. An increase in the size of show lists translates directly to a larger supply of cattle ready for slaughter. A more robust availability of market ready inventories means that packers can more easily procure cattle to maintain capacity within their slaughter facilities. It is imperative for packers to maintain a consistent flow of cattle through their facilities to avoid operating below plant capacity, so an increase in supply makes the procurement of cattle to fill empty hooks a much more manageable situation. Another impact from the increase in supply is that packers are not pressed to raise their bids due to the abundance of available cattle, potentially resulting in less leverage from the feeders' perspective. The feeder then must decide whether to liquidate in the short-run or hold on to the cattle for a potentially improved marketing situation. Overall, we would expect an increased supply of market ready cattle to weaken basis.

The coefficient on beef cold storage is expected to have a negative sign. As the inventories of boxed beef in cold storage increases, we would expect that this would have a negative impact on wholesale beef prices as the packers are pressed to market a large supply of a non-storable commodity. An increased supply in wholesale beef should depress retail beef prices. Packers, the primary source of wholesale beef, will not be incentivized to run any more cattle through their plants than necessary to meet operational capacity especially if they already have good stocks of beef in the freezer. Cold storage allows a longer marketing window than fresh beef; however, packers will still need to move product because they must still run their plants at capacity. As a result of decreased beef prices, packers will be less aggressive when negotiating with feeders which should result in a negative impact on basis.

The coefficient on pork cold storage is expected to be positive, but the sign is contingent upon a few factors. Pork demand has been increasing over time. An increased level of pork cold storage could be a result of the long term growth in demand. Typically, when pork demand increases or vice-versa with beef demand, it is a sign of increased meat demand as whole; therefore, as pork demand increases, beef could also experience an increase in demand. Conversely, if pork cold storage increases, then we would expect the price of pork to decrease as well. If the increase in demand for all meats positively affects beef greater than the decrease in the decrease in the price of pork, then the increase in the value of beef could have a positive impact on fed cattle basis. The same scenario could additionally be argued for chicken cold storage.

We would expect the sign of the coefficient of beef retail prices to be positive. As the value of retail beef increase, this is a positive sign of beef demand. As beef becomes more valuable, then the value of the animal, fed cattle, also becomes more valuable. If the increase in cash price is greater than the increase in the live cattle futures, then this could potentially strengthen fed cattle basis.

The signs on pork retail prices and chicken retail prices are expected to be positive. An increase in the price of pork should lead to a decrease in the quantity demanded of pork. Additionally, as pork price increases relative to the price of beef, then we would expect a positive impact on beef demand. In turn, this should have a positive impact on the value of the animal and have a positive impact on fed cattle basis. The same intuition holds for chicken retail prices.

Lastly, monthly dummy variables were included to capture seasonal patterns that exist in fed cattle basis.

Some of the variables included in these econometric models were highly correlated with one another. With high levels of correlation, the interpretation of the β coefficients can become difficult as the signs on the coefficients can flip. To account for the issues correlation among regressors can pose on interpreting the results, we developed a preferred model, Model 12, that does not include variables with levels of correlation greater than 0.50.

In situations where correlation is ignored because the analyst is only concerned with the accuracy of the forecast predictions, we developed Model 13. This preferred model ignores the presence of high levels of correlation and the impact the correlation can have on the signs associated with β coefficients. This model is solely focused on producing the most accurate predictions in terms of minimized errors.

4.2 Identification and Estimation of Structural Breaks

For these purposes, the identification of structural breaks was performed to better understand the number of structural breaks that occur in the determinants of basis as well as when in time the breaks occur. The advantage of identifying structural breaks is the potential for improving forecast performance by removing determinants that do no impact the dependent variable or by removing time periods of data that may be harboring forecast performance. There are several ways to identify structural breaks in markets. One approach is to use the Chow (1960) test and a second approach is the Bai-Perron (2003) test.

The Chow test is used to identify a single market structural break, but this test does not exist without some distinct limitations which can be found throughout the literature. Hansen (2001) explains the limitations of the Chow test in much greater detail, but we will focus on two primary limitations: the subjective nature of choosing the break date and the allowance of only two market regimes. When utilizing the Chow test, the break date is an exogenous variable that is chosen at the discretion of the analyst. This means that the break date must be chosen subjectively or there must be a distinct attribute within the data that provides strong evidence of a market structural break. As a result, problems can easily arise if the exact date of a structural break cannot be identified within the data. Additionally, the Chow test can only be utilized in testing for a single break separating the data into two market regimes. This limitation eliminates the researcher's ability to test whether the market has experienced multiple market breaks and should truly be broken into several market regimes. Due to the fact that there was no clear and precise date that could be identified as a market structural break and that there was no evidence to support that there was only a single structural break within fed cattle basis, the Chow test was not utilized for these research efforts.

Due to the inability to subjectively select a single structural break within fed cattle basis, the Bai-Perron (BP) test was the preferred method utilized in these analyses. In a sequential manner, the BP test attempts to identify a single structural break and if found, proceeds to test for the potential for multiple structural breaks. If the BP test rejects the null hypothesis that no structural break is present, then the test favors the alternative hypothesis of a single structural break. The BP test proceeds to test for structural breaks within the two subsections, data prior to the break and data post break. The BP test continues to identify structural breaks until the null hypothesis fails to reject the presence of no additional structural breaks.

Within the specifications of the BP test, the researcher determines the maximum number of breaks (M) to allow within the data. For these research efforts, the maximum number of breaks that were tested for was M = 5. As outlined in Twine, et al. (2016), a maximum break value of M = 5 should be sufficient when used in empirical studies. Additionally, the researcher must also define the minimum percentage of the data series necessary to constitute a market regime. This is primarily dependent on the size and properties of the data series being examined. The inclusion of this "trimming factor" is to ensure that the BP test identifies true market regimes rather than temporary market shocks. The requirement of a minimum number of observations necessary to comprise a market regime helps support the validity of each segment of the BP test that is identified. After testing various combinations of trimming factor (v) and M, Twine et al (2016) invoked a trimming factor (v) of 0.15 requiring each regime length to be comprised of at least 15% of the data series. In addition, Bai-Perron (2003) caution against using small values for the trimming factor specification out of fear of distorting the BP test. For these purposes, the trimming factor (v) was estimated using both $v = 0.15$ and $v = 0.20$. With very little differentiation between the two trimming factors in our results, the tests were estimated using the less restrictive $v = 0.15$.

While interpreting the results of the BP tests, the recommended strategy outlined by Bai-Perron (2003) was followed. The first step to interpreting the BP test was to first analyze the results of the UD max and WD max tests which simply test for the presence of at least one structural break within the data. The UD max and WD max test the null hypothesis of no break being present within the data series and an alternative hypothesis of an unknown number of breaks with a maximum being specified by the value for M. If we fail to reject the null hypothesis of no breaks using the UD Max and WD Max tests, then we can conclude that there is no structural break present in the data series. If we reject the null hypothesis of the UD Max and WD Max tests, then we can conclude that there is at least one structural break present in the series.

After rejecting the UD Max and WD Max tests, we then look to the supF(l + 1|l) test. Using a sequential method, the supF(l + 1|l) test determines the number of breaks. The number of breaks being tested is represented by l which ranges from l=0 up to the maximum l=M. The first sequence, l=0, tests the null hypothesis of no breaks and the alternative hypothesis of one break, l + 1. If the test returns a statistically significant critical value, then we reject the null hypothesis of no breaks in favor of the alternative hypothesis of one break. This sequence continues up to l=M number of breaks. When the test first returns an insignificant critical value, then we can fail to reject l breaks in favor of the alternative hypothesis l + 1 breaks. As an example, when l=2 and is the first value of l that fails to reject l + 1 breaks (3 breaks), then we conclude that the data series contains 2 structural breaks.

4.3 Out-of-Sample Estimations

Out-of-sample testing of the econometric models was the final method utilized for model comparisons. With out-of-sample testing, the accuracy of each model's forecasting abilities is truly tested because the estimates are produced without using the total range of data available. By limiting the data included in the estimations, the forecasting models are required to predict values outside of the data sample that were used to create the OLS estimations. More narrowly, the researcher knows the actual values of the dependent variable, but is testing how accurate the model performs when making forward looking predictions consistent with real-world, live situations faced by forecasters.

When compared to in-sample testing, out-of-sample testing is a much better test of true prediction accuracy because the forecasts are being tested for their ability to perform well with more unknown values in the equation. Models can often be a good fit when modeled using in-sample regressions, but when the analyst attempts to use the same model in an out-of-sample scenario, then the model's prediction errors can increase drastically; therefore, revealing the model's limitations of the model to predict the dependent variable when more unknown variables are introduced. The notable increase in the errors is largely due to the difficulty in predicting the values for all the regressors included in the model. As a result of this complication, simpler models can often outperform more complex models when compared in out-of-sample testing.

For the out-of-sample testing portion of these research efforts, Models 1, 2, 7, 11, 12, and 13 were tested. For each model, the data used for econometric estimations began in January 2004 through December 2011. After each model was estimated using this 7-year time frame, the estimations were used to predict the dependent variable, fed cattle basis, for the next year, January 2012 through December 2012. The values for predicted basis were stored and were then differenced from actual basis values to determine the prediction errors for 2012. After predicting the basis values for the next 12 months, the model is then re-estimated using data from January 2004 through January 2012 to forecast the following year, January 2013 through December 2013. This process is repeated to forecast basis for January 2013 through September 2016.

Models 1, 2, and 7 utilized information that is already known, lagged basis, or are monthly dummy variables. For this reason, out-of-sample application for these three models is very straight forward. In contrast, Models 11, 12, and 13 contain several variables that must be predicted in order to make true out-of-sample predictions. There are several methods for approaching this situation, but the use of lagged variables was utilized for these research efforts. All the variables, excluding lagged basis, seasonality, and corn futures price, in Models 11, 12, and 13 were predicted using either a 1-period or 12-period lag. The choice to use a 1-period or 12-period lag was subjective based on the assumption of more recent information having a larger impact on the variable or alternatively the variable possessing more of a seasonal pattern.

Choice-select spread, beef cold storage, pork cold storage, chicken cold storage, beef retail price, pork retail price, and chicken retail price were all forecasted using a 1-period lag. Weights and market ready cattle were forecasted using a 12-period lag. Corn futures price was forecasted using the nearby futures contract as the expected price. Models 11-B, 12-B, and 13-B include all the same variables as Models 11, 12, and 13, but use a composite value of the lagged variables when creating predictions. The composite value is a simple average of a 1-period and a 12-period lag and is primarily used to average the impacts that either lag length can have on forecasts. Corn futures price continued the use of the nearby futures contract as a price forecast for 11-B, 12-B, and 13-B.

The out-of-sample models were all compared based on the several diagnostic measures described in the end of Chapter 3. Several different diagnostic measures were used to record how prediction accuracy across models would be altered depending on which form of prediction errors were analyzed. The out-of-sample models were also compared to in-sample performance to examine whether forecast accuracy was altered by testing the out-of-sample methods. In addition to diagnostic measures, out-of-sample models were compared using paired t-tests to examine the if tests are statistically different from each other.

Additionally, out-of-sample models were compared to a 3-year and 4-year historical averaged basis model to see if accuracy was gained by implementing the use of econometric models. Historical averaged basis forecasts are easy to calculate, so for the producer who wants a very simple basis expectation, historical averages have consistently been the preferred choice. The comparison of econometric models to simpler forecasting methods, such as historical averages, is to determine if the increased complexity and effort to produce the econometric models actually provides the producer with additional insight when making basis expectations and in turn, marketing decisions. If there is no clear statistical difference between a complex and more time consuming econometric model, then the argument could be made the producer is better off using a simple basis forecast and spend more of their time focusing on efficient and low cost management practices.

Chapter 5 - Results

5.1 In-Sample Estimations

Table 5-1 contains the results for Models 1 – 4 which, as mentioned earlier, are a subset of all the variables tested here. Within a majority of the models, most of the variables that were included based on the research efforts of Parcell, Schroeder, and Dhuyvetter (2000), possessed the expected signs on the coefficients. The level of significance varied depending on how much the model deviated from their preferred model.

Model 1 tested basis as a function of lagged basis, a one period lag of the dependent variable. The coefficient for lagged basis was positive as expected and was statistically significant at the 99% confidence level. Lagged basis had a β coefficient of 0.5968 suggesting that for every $1/cwt increase in lagged basis, basis will increase $0.5968/cwt.

Model 2 tested basis as a function of seasonal dummy variables with January as the default month, meaning all the β coefficients for February through December are relative to January. In Model 2, May had a β coefficient value of 4.6324 suggesting that in the month of May, basis will be $4.6324/cwt stronger than in the month of January. The signs on the coefficients vary month to month, but only 4 individual months were statistically significant. March and April were statistically significant at a 95% confidence level while May and June were statistically significant at a 99% confidence level. The signs for these month coefficients were all positive suggesting that, when only accounting for seasonality, basis is stronger in these 4 months when compared to January. Goodness of fit was slightly decreased as adjusted R-squared was lower than when using only lagged basis. This means that less of the variation in

Table 5-1 Regression Results for In-Sample Econometric Models of National Fed Cattle Basis (Models 1 - 4) for January 2003 through September 2016

	Dependent Variable (basis, $/cwt)			
Variable	Model 1	Model 2	Model 3	Model 4
Intercept	0.1628	-0.4842	12.3914***	46.2429***
	(0.1564)	(0.5510)	(3.8087)	(4.6938)
Lagged Fed Cattle Basis	0.5968***			
	(0.0627)			
Weight			-0.0072**	-0.0446***
			(0.0034)	(0.0046)
Corn Futures Price			-0.2236*	-0.3188***
			(0.1159)	(0.1066)
Choice-Select Spread			0.1230***	0.0580**
			(0.0342)	(0.0275)
Market Ready Cattle			-0.0027*	-0.0030***
			(0.0014)	(0.0011)
Beef Cold Storage			-0.0201***	-0.0057
			(0.0047)	(0.0040)
Pork Cold Storage			0.0173***	0.0077***
			(0.0028)	(0.0026)
Chicken Cold Storage			-0.0037	-0.0037**
			(0.0024)	(0.0019)
Beef Retail				0.0202***
				(0.0067)
Pork Retail				0.0348***
				(0.0125)
Chicken Retail				-0.0275
				(0.0215)
Monthly Dummy (Default = January)				
February		-0.2816		
		(0.7792)		
March		1.8356**		
		(0.7792)		
April		1.9459**		
		(0.7792)		
May		4.6324***		
		(0.7792)		
June		2.0906***		
		(0.7792)		

Table 5-1 Regression Results for In-Sample Econometric Models of National Fed Cattle Basis (Models 1 - 4) for January 2003 through September 2016, Continued…

	Dependent Variable (basis, $/cwt)			
Variable	Model 1	Model 2	Model 3	Model 4
July		0.5198		
		(0.7792)		
August		0.3585		
		(0.7792)		
September		-0.5381		
		(0.7792)		
October		-0.3590		
		(0.7941)		
November		0.1202		
		(0.7941)		
December		-0.2450		
		(0.7941)		
RMSE	1.98	1.99	2.04	1.57
Adjusted R^2	0.3536	0.3057	0.2833	0.5707
No. Observations	165	165	165	165

Note: Three, two, and one asterisk(s) denotes statistical significance at the 0.01, 0.05, and 0.10 confidence levels, respectively. Values in parentheses are standard errors.

basis was explained by seasonality than lagged basis alone. Throughout the models including the seasonality dummy variables, very few of the monthly β coefficients are returned as statistically significant. It should be noted that the seasonal dummy variables were tested for joint significance using an F-test and the results of the test showed that seasonality was jointly significant at the 99% confidence level. Based on these findings, we continued to include seasonality while estimating in-sample models and when identifying the preferred models, Models 12 and 13.

Model 3 estimated basis as a function of market fundamental variables. As expected, the β coefficient for weights was negative and was statistically significant at the 95% confidence level. Corn futures price also had the expected sign, but was only marginally statistically significant at the 90% confidence level. The Choice-Select spread had the expected positive sign on the β coefficient and was statistically significant at the 99% confidence level. The β coefficients for market ready cattle and beef cold storage both had the expected negative sign and were both statistically significant. Beef cold storage was statistically significant to the 99% confidence level while market ready cattle was only marginally significant at the 90% confidence level. The β coefficient for pork cold storage had the expected positive sign and was statistically significant at the 99% confidence level. Unexpectedly, the β coefficient for chicken cold storage was negative, the opposite of our null hypothesis. These results suggest that pork which was positive and statistically significant has a larger impact on fed cattle basis than chicken cold storage.

Model 4 contains the same variables as Model 3, the market fundamental variables, but also includes retail meat prices. The variables in Model 4 that were also used in Model 3 possessed all the same signs on the β coefficients. Even though the signs were consistent across these two models, the level of significance and magnitude of the β's were altered with the inclusion of retail meat prices. Weights, corn futures prices, and market ready cattle all maintained the same sign on their respective β coefficients, but the level of significance for these variables all increased to the 99% confidence level. Another interesting change was the beef cold storage variable being insignificant in Model 4, but was significant at the 99% confidence level in Model 3. The inclusion of retail meat prices appeared to improve in-sample performance. As expected, beef retail price and pork retail price had a positive sign on their respective β coefficients and were significant at the 99% confidence level. On the contrary, chicken retail price had a negative sign on its respective β coefficient, but this variable was not too worrisome as the variable was insignificant.

Table 5-2 contains the results for Models 5-7. Model 5 estimated basis as a function of lagged basis and market fundamental variables. The β coefficient on corn futures price possessed the same sign of negative, but was not statistically significant and the impact on basis decreased in magnitude. Additionally, choice-select spread still possessed a positive sign on the β coefficient, but was not statistically significant in this econometric model. The changes in statistical significance for both corn futures price and choice-select spread could be due to the fact that lagged basis is included on the right hand side of the equation which could capture a large portion of the impact corn futures price and choice-select spread have on fed cattle basis.

Model 6 estimated basis as a function of lagged basis, market fundamental variables, and retail meat prices. The β coefficient for beef cold storage in Model 6 is statistically insignificant. The inclusion of weights and market ready cattle could be capturing such a large portion of the beef supply and availability story within the supply chain, that beef cold storage is no longer a significant variable. Weights and market ready cattle are also built using data of live animals which is much closer in the supply chain to fed cattle than is beef cold storage. Additionally, beef retail price is statistically significant at the 95% confidence level. This variable might be a better determinant of fed cattle basis than is beef cold storage which is not statistically significant. Unexpectedly, the β coefficient on chicken cold storage is negative and was marginally significant. Contrary to pork cold storage, as chicken cold storage increases fed cattle basis is negatively impacted. When chicken cold storage increases, the supply of chicken will increase and the price of chicken will decrease; therefore, consumers will purchase less beef in favor of chicken. This will most likely depress prices the beef retail sector which will in turn depress prices of live cattle; therefore, decreasing basis.

Table 5-2 Regression Results for In-Sample Econometric Models of National Fed Cattle Basis (Models 5 - 7) for January 2003 through September 2016

	Dependent Variable (basis, $/cwt)		
Variable	Model 5	Model 6	Model 7
Intercept	10.2665***	38.2659***	0.0166
	(3.2678)	(4.9532)	(0.4392)
Lagged Fed Cattle Basis	0.4988***	0.2542***	0.6171***
	(0.0650)	(0.0662)	(0.0642)
Weight	-0.0073**	-0.0365***	
	(0.0029)	(0.0049)	
Corn Futures Price	-0.1465	-0.2705***	
	(0.0996)	(0.1029)	
Choice-Select Spread	0.0450	0.0315	
	(0.0310)	(0.0272)	
Market Ready Cattle	-0.0043***	-0.0038***	
	(0.0012)	(0.0011)	
Beef Cold Storage	-0.0100**	-0.0037	
	(0.0042)	(0.0039)	
Pork Cold Storage	0.0123***	0.0077***	
	(0.0025)	(0.0025)	
Chicken Cold Storage	-0.0026	-0.0031*	
	(0.0021)	(0.0018)	
Beef Retail		0.0145**	
		(0.0066)	
Pork Retail		0.0313***	
		(0.0120)	
Chicken Retail		-0.0288	
		(0.0206)	
Monthly Dummy (Default = January)			
February			-0.4836
			(0.6171)
March			1.8073***
			(0.6167)
April			0.6112
			(0.6322)
May			3.2296***
			(0.6338)
June			-0.9700
			(0.6942)

Table 5-2 Regression Results for In-Sample Econometric Models of National Fed Cattle Basis (Models 5 - 7) for January 2003 through September 2016, Continued…

	Dependent Variable (basis, $/cwt)		
Variable	Model 5	Model 6	Model 7
July			-0.9723
			(0.6360)
August			-0.1642
			(0.6191)
September			-0.9613
			(0.6183)
October			-0.1122
			(0.6290)
November			0.1397
			(0.6285)
December			-0.5212
			(0.6291)
RMSE	1.74	1.50	1.57
Adjusted R^2	0.4763	0.6060	0.5651
No. Observations	165	165	165

Note: Three, two, and one asterisk(s) denotes statistical significance at the 0.01, 0.05, and 0.10 percent levels, respectively. Values in parentheses are standard errors.

Model 7 estimated basis as a function of lagged basis and the seasonal dummy variables. The β coefficient on lagged basis had the expected sign, positive, and was statistically significant at the 99% confidence level. The β coefficients on the dummy variables March and May are statistically significant at the 99% confidence level. In Model 7, only these 2 months are individually, statistically significant compared to 4 months in Model 2. This could be a result of the lagged basis variable capturing some of the seasonality aspects of basis making a fewer number of the months individually significant. Model 7 had an R-squared value of 0.57 meaning lagged basis and seasonality explained 57% of the variation in fed cattle basis. Model 1 and 2 had R-squared values of 0.35 and 0.31, respectively, suggesting that the combination of lagged basis and seasonality in the same model explains more of the variation in fed cattle basis than the variables individually.

Table 5-3 contains the results for Models 8-10. Model 8 estimated basis as a function of market fundamentals and seasonal dummy variables. Contrary to economic intuition, the β coefficient on weights was positive suggesting that an increase in the average weights of live cattle would increase fed cattle basis. Although this does not make economic sense, the β coefficient on weights in this model is statistically insignificant. It should be noted that corn futures price, choice-select spread, and beef cold storage possess their expected signs and are statistically significant at the 99% confidence level. The monthly dummy variables March, April, May, and June are all statistically significant at the 90% confidence level or greater.

Model 9 estimated basis as a function of market fundamentals, retail meat prices, and seasonal dummy variables. All the signs on the β coefficients were all consistent with the other models tested, but the statistical difference varied. Weights, corn futures price, pork cold storage, chicken cold storage, and pork retail price were all statistically significant at the 95% confidence level or greater. Choice-select spread, market ready cattle, and beef retail price were marginally significant. May was statistically significant at the 95% confidence level and was the only monthly dummy variable that was statistically significant.

Model 10 estimated basis as a function of lagged basis, market fundamentals and seasonal dummy variables. Lagged basis was positive as expected and was statistically significant at the 99% confidence level. Corn futures price was marginally significant and was surprisingly the only market fundamental variable to possess a level of significance. Similar to Model 7, March and May are the only statistically significant monthly dummy variables in Model 10. Due to the fact that fewer individual months appear to be significant in models in

Table 5-3 Regression Results for In-Sample Econometric Models of National Fed Cattle Basis (Models 8 - 10) for January 2003 through September 2016

	Dependent Variable (basis, $/cwt)		
Variable	Model 8	Model 9	Model 10
Intercept	-1.9823	39.4359***	0.5802
	(4.3865)	(7.2635)	(3.8446)
Lagged Fed Cattle Basis			0.5129***
			(0.0749)
Weight	0.0054	-0.0384***	0.0017
	(0.0042)	(0.0067)	(0.0037)
Corn Futures Price	-0.3238***	-0.3915***	-0.1585*
	(0.1052)	(0.1082)	(0.0949)
Choice-Select Spread	0.1035***	0.0523*	0.0381
	(0.0347)	(0.0309)	(0.0317)
Market Ready Cattle	-0.0008	-0.0028*	-0.0016
	(0.0018)	(0.0016)	(0.0016)
Beef Cold Storage	-0.0129***	-0.0052	-0.0065
	(0.0044)	(0.0040)	(0.0040)
Pork Cold Storage	0.0083**	0.009***	0.0043
	(0.0036)	(0.0034)	(0.0032)
Chicken Cold Storage	-0.0053**	-0.0042**	-0.0025
	(0.0022)	(0.0019)	(0.0020)
Beef Retail		0.0139*	
		(0.0073)	
Pork Retail		0.0390***	
		(0.0126)	
Chicken Retail		-0.0287	
		(0.0224)	
Monthly Dummy (Default = January)			
February	-0.2493	-0.0609	-0.2170
	(0.8294)	(0.7062)	(0.7235)
March	1.6335**	0.4585	1.6177**
	(0.7337)	(0.6561)	(0.6400)
April	1.4192*	-0.7338	0.4473
	(0.7846)	(0.7377)	(0.6989)
May	3.9439***	1.6600**	3.0199***
	(0.7836)	(0.7421)	(0.6968)
June	1.8481**	0.8051	-0.4575
	(0.7489)	(0.6601)	(0.7350)

Table 5-3 Regression Results for In-Sample Econometric Models of National Fed Cattle Basis (Models 8 - 10) for January 2003 through September 2016, Continued…

	Dependent Variable (basis, $/cwt)		
Variable	Model 8	Model 9	Model 10
July	0.7089	0.3343	-0.5327
	(0.7540)	(0.6449)	(0.6823)
August	0.3164	0.2242	-0.0948
	(0.7475)	(0.6352)	(0.6548)
September	-0.9152	-0.4340	-1.0024
	(0.7353)	(0.6309)	(0.6415)
October	-0.7838	-0.3272	-0.3546
	(0.7638)	(0.6538)	(0.6692)
November	-0.0196	0.4246	0.1043
	(0.7779)	(0.6752)	(0.6788)
December	-0.2568	0.0053	-0.5106
	(0.7813)	(0.6787)	(0.6825)
RMSE	1.74	1.46	1.52
Adjusted R^2	0.4379	0.5962	0.5724
No. Observations	165	165	165

Note: Three, two, and one asterisk(s) denotes statistical significance at the 0.01, 0.05, and 0.10 percent levels, respectively. Values in parentheses are standard errors.

which lagged basis and seasonality are both included, the theory that lagged basis captures aspects of seasonality is further solidified.

Table 5-4 contains the results for Models 11-13. Model 11 estimated basis as a function of lagged basis, market fundamentals, retail meat prices, and seasonal dummy variables. Lagged basis, weights, corn futures price, and pork retail price were statistically significant at the 99% confidence level. Pork cold storage was statistically significant at the 95% confidence level and market ready cattle was marginally significant at the 90% confidence level. May was statistically significant at the 95% confidence level and was the only monthly dummy variable that was statistically significant. Model 11 also had the highest adjusted R-squared value for any of the models tested which is consistent with Model 11 containing the most complete set of right hand side variables.

Model 12 was the preferred model that took into account potential correlation issues. Lagged basis and beef retail price were statistically significant at the 99% confidence level. Beef cold storage was statistically significant at the 95% confidence level. Of the monthly dummy variables, March and May were positive and significant at the 99% confidence level while September was negative and statistically significant at the 95% confidence level.

Model 13 was the preferred model that ignored potential correlation problems and focused solely on prediction accuracy. Lagged basis, weights, corn futures price, and pork retail price were all statistically significant at the 99% confidence level. Pork cold storage was marginally significant at the 90% confidence level. Of the monthly dummy variables, May was statistically significant at the 99% confidence level while March was marginally significant at the 90% confidence level. Model 13 has an R-squared value very similar to that of Model 11, but with fewer coefficients included. This may prove to be an attractive quality in the out-of-sample evaluations.

Table 5-4 Regression Results for In-Sample Econometric Models of National Fed Cattle Basis (Models 11 - 13) for January 2003 through September 2016

	Dependent Variable (basis, $/cwt)		
Variable	Model 11	Model 12	Model 13
Intercept	29.9384***	1.4219	23.6868***
	(7.1941)	(1.6096)	(5.5255)
Lagged Fed Cattle Basis	0.3311***	0.4751***	0.3809***
	(0.0765)	(0.0752)	(0.0729)
Weight	-0.0293***		-0.0285***
	(0.0067)		(0.0059)
Corn Futures Price	-0.2856***	-0.1276	-0.3066***
	(0.1049)	(0.0838)	(0.0887)
Choice-Select Spread	0.0234	0.0352	0.0283
	(0.0299)	(0.0306)	(0.0290)
Market Ready Cattle	-0.0027*	-0.0015	-0.0021
	(0.0015)	(0.0015)	(0.0015)
Beef Cold Storage	-0.0029	-0.0082**	
	(0.0038)	(0.0035)	
Pork Cold Storage	0.0066**		0.0056*
	(0.0032)		(0.0029)
Chicken Cold Storage	-0.0027		
	(0.0018)		
Beef Retail	0.0082	0.0059***	
	(0.0070)	(0.0018)	
Pork Retail	0.0327***		0.0401***
	(0.0120)		(0.0070)
Chicken Retail	-0.0225		
	(0.0212)		
Monthly Dummy (Default = January)			
February	-0.0958	-0.1444	-0.0600
	(0.6662)	(0.7054)	(0.6624)
March	0.7793	1.6008***	1.1077*
	(0.6233)	(0.6159)	(0.5946)
April	-0.7711	0.4548	-0.5445
	(0.6959)	(0.6349)	(0.6601)
May	1.6914**	2.8668***	1.8896***
	(0.7000)	(0.6533)	(0.6642)
June	-0.3807	-0.6763	-0.5396
	(0.6803)	(0.6926)	(0.6606)

Table 5-4 Regression Results for In-Sample Econometric Models of National Fed Cattle Basis (Models 11 - 13) for January 2003 through September 2016

	Dependent Variable (basis, $/cwt)		
Variable	Model 11	Model 12	Model 13
July	-0.3551	-0.8719	-0.4873
	(0.6288)	(0.6331)	(0.6210)
August	-0.0098	-0.4403	-0.0044
	(0.6015)	(0.6123)	(0.5983)
September	-0.6321	-1.1927**	-0.7089
	(0.5969)	(0.6071)	(0.5890)
October	-0.1728	-0.6461	-0.2178
	(0.6178)	(0.6399)	(0.6096)
November	0.4176	-0.3013	0.3376
	(0.6368)	(0.6353)	(0.6237)
December	-0.1919	-0.8602	-0.2839
	(0.6418)	(0.6424)	(0.6285)
RMSE	1.38	1.50	1.40
Adjusted R^2	0.6407	0.5900	0.6386
No. Observations	165	165	165

Note: Three, two, and one asterisk(s) denotes statistical significance at the 0.01, 0.05, and 0.10 percent levels, respectively. Values in parentheses are standard errors.

Aligned with our initial hypotheses, the results provided robust conclusions for several variables across the multiple models estimated. Lagged basis, choice-select spread, pork cold storage, beef retail price, and pork retail price had positive signs on their β coefficients for every model in which they were included. Alternatively, corn futures price, market ready cattle, and beef cold storage all had negative signs on their β coefficients for every model in which they were included. Unexpectedly, chicken cold storage and chicken retail price both had negative signs on their β coefficients and this sign was consistent for all the models in which these variables were included. It should be noted that chicken retail price was not statistically significant in any of the models that it was included and chicken cold storage varied in statistical significance.

It should be noted that regional shifts in the national live negotiated marketings were considered. We created a variable that represents the percentage of the national live negotiated monthly volume is represented by individual states. After creating the variables, we then re-estimated Model 13 with the inclusion of individual states portion of the national live negotiated monthly volume. The results indicated that regional affects were jointly significant. Future research could further explore how regional affects influence fed cattle basis.

Comparisons of Errors:

In-sample estimations were further compared using a host of diagnostic measures; the equations of which are included in Chapter 3. Table 5-5 contains the comparisons of the in-sample diagnostic measures. Model 4 had the lowest value for MPE (26.82%) which is important for analysts who are concerned with the direction of the error, positive of negative. Model 13 had the lowest value for MAPE meaning that the errors of this model were the smallest when considered as an absolute percentage of the actual value. More narrowly, on average, Model 13 had the smallest errors when averaged as a percent of the actual value of basis.

Model 11 had the lowest MAE, MSE, RMSE, and SSE values. With regards to MAE, this means that Model 11, on average, had the smallest absolute error when estimating basis during in-sample estimations. Without regards for direction of the error, positive or negative, Model 11's in sample estimates, on average, were the closest to predicting basis out of all models tested. A key reason to include squared error is to penalize models that produce forecasts with very large errors. Model 11 performs the best out of the models for squared error measures including MSE, RMSE, and SSE. In general, we can conclude that Model 11 forecasted consistently with a minimal number of prediction errors of great magnitude. These results should be taken lightly due to the fact that Model 11 contains all the variables used as estimators within this study. The primary concern of this fact being that the inclusion of so many variables may be overfitting the data of the dependent variable, fed cattle basis. In-sample estimation is a backward looking procedure, meaning that every variable value is known. The true test of prediction accuracy will come in the out-of-sample portion of these research efforts to see if the complexity of some of these models can outperform the simpler models.

Table 5-5 MAE, MAPE, MPE, MSE, RMSE, and SSE Measures for In-Sample Econometric Model Estimations

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13
MAE	1.41	1.49	1.57	1.21	1.27	1.13	1.14	1.36	1.14	1.11	**1.05**	1.13	1.07
MAPE	150.42	180.47	158.94	180.65	176.58	155.83	142.88	178.50	180.48	143.55	156.39	163.69	**142.32**
MPE	119.29	84.74	87.28	**26.82**	120.88	56.61	105.68	30.63	37.52	82.43	69.34	51.44	74.06
MSE	3.91	3.94	4.17	2.45	3.03	2.24	2.45	3.04	2.14	2.30	**1.89**	2.24	1.96
RMSE	1.98	1.99	2.04	1.57	1.74	1.50	1.57	1.74	1.46	1.52	**1.38**	1.50	1.40
SSE	645.02	650.32	688.81	404.67	500.20	369.06	404.70	502.36	353.51	379.63	**312.32**	368.95	322.99

Note: Bold values indicate the best performing model for each diagnostic measure

In-Sample Paired t-Tests:

To better compare the different models, paired t-tests were used to determine if the models were statistically different from one another. The t-tests compared the absolute error, squared error, percent error, and absolute percent errors for every monthly in-sample estimate of all 13 models. If the t-test returns a value less than 0.05, we can conclude with a 95% level of confidence that the two models are statistically different from one another. Marginal statistical significance is referring to values less than 0.15 indicating statistical significance at the 85% confidence level.

The paired t-test matrices comparing in-sample squared errors for Models 1 - 13 can be found in Table 5-6. In terms of squared errors, Model 11 was statistically different from all other models that were tested except Model 13. Other than Model 11 and Model 9, Model 13 was statistically different from all other models tested. It should be noted that Model 13 was only marginally statistically different from Model 6.

Table 5-6 Results of In-Sample Paired t-Test of Squared Errors (Model 1 - 13) for January 2003 through September 2016

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13
MSE	3.91	3.94	4.17	2.45	3.03	2.24	2.45	3.04	2.14	2.30	1.89	2.24	1.96
Model 1	-	0.9526	0.5154	**0.0034**	**0.0007**	**0.0001**	**0.0005**	0.0777	**0.0008**	**0.0002**	**0.0000**	**0.0003**	**0.0000**
Model 2		-	0.5545	**0.0002**	**0.0313**	**0.0000**	**0.0000**	**0.0006**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**
Model 3			-	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0008**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**
Model 4				-	0.0813	0.0853	0.9995	**0.0295**	**0.0127**	0.5727	**0.0013**	0.3823	**0.0088**
Model 5					-	**0.0014**	**0.0333**	0.9692	**0.0148**	**0.0052**	**0.0002**	**0.0094**	**0.0005**
Model 6						-	0.3738	**0.0038**	0.5733	0.7589	**0.0073**	0.9975	0.0547
Model 7							-	**0.0138**	0.2541	0.0517	**0.0032**	0.0867	**0.0057**
Model 8								-	**0.0001**	**0.0002**	**0.0000**	**0.0001**	**0.0000**
Model 9									-	0.4937	**0.0422**	0.6355	0.1782
Model 10										-	**0.0061**	0.4696	**0.0197**
Model 11											-	**0.0057**	0.1981
Model 12												-	**0.0206**
Model 13													-

Note: Bold values indicate statistical significance at a 95% confidence level

Table 5-7 contains the paired t-test matrices comparing in-sample absolute errors for Models 1 – 13. In general, Models 4 – 13 were statistically different from Models 1 – 3. Statistical difference varied among Models 7 – 13. Model 11 was the best performing model in terms of in-sample absolute error was at least marginally statistically different from all models tested excluding Models 10, 12, and 13. Overall in terms of in-sample absolute errors, Models 9 – 13 were not statistically different from one another.

Table 5-7 Results of In-Sample Paired t-Test of Absolute Errors (Model 1 - 13) for January 2003 through September 2016

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13
MAE	1.41	1.49	1.57	1.21	1.27	1.13	1.14	1.36	1.14	1.11	1.05	1.13	1.07
Model 1	-	0.4204	0.0734	**0.0433**	**0.0181**	**0.0007**	**0.0006**	0.5924	**0.0077**	**0.0001**	**0.0001**	**0.0006**	**0.0001**
Model 2		-	0.3633	**0.0032**	**0.0162**	**0.0001**	**0.0000**	**0.0281**	**0.0001**	**0.0000**	**0.0000**	**0.0000**	**0.0000**
Model 3			-	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0024**	**0.0000**	**0.0000**	**0.0000**	**0.0000**	**0.0000**
Model 4				-	0.4859	**0.0134**	0.3984	0.0505	0.0713	0.1610	**0.0018**	0.2168	**0.0109**
Model 5					-	**0.0245**	0.0508	0.2292	0.1285	**0.0056**	**0.0020**	**0.0290**	**0.0050**
Model 6						-	0.8614	**0.0020**	0.7828	0.6996	0.0569	0.9288	0.1802
Model 7							-	**0.0013**	0.9973	0.2138	0.0815	0.5940	0.1254
Model 8								-	**0.0004**	**0.0000**	**0.0000**	**0.0001**	**0.0000**
Model 9									-	0.5670	**0.0095**	0.7597	0.0760
Model 10										-	0.2360	0.4498	0.4084
Model 11											-	0.0805	0.4791
Model 12												-	0.1654
Model 13													-

Note: Bold values indicate statistical significance at a 95% confidence level

Table 5-8 contains the paired t-test matrices comparing in-sample percent errors for Models 1 – 13. When comparing the competing models, a majority of all the in-sample percent errors were not statistically different from one another. One consistent trend was that Models 9 – 13 were all statistically different from Model 7. Since Model 7 had a higher MPE value and was statistically different from Models 9 – 13, Models 9 – 13 would be preferred to Model 7.

Table 5-8 Results of In-Sample Paired t-Test of Percent Errors (Model 1 - 13) for January 2003 through September 2016

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13
MPE	119.29	84.74	87.28	26.82	120.88	56.61	105.68	30.63	37.52	82.43	69.34	51.44	74.06
Model 1	-	0.6219	0.3300	0.0534	0.9371	**0.0441**	0.7232	0.1806	0.1124	0.3504	0.1830	0.1805	0.1678
Model 2		-	0.9592	0.2409	0.6147	0.6095	0.5838	**0.0301**	0.2145	0.9512	0.7269	0.3217	0.8055
Model 3			-	**0.0422**	0.2924	0.1612	0.5053	0.1792	0.1279	0.8369	0.4756	0.2596	0.5782
Model 4				-	0.0699	0.1235	**0.0307**	0.9047	0.4577	**0.0496**	0.0588	0.2508	0.1110
Model 5					-	0.0543	0.6838	0.1926	0.1281	0.3252	0.1823	0.1919	0.1697
Model 6						-	0.0818	0.5563	0.4483	0.2534	0.4142	0.8519	0.3746
Model 7							-	0.0585	**0.0209**	**0.0153**	**0.0276**	**0.0241**	**0.0112**
Model 8								-	0.7631	0.1223	0.2904	0.3296	0.2846
Model 9									-	**0.0399**	0.0802	0.2104	0.1506
Model 10										-	0.2184	0.0615	0.4980
Model 11											-	0.3126	0.6579
Model 12												-	0.3338
Model 13													-

Note: Bold values indicate statistical significance at a 95% confidence level

Table 5-9 contains the paired t-test matrices comparing in-sample absolute percent errors for Models 1 – 13. Overall in terms of absolute percent errors, there were no competing models that were statistically different from one another at a 95% confidence level. There were a few marginal differences such as Models 10, 12, and 13 being marginally statistically different from Model 9. Additionally, Model 13 is marginally statistically different from Model 11.

Table 5-9 Results of In-Sample Paired t-Test of Absolute Percent Errors (Model 1 - 13) for January 2003 through September 2016

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13
MAPE	150.42	180.47	158.94	180.65	176.58	155.83	142.88	178.50	180.48	143.55	156.39	163.69	142.32
Model 1	-	0.5180	0.7717	0.1207	0.1455	0.8264	0.8420	0.4451	0.2268	0.8282	0.8312	0.6373	0.8014
Model 2		-	0.6096	0.9965	0.9270	0.5893	0.2041	0.9257	0.9999	0.2079	0.4695	0.4601	0.2522
Model 3			-	0.3884	0.5779	0.8523	0.5117	0.6315	0.4324	0.4756	0.8919	0.8647	0.3339
Model 4				-	0.8169	0.1981	0.2660	0.9455	0.9905	0.1761	0.2790	0.4154	0.1632
Model 5					-	0.4163	0.3561	0.9551	0.8518	0.2563	0.4328	0.5868	0.2920
Model 6						-	0.6253	0.6043	0.3254	0.5763	0.9712	0.7744	0.4783
Model 7							-	0.3472	0.1605	0.9398	0.3449	0.3447	0.9608
Model 8								-	0.9268	0.2924	0.5318	0.4644	0.3267
Model 9									-	0.0770	0.1840	0.0966	0.0937
Model 10										-	0.1881	0.2164	0.9047
Model 11											-	0.6778	0.1068
Model 12												-	0.3024
Model 13													-

Note: Bold values indicate statistical significance at a 95% confidence level

5.2 Identification and Estimation of Structural Breaks

A subset of the 13 models was used to test for structural breaks: Models 1, 2, 7, 11, 12, and 13. Post in-sample evaluations, these 6 models were chosen as the best candidates for the out-of-sample testing portion of these research efforts, so we likewise consider them in our structural change assessment. Models 1, 2, and 7 were tested because they contain only parameters that are known, lagged basis and seasonality; therefore, they could be estimated without the use of additional forecasts. Models 11 was chosen because this model is a function of all the parameters tested in this study and was shown as promising in our in-sample assessment. Models 12 and 13 were included as the study's preferred models. For these reasons mentioned, the structural change tests were only conducted for these specified models.

Model 1 was tested using the BP test for multiple structural changes and found no structural breaks within this data series. We failed to reject the UD Max and WD Max null hypotheses for the presence of at least one structural break. Additionally, the supF(l + 1|l) test failed to reject no breaks in favor of the alternative hypothesis of one structural break.

The UD Max and WD Max test results for Models 2, 7, 11, 12, and 13 returned a statistically significant critical value at a 99% level of confidence; therefore, we rejected the null hypothesis of no structural break being present in the determinants of basis. Based on these findings, we conclude that all Models 2, 7, 11, 12, and 13 all contain at least one structural break in the regressors that determine basis.

After concluding the presence of at least one structural break, we look to the results of the supF(l + 1|l) test. The results should be interpreted sequentially beginning with the null hypothesis of no breaks (l=0) and the alternative hypothesis of l + 1 breaks. This process begins by testing l=0 breaks and will continue until the maximum number of breaks, l=M, is reached. In the output provided by SAS, the column notated as "New Break" represents the specific observation point in the data series at which the break occurs. If there are multiple breaks present, then a structural break is present at each observation point specified under the "New Break" column. The level of statistical significance for each break point is shown in the "Pr > supF(l + 1|l)" column. Taking into consideration the method for interpreting the supF(l + 1|l) test, we can determine the number of breaks and location of breaks for each data series.

Table 5-10 Model 2 supF(l+1|l) Test

l	New Break	supF(l+1|l)	Pr > supF(l+1|l)
0	132	495.5353	<.0001
1	**33**	**72.8979**	**<.0001**
2	89	28.5470	0.3553
3	60	3068.7707	<.0001
4	0	.	<.0001
5	0	.	<.0001

As an example, we will examine the results of the supF(l + 1|l) test for Model 2 as shown in Table 5-10. We reject the supF(l + 1|l) test for 1 and 2 structural breaks (l=0 and l=1), but we fail to reject the supF(l + 1|l) test for 3 structural breaks (l=2); therefore, we can conclude that there are 2 structural breaks present in the determinants of basis tested in Model 2.

Table 5-11 Model 2 Bai-Perron Break Dates

Number of Breaks	Break	Break Dates	95% Confidence Limits	
2	33	September-05	1	65
	132	December-13	128	136

After determining that there are 2 (l=1+1) breaks in the data series, we can identify the exact number of the observation on which the break occurs and in turn determine the exact date of the structural breaks. Table 5-11 summarizes the results from the BP test output for Model 2.

The “Break” column identifies the observation on which the break occurs and the “95% Confidence Limit” provides the range within a 95% level of confidence that the breaks occurs. The first break occurs at data point 33 which is September 2005 and the second break date occurs at data point 132 which is December 2013.

Table 5-12 Models 2, 7, 11, 12, and 13 Bai-Perron Break Dates

Model	Number of Breaks	Break	Break Dates	95% Confidence Limits	
2	2	33	September-05	1	65
		132	December-13	128	136
7	3	39	March-06	31	47
		106	October-11	97	115
		130	October-13	128	132
11	2	31	July-05	30	32
		131	November-13	130	132
12	2	42	June-06	41	43
		132	December-13	131	133
13	2	31	July-05	30	32
		130	October-13	129	131

The preceding method was repeated for Models 7, 11, 12, and 13 and the break dates are summarized in table 5-12. The confidence range varies amongst models, but the range is reduced greatly for Models 11, 12, and 13 when compared to Models 2 and 7. At the 95% confidence level, Models 2, 11, 12, and 13 all contained 2 structural breaks while Model 7 contained 3 structural breaks. The results of BP structural change tests consistently suggest the presence of structural breaks within 2005-2006 and the 4^{th} Quarter of 2013.

Regime Results:

After interpreting the results of the supF(l + 1|l) test and determining the location and number of structural breaks, then the model is broken into regimes. Each of the identified regimes are then estimated using the same variables used with the corresponding models, but only including the observations within that regimes timeline. This yields coefficients that are regime specific.

Table 5-13 shows the results from the BP testing for Model 2. Regime 1 ranges from January 2003 to September 2005, Regime 2 ranges from October 2005 to December 2013, and Regime 3 ranges from January 2014 to September 2016. These breaks could potentially be the result of several factors in the cattle industry. Considering the break in 2005, ethanol mandates in 2007 contributing to increased corn prices potentially could have resulted in a new market regime. Additionally, the record cattle prices experienced in 2014 could have marked a change in the seasonality of fed cattle basis. From these results we can interpret which variables are significant and whether their significance or signs have changed for different regime periods. For example prior to Regime 3, the β coefficient on February was positive and insignificant, but during Regime 3 the β coefficient on February was negative and statistically significant at the 99% confidence level. The months of March and April were statistically significant at above the 95% confidence level during Regime 1 and 2, but during Regime 3 were no longer statistically significant. May was consistently statistically significant at the 99% confidence level for all 3 regimes. Another interesting observation was the increase and direction of the impact that Quarter 4 has on basis. During Regime 1, October, November, and December were all positive and statistically insignificant; however, during Regime 3 these 3 months were all negative with a β coefficient smaller than -5 and were statistically significant at the 99% confidence level. This notable shift in seasonality impacts on basis could potentially be the result of tight supply of cattle in 2014 and 2015. With fewer cattle available, the feeding industry held cattle on feed longer which resulted in very heavy fed cattle harvested during this time.

Table 5-13 Bai-Perron Test Results for Model 2 of National Fed Cattle Basis for January 2003 through September 2016

	Dependent Variable (basis, $/cwt)		
Variable	Regime 1	Regime 2	Regime 3
Intercept	-0.7169	-1.7922***	3.2364***
	(1.0491)	(0.6243)	(1.1474)
Monthly Dummy (Default = January)			
February	0.1552	0.3475	-2.3957***
	(0.3938)	(0.4109)	(0.2423)
March	4.1458***	1.5348**	0.3274
	(0.6007)	(0.6357)	(1.2866)
April	3.2062***	2.5549***	-0.9383
	(0.6626)	(0.5809)	(0.7691)
May	4.46710***	4.7352***	4.5235***
	(1.2485)	(0.8802)	(1.2615)
June	2.2819*	2.9966***	-0.5169
	(1.1946)	(0.7049)	(2.1074)
July	1.504700	0.0006	0.9192
	(1.5091)	(0.7836)	(1.8341)
August	0.6414	0.7568	-0.9864
	(1.1764)	(0.7145)	(0.9824)
September	0.8298	-0.0565	-3.1902**
	(1.3707)	(0.8360)	(1.5632)
October	1.4712	0.9194	-5.5437***
	(2.0776)	(0.7873)	(0.8413)
November	2.4964	1.4423**	-5.8078***
	(1.7613)	(0.6944)	(1.6524)
December	0.3148	1.2401***	-5.0899***
	(0.8771)	(0.4389)	(0.6597)

Note: UDMaxF < .001, WDMaxF < .001, and supF(l+1|l) = 2. Three, two, and one asterisk(s) denotes statistical significance at the 0.01, 0.05, and 0.10 percent levels, respectively. Values in parentheses are standard errors. No. of observations = 165. R-squared = 0.3523

Table 5-14 shows the results from the BP testing for Model 7. Regime 1 ranges from January 2003 to March 2006, Regime 2 ranges from April 2006 to October 2011, Regime 3 ranges from November 2011 to October 2013, and Regime 4 ranges November 2013 to September 2016. Lagged basis is positive and statistically significant at the 99% confidence level

Table 5-14 Bai-Perron Test Results for Model 7 of National Fed Cattle Basis for January 2003 through September 2016

	Dependent Variable (basis, $/cwt)			
Variable	Regime 1	Regime 2	Regime 3	Regime 4
Intercept	-0.2660	-1.5042**	-1.6238	4.2624***
	(0.5603)	(0.6631)	(1.3437)	(0.4487)
Lagged Fed Cattle Basis	0.7697***	0.5254***	0.6168***	0.7486***
	(0.1535)	(0.0920)	(0.2101)	(0.1173)
Monthly Dummy (Default = January)				
February	0.0295	1.1884*	1.1954	-5.8445***
	(0.5914)	(0.7061)	(1.7862)	(0.7601)
March	4.0023***	1.3600*	2.6942**	-1.3279
	(0.8037)	(0.7771)	(1.3725)	(1.5954)
April	0.1161	2.2036***	3.1078**	-4.6322***
	(0.8703)	(0.6883)	(1.3742)	(1.1074)
May	2.1002**	3.5619***	5.4780***	1.7771
	(1.0189)	(0.8535)	(1.5253)	(1.1726)
June	-1.0555	1.2269	0.6488	-7.3519***
	(0.8757)	(0.7502)	(1.7633)	(1.9052)
July	-0.1507	-0.4755	-2.3165	-2.1427***
	(0.9080)	(0.8067)	(1.7866)	(0.7417)
August	-0.4160	1.0379	2.8944**	-5.1233***
	(0.6644)	(0.6987)	(1.4440)	(1.0992)
September	0.4371	0.1323	0.5572	-5.9005***
	(1.0330)	(0.7792)	(1.8387)	(1.5479)
October	0.1799	1.3915*	2.7924*	-6.0839***
	(0.9257)	(0.7956)	(1.5335)	(0.5491)
November	1.1427	1.5268*	2.7723	-5.2699***
	(0.7099)	(0.7884)	(2.0663)	(1.1238)
December	-0.8489	1.1558*	0.7244	-4.1138***
	(1.3595)	(0.6687)	(1.1295)	(0.4534)

Note: UDMaxF < .001, WDMaxF < .001, and supF(l+1|l) = 3. Three, two, and one asterisk(s) denotes statistical significance at the 0.01, 0.05, and 0.10 percent levels, respectively. Values in parentheses are standard errors. No. of observations = 165. R-squared = 0.5969 for all 4 regimes. The May monthly dummy variable was positive and statistically significant for Regimes 1 – 3; however, was not statistically significant for Regime 4. Barring a few exceptions of statistical significance, the months of June through December were consistently not statistically significant throughout Regimes 1 – 3; however, in Regime 4, the months June through December all had negative β coefficients and were statistically significant at the 99% confidence level. Additionally, in Regime 4, February and April were also negative and statistically significant at the 99% confidence level.

Table 5-15 shows the results from the BP testing for Model 11. Regime 1 ranges from January 2003 to July 2005, Regime 2 ranges from August 2005 to November 2013, and Regime 3 ranges from December 2013 to September 2016. The β coefficient on lagged basis was positive and statistically significant at the 95% confidence level for Regime 2 and 3. It should be noted that the β coefficient on lagged basis was negative for Regime 1, but the coefficient was not statistically significant. Opposite economic intuition, corn futures price had a positive β coefficient for Regime 1 and it was statistically significant at the 99% confidence level. Pork retail price was positive and very statistically significant for Regime 1 and 2, but possessed a negative sign and was statistically insignificant for Regime 3. There were several monthly dummy variables including: June, September, October, November, and December that possessed very negative β coefficients and were statistically significant at the 99% confidence level.

Table 5-15 Bai-Perron Test Results for Model 11 of National Fed Cattle Basis for January 2003 through September 2016

	Dependent Variable (basis, $/cwt)		
Variable	Regime 1	Regime 2	Regime 3
Intercept	90.9014***	30.4741***	-20.4635
	(27.4139)	(10.7887)	(54.8278)
Lagged Fed Cattle Basis	-0.2608	0.2550***	0.7396**
	(0.1904)	(0.0767)	(0.2912)
Weight	-0.1262***	-0.0309***	-0.0143
	(0.0295)	(0.0088)	(0.0332)
Corn Futures Price	4.4478***	-0.2716**	0.7636
	(1.3990)	(0.1073)	(1.7762)
Choice-Select Spread	0.0278	-0.0084	0.1832
	(0.0429)	(0.0327)	(0.1299)
Market Ready Cattle	-0.0023	-0.0032**	0.0206**
	(0.0019)	(0.0013)	(0.0090)
Beef Cold Storage	0.0362***	-0.0023	0.0156
	(0.0108)	(0.0037)	(0.0209)
Pork Cold Storage	0.0522***	0.0054	-0.0551*
	(0.0122)	(0.0033)	(0.0332)
Chicken Cold Storage	-0.0115**	-0.0032*	0.0270*
	(0.0053)	(0.0018)	(0.0151)
Beef Retail	-0.0014	-0.0144	-0.0481**
	(0.0260)	(0.0119)	(0.0232)
Pork Retail	0.2252***	0.0555***	-0.0288
	(0.0807)	(0.0157)	(0.0484)
Chicken Retail	-0.2291**	0.0049	0.4418
	(0.1132)	(0.0187)	(0.3039)
Monthly Dummy (Default = January)			
February	-0.5640	1.0547*	-5.9083*
	(0.7402)	(0.6064)	(3.3280)
March	1.4302	0.5538	0.1019
	(1.1314)	(0.6897)	(1.9253)
April	-0.4591	0.4363	-1.786
	(2.0801)	(0.6288)	(2.2841)
May	4.0314**	2.0889***	3.2109
	(1.7061)	(0.7625)	(2.5526)
June	7.1793***	1.0919*	-11.6026***
	(1.5926)	(0.5945)	(4.1003)

Table 5-15 Bai-Perron Test Results for Model 11 of National Fed Cattle Basis for January 2003 through September 2016, Continued…

	Dependent Variable (basis, $/cwt)		
Variable	Regime 1	Regime 2	Regime 3
July	9.8932***	-0.8157	-5.9831*
	(1.4136)	(0.6339)	(3.0683)
August	8.5309***	0.5047	-6.7432**
	(1.7151)	(0.5780)	(2.9658)
September	7.6322***	-0.0367	-5.8515***
	(1.5689)	(0.6723)	(1.9847)
October	8.3814***	0.8666	-8.322***
	(1.5875)	(0.6894)	(1.6585)
November	8.7831***	1.4653**	-11.9872***
	(1.2659)	(0.7305)	(3.4762)
December	3.3870***	1.4290**	-9.7628***
	(1.1811)	(0.6644)	(2.7654)

Note: UDMaxF < .001, WDMaxF < .001, and supF(l+1|l) = 2. Three, two, and one asterisk(s) denotes statistical significance at the 0.01, 0.05, and 0.10 percent levels, respectively. Values in parentheses are standard errors. No. of observations = 165. R-squared = 0.6889

Table 5-16 shows the results from the BP testing for Model 12. Regime 1 ranges from January 2003 to June 2006, Regime 2 ranges from July 2006 to December 2013, and Regime 3 ranges from January 2014 to September 2016. Lagged basis was positive and statistically significant at the 99% confidence level for Regime 2 and 3. Choice-select spread was positive and statistically significant at the 95% confidence level for Regime 1 and 3. It should be noted that the sign was negative for choice-select for Regime 2, but this β coefficient was not statistically significant. The β coefficient on market ready cattle was statistically significant at the 99% confidence level for Regime 3, but the sign was flipped to positive. Again, the months of February, April, June, July, August, September, October, November, and December were all negative and statistically significant at the 99% confidence level for Regime 3.

Table 5-16 Bai-Perron Test Results for Model 12 of National Fed Cattle Basis for January 2003 through September 2016

	Dependent Variable (basis, $/cwt)		
Variable	Regime 1	Regime 2	Regime 3
Intercept	4.4518	-3.9809**	14.6423
	(4.3031)	(1.9308)	(11.3435)
Lagged Fed Cattle Basis	0.2286	0.4711***	0.6347***
	(0.1914)	(0.0935)	(0.1441)
Corn Futures Price	1.9886*	-0.0870	0.4206
	(1.1074)	(0.1005)	(1.0142)
Choice-Select Spread	0.0963***	-0.0209	0.2576**
	(0.0310)	(0.0343)	(0.1022)
Market Ready Cattle	-0.0001	-0.0024	0.0154***
	(0.0025)	(0.0015)	(0.0051)
Beef Cold Storage	-0.0157***	0.0001	0.0052
	(0.0047)	(0.0032)	(0.0074)
Beef Retail	-0.0084	0.0074**	-0.0280*
	(0.0085)	(0.0037)	(0.0166)
Monthly Dummy (Default = January)			
February	-0.4422	1.5574**	-7.5848***
	(0.7698)	(0.6772)	(1.6712)
March	2.884***	1.4266**	-1.3381
	(0.8177)	(0.6619)	(1.7025)
April	0.4269	2.1341***	-3.9552***
	(0.7347)	(0.6207)	(1.3236)
May	1.2295	3.8469***	1.254
	(0.8250)	(0.8116)	(1.4569)
June	-0.3769	1.3478**	-10.0068***
	(0.5155)	(0.6572)	(2.0942)
July	0.4877	-0.7401	-4.5134***
	(0.7351)	(0.7233)	(1.4079)
August	-0.0443	1.1000*	-6.7614***
	(0.5761)	(0.6641)	(1.3764)
September	0.1397	0.1451	-7.3778***
	(0.4617)	(0.7426)	(1.8602)
October	-0.1303	1.3520*	-6.3414***
	(0.6221)	(0.7853)	(1.5238)
November	1.2061*	1.3787*	-6.4119***
	(0.7017)	(0.8300)	(1.3190)

Table 5-16 Bai-Perron Test Results for Model 12 of National Fed Cattle Basis for January 2003 through September 2016, Continued…

	Dependent Variable (basis, $/cwt)		
Variable	Regime 1	Regime 2	Regime 3
December	-0.0417	0.8803	-4.6848***
	(1.0966)	(0.6841)	(1.0668)

Note: UDMaxF < .001, WDMaxF < .001, and supF(l+1|l) = 2. Three, two, and one asterisk(s) denotes statistical significance at the 0.01, 0.05, and 0.10 percent levels, respectively. Values in parentheses are standard errors. No. of observations = 165. R-squared = 0.6325

Table 5-17 shows the results from the BP testing for Model 13. Regime 1 ranges from January 2003 to July 2005, Regime 2 ranges from August 2005 to October 2013, and Regime 3 ranges from November 2013 to September 2016. For Regime 2 and 3, lagged basis was positive and statistically significant at the 99% confidence level. Opposite economic intuition, corn futures price had a positive β coefficient for Regime 1 and it was statistically significant at the 99% confidence level. Alternatively, corn futures price had a negative β coefficient for Regime 2 and it was statistically significant at the 99% confidence level. As an input cost of production increased, we would expect a weakening in basis. Excluding lagged basis, all of the supply and demand influencers that we would expect to impact basis were statistically insignificant for Regime 3. The June and November monthly dummy variables were statistically significant at the 95% confidence level for Regimes 1 – 3. In line with previous models, the months of February, April, June, July, August, September, October, November, and December were all negative and statistically significant at the 99% confidence level for Regime 3.

Table 5-17 Bai-Perron Test Results for Model 13 of National Fed Cattle Basis for January 2003 through September 2016

	Dependent Variable (basis, $/cwt)		
Variable	Regime 1	Regime 2	Regime 3
Intercept	89.0698***	18.8241**	23.6518
	(25.0939)	(8.0371)	(43.9489)
Lagged Fed Cattle Basis ($/cwt)	-0.1531	0.3159***	0.5193***
	(0.2148)	(0.0749)	(0.1393)
Weight (lbs)	-0.1011***	-0.0236***	-0.0166
	(0.0253)	(0.0076)	(0.0277)
Corn Futures Price ($/cwt)	3.8716***	-0.3034***	-0.0106
	(1.2795)	(0.1131)	(1.4643)
Choice-Select Spread ($/cwt)	0.0708**	-0.0282	0.1388
	(0.0321)	(0.0267)	(0.1299)
Market Ready Cattle ('000 head)	-0.0028*	-0.0023	0.0070
	(0.0017)	(0.0014)	(0.0045)
Pork Cold Storage (mil. lbs)	0.0333***	0.0028	-0.0014
	(0.0103)	(0.0022)	(0.0130)
Pork Retail ($/cwt)	0.0461*	0.0381***	0.0101
	(0.0269)	(0.0084)	(0.0327)
Monthly Dummy (Default = January)			
February	-0.7593	0.9826*	-5.6696***
	(0.7315)	(0.5645)	(1.5094)
March	-0.0301	0.8912	-1.3574
	(1.0177)	(0.5470)	(1.8814)
April	-3.1356***	0.9073*	-4.4849***
	(0.9949)	(0.4960)	(1.2101)
May	0.0439	2.6003***	0.6142
	(1.0134)	(0.6212)	(1.6739)
June	2.5897**	1.1537**	-8.2687***
	(1.1438)	(0.5532)	(1.9430)
July	5.2872***	-0.8571	-3.4658***
	(1.4920)	(0.6395)	(1.1987)
August	4.7991***	0.6680	-5.5522***
	(1.6747)	(0.5674)	(1.2112)
September	4.3145***	0.0731	-6.1800***
	(1.5148)	(0.6795)	(1.7335)
October	4.1772***	1.0083	-6.5434***
	(1.5421)	(0.6813)	(1.4056)

Table 5-17 Bai-Perron Test Results for Model 13 of National Fed Cattle Basis for January 2003 through September 2016, Continued…

	Dependent Variable (basis, $/cwt)		
Variable	Regime 1	Regime 2	Regime 3
November	5.6072***	1.6227**	-6.7497***
	(1.5090)	(0.7102)	(1.4131)
December	0.8888	1.3007**	-4.9423***
	(1.2238)	(0.6467)	(1.1727)

Note: UDMaxF < .001, WDMaxF < .001, and supF(l+1|l) = 2. Three, two, and one asterisk(s) denotes statistical significance at the 0.01, 0.05, and 0.10 percent levels, respectively. Values in parentheses are standard errors. No. of observations = 165. R-squared = 0.6783

Overall, the regime dates were relatively consistent across all models tested. There appears to be a fairly consistent indication of a break occurring during 2005 or 2006. The timing and confidence intervals vary across models, but there is a good evidence of a break occurring in 2005 or 2006, depending on the model. It is much more apparent that of the parameters tested, we can robustly conclude that there was a structural break in the determinants of fed cattle basis in the fourth quarter of 2013. This break seems intuitive due to the fact that this aligns well with the widening in the range of basis that began occurring around this time.

5.3 Out-of-Sample Estimations

Table 5-18 shows a comparison of MAE, MAPE, MPE, MSE, RMSE, and SSE for the out-of-sample testing of the econometric models tested as well as a 3-year and 4-year historical average. The diagnostic measures returned mixed results as far as prediction accuracy amongst models. In terms of minimizing MAE, Model 13-B was the best performing model for the out-of-sample testing (MAE = 1.74). It should be noted that Model 7 and 13 also performed well while minimizing MAE, but not to the extent of Model 13-B. For forecasting purposes, these results suggest that producers who are prioritizing the minimization of prediction errors without concern for which direction of basis the prediction falls should utilize Model 13-B. This model demonstrates the benefit of compositing lagged variables to average the relative impacts. When comparing MAE measures, the out-of-sample estimations did not perform as well as in-sample estimations. The best performing in-sample model was Model 11 (MAE = 1.05). On average, Model 13-B had a prediction error nearly $0.70/cwt larger than the best performing in-sample estimation. Excluding Model 2, all econometric models outperformed the 3-year and 4-year historical average models based solely on point estimate, averages of prediction errors. When comparing the years forecasted in the out-of-sample testing, the 2012 and 2013 MAEs for all econometric models tested had, on average, absolute prediction errors that were $1.14/cwt smaller than the 2014 and 2015 absolute prediction errors. The only models to produce smaller absolute prediction errors during 2014-2015 vs 2012-2013 were the 3-year and 4-year historical average model.

When comparing minimization of MAPE for the out-of-sample testing, Model 1 was the best performing model (MAPE = 129.18%). Model 1 was the simplest model estimated utilizing only lagged basis as a regressor. For the producer that is most concerned with minimizing prediction errors as a percent of actual basis, these analyses suggest that an econometric model with only lagged basis would be the most effective to minimize MAPE. The out-of-sample estimation of Model 1 outperformed the best in-sample estimation, which was produced by Model 13 (MAPE = 142.32%), by approximately 13%. In terms of MAPE, all out-of-sample econometric models outperformed both the 3-year and 4-year historical average models.

Table 5-18 MAE, MAPE, MPE, MSE, RMSE, and SSE Diagnostic Measures for Out-of-Sample Econometric Model Estimations for January 2012 through September 2016

	Model 1	Model 2	Model 7	Model 11	Model 11-B	Model 12	Model 12-B	Model 13	Model 13-B	3-Year Hist Avg	4-Year Hist Avg
MAE	1.97	2.30	1.74	1.88	1.89	1.83	1.86	1.76	**1.74**	2.06	1.98
MAPE	**129.18**	145.93	133.60	193.30	143.92	172.78	156.77	155.07	152.68	451.98	370.52
MPE	107.11	117.61	109.17	**24.80**	100.88	54.32	87.06	64.76	76.96	-124.13	-63.01
MSE	7.21	8.16	5.27	5.07	6.23	5.04	5.39	**4.67**	4.91	7.06	6.39
RMSE	2.69	2.86	2.30	2.25	2.50	2.24	2.32	**2.16**	2.22	2.66	2.53
SSE	411.03	465.34	300.27	289.18	354.94	287.26	307.06	**266.13**	279.76	402.35	364.06

Note: Bold values indicate the best performing model for each diagnostic measure

In terms of minimizing MPE, Model 11 was the best performing model for out-of-sample testing (MPE = 24.80%). When making forecasting decisions, these results suggest that producers who are prioritizing the minimization of prediction errors and the direction of the prediction errors should utilize Model 11. Every econometric model that was estimated out-of-sample had a positive MPE which means that, on average, the models are over predicting basis. Depending on what segment of the supply chain the analyst is involved, this can be a positive or a negative attribute of the models. From the perspective of a feedlot marketing live cattle, they would be worse off using a forecasting model that, on average, over predicts basis. The out-of-sample estimation of Model 11 outperformed the best in-sample estimation, which was produced by Model 4 (MPE = 26.82%), by approximately 2%. Model 11 and 12 were the only econometric models to outperform the 4-year historical average.

In terms of minimizing MSE, Model 13 was the best performing model for out-of-sample testing (MSE = 4.67). Model 13 also minimized RMSE (2.16) and SSE (266.13). The out-of-sample estimations performed poorly when compared to the in-sample estimations. The best performing out-of-sample estimation, Model 13, had squared errors that were, on average, \$0.50/cwt larger than the worst performing in-sample model, Model 3. Using squared error diagnostic measurements is intended to penalize models that produce very large prediction errors. As shown in table 5-18, the out-of-sample MSE measures are, in most cases, over 2 times larger than their corresponding in-sample MSE measures. This speaks to the severe increase in difficulty created by the unknown factors that must be estimated while testing models out-of-sample. The notable increase in prediction errors also aligns with the increased unpredictability and volatility that has plagued the beef markets over the past several years. When comparing the years forecasted in the out-of-sample testing, the 2012 and 2013 MSEs for all econometric models tested had, on average, squared prediction errors that were $5.86/cwt smaller than the 2014 and 2015 squared prediction errors.

Out-of-Sample Paired t-Tests:

Table 5-19 contains the results from the paired t-tests for out-of-sample squared prediction errors for Models: 1, 2, 7, 11, 11-B, 12, 12-B, 13, 13-B, 3-year historical average, and 4-year historical average. Overall, the econometric models and historical average models were generally not statistically different from one another. Several of the econometric models including: Models 7, 11, 12, 12-B, 13, and 13-B were statistically different from Model 2. It should be noted that Model 13 and 13-B were marginally statistically different from the 3-year historical average model, but were not statistically different from the 4-year historical average model. If the historical average models, which are much simpler forecasts to implement, produce squared prediction errors that are statistically the same as complex econometric models, then the producer has cause to question whether the estimates produced by the more complex models is worth the time to create the estimations.

Table 5-19 Results of Out-of-Sample Paired t-Test of Squared Errors (Models 1, 2, 7, 11, 11-B, 12, 12-B, 13, 13-B, 3-Year Historical Average, and 4-Year Historical Average) for January 2012 through September 2016

	Model 1	Model 2	Model 7	Model 11	Model 11-B	Model 12	Model 12-B	Model 13	Model 13-B	3-Year Hist Avg	4-Year Hist Avg
MSE	7.21	8.16	5.27	5.07	6.23	5.04	5.39	4.67	4.91	7.06	6.39
Model 1	-	0.5418	0.0781	0.1109	0.4750	0.1011	0.1711	0.0530	0.0779	0.9081	0.5403
Model 2		-	**0.0033**	**0.0111**	0.1379	**0.0140**	**0.0261**	**0.0018**	**0.0068**	0.5526	0.3348
Model 7			-	0.8081	0.3785	0.7578	0.8733	0.3704	0.6390	0.2230	0.4277
Model 11				-	0.1793	0.9519	0.7033	0.3381	0.7965	0.1878	0.3542
Model 11-B					-	0.2547	0.4714	0.0835	0.1580	0.5934	0.9171
Model 12						-	0.3791	0.2224	0.6970	0.1900	0.3486
Model 12-B							-	0.1561	0.1878	0.2756	0.4905
Model 13								-	0.4605	0.1118	0.2211
Model 13-B									-	0.1495	0.2904
3 Year Hist Avg										-	**0.0160**
4 Year Hist Avg											-

Note: Bold values indicate statistical significance at a 95% confidence level

Table 5-20 contains the results from the paired t-tests for out-of-sample absolute prediction errors for Models: 1, 2, 7, 11, 11-B, 12, 12-B, 13, 13-B, 3-year historical average, and 4-year historical average. Overall, the econometric models and historical average models were generally not statistically different from one another; however, the econometric models were all statistically different from Model 2. In terms of absolute errors, there was not a single econometric model that was statistically different from either the 3-year or 4-year historical average models.

Table 5-20 Results of Out-of-Sample Paired t-Test of Absolute Errors (Models 1, 2, 7, 11, 11-B, 12, 12-B, 13, 13-B, 3-Year Historical Average, and 4-Year Historical Average) for January 2012 through September 2016

	Model 1	Model 2	Model 7	Model 11	Model 11-B	Model 12	Model 12-B	Model 13	Model 13-B	3-Year Hist Avg	4-Year Hist Avg
MAE	1.97	2.30	1.74	1.88	1.89	1.83	1.86	1.76	1.74	2.06	1.98
Model 1	-	0.1778	0.1183	0.6594	0.6719	0.4757	0.5611	0.2685	0.2322	0.7298	0.9614
Model 2		-	**0.0036**	**0.0348**	**0.0338**	**0.0313**	**0.0391**	**0.0047**	**0.0043**	0.4101	0.2796
Model 7			-	0.3202	0.3305	0.4980	0.3674	0.8560	0.9763	0.2062	0.3427
Model 11				-	0.9730	0.6531	0.8910	0.1888	0.2427	0.4970	0.6969
Model 11-B					-	0.7376	0.8748	0.3261	0.2468	0.5156	0.7215
Model 12						-	0.7723	0.2788	0.2441	0.3905	0.5616
Model 12-B							-	0.3126	0.1083	0.4314	0.6261
Model 13								-	0.6817	0.2523	0.3888
Model 13-B									-	0.2242	0.3459
3 Year Hist Avg										-	0.1323
4 Year Hist Avg											-

Note: Bold values indicate statistical significance at a 95% confidence level

Table 5-20 contains the results from the paired t-tests for out-of-sample percent prediction errors for Models: 1, 2, 7, 11, 11-B, 12, 12-B, 13, 13-B, 3-year historical average, and 4-year historical average. Overall, the econometric models and historical average models were generally not statistically different from one another; however, the 3-year historical average was marginally different from Models: 1, 2, 7, and 11-B. Additionally, Model 11 and 13 were marginally different than model 11-B. For the producer concerned with prediction errors as a percent of actual basis, the 3-year or 4-year historical average models would provide a simple form of basis forecasting that would be statistically the same as a more complex econometric model.

Table 5-21 Results of Out-of-Sample Paired t-Test of Percent Errors (Models 1, 2, 7, 11, 11-B, 12, 12-B, 13, 13-B, 3-Year Historical Average, and 4-Year Historical Average) for January 2012 through September 2016

	Model 1	Model 2	Model 7	Model 11	Model 11-B	Model 12	Model 12-B	Model 13	Model 13-B	3-Year Hist Avg	4-Year Hist Avg
MPE	107.11	117.61	109.17	24.80	100.88	54.32	87.06	64.76	76.96	-124.13	-63.01
Model 1	-	0.7541	0.8712	0.1970	0.7615	0.1939	0.3391	0.1903	0.2777	0.1335	0.1871
Model 2		-	0.7385	0.2355	0.6475	0.2785	0.4203	0.2432	0.3499	0.1235	0.1706
Model 7			-	0.2136	0.7112	0.2172	0.3112	0.1990	0.2866	0.1299	0.1810
Model 11				-	0.1446	0.2986	0.2352	0.2707	0.2080	0.3704	0.5362
Model 11-B					-	0.1668	0.5231	0.1126	0.2025	0.1465	0.2048
Model 12						-	0.2374	0.5374	0.2760	0.2605	0.3794
Model 12-B							-	0.2637	0.4858	0.1736	0.2479
Model 13								-	0.2009	0.2286	0.3311
Model 13-B									-	0.1975	0.2842
3 Year Hist Avg										-	0.2170
4 Year Hist Avg											-

Note: Bold values indicate statistical significance at a 95% confidence level

Table 5-21 contains the results from the paired t-tests for out-of-sample percent prediction errors for Models: 1, 2, 7, 11, 11-B, 12, 12-B, 13, 13-B, 3-year historical average, and 4-year historical average. The 3-year historical average model was statistically different, at a 95% confidence level, from Models: 1, 2, 7, 11-B, 12-B, and 13-B. The 3-year historical average model was also marginally different, at an 85% confidence level, from Models: 11, 12, and 13. As shown previously in Table 5-18, the 3-year historical average was the worst performing out-of-sample model in terms of MAPE. If the analyst is concerned with absolute prediction error as a percent of basis, then the notable statistical difference and difference in MAPE would suggest the use of an econometric model in favor of a 3-year historical average model. Additionally, at an 85% confidence level, the 4-year historical average was marginally statistically different from all out-of-sample models with the exception of Model 11.

Table 5-22 Results of Out-of-Sample Paired t-Test of Absolute Percent Errors (Models 1, 2, 7, 11, 11-B, 12, 12-B, 13, 13-B, 3-Year Historical Average, and 4-Year Historical Average) for January 2012 through September 2016

	Model 1	Model 2	Model 7	Model 11	Model 11-B	Model 12	Model 12-B	Model 13	Model 13-B	3-Year Hist Avg	4-Year Hist Avg
MAPE	129.18	145.93	133.60	193.30	143.92	172.78	156.77	155.07	152.68	451.98	370.52
Model 1	-	0.5700	0.7007	0.3023	0.4447	0.2505	0.1100	0.3931	0.3697	**0.0300**	0.0519
Model 2		-	0.6030	0.3371	0.9158	0.4335	0.6760	0.6733	0.7721	**0.0412**	0.0739
Model 7			-	0.2847	0.5046	0.2285	0.0769	0.3626	0.3387	**0.0328**	0.0574
Model 11				-	0.3430	0.4702	0.4828	0.2920	0.3254	0.1103	0.2019
Model 11-B					-	0.3292	0.3550	0.5582	0.6237	**0.0394**	0.0706
Model 12						-	0.5505	0.2923	0.3229	0.0697	0.1276
Model 12-B							-	0.9292	0.7707	**0.0488**	0.0883
Model 13								-	0.7861	0.0509	0.0917
Model 13-B									-	**0.0481**	0.0866
3 Year Hist Avg										-	0.0979
4 Year Hist Avg											-

Note: Bold values indicate statistical significance at a 95% confidence level

Nonparametric Out-of-Sample Comparisons:

T-tests assume parameters are independent and identically distributed. If the known parameters are not independent, then the t-tests can return biased results. An alternative approach to t-tests would be the use of nonparametric comparisons. One example would be to count the frequency that the out-of-sample prediction errors for a model are more accurate than a competing model. This approach was used to compare the absolute errors for the out-of-sample models we tested. Table 5-23 displays the percent of the time that an individual model produces a prediction error greater than a competing model. For example, in row two, column one, we can see that Model 1 was more accurate than Model 2 52.63% of the time. As shown in table 5-23, a majority of the percentages are approximately 50%. The results indicated no notable change in model performance when compared through this nonparametric approach.

Table 5-23 Nonparametric Comparisons of Out-of-Sample Absolute Prediction Errors for January 2012 through September 2016

	Model 1	Model 2	Model 7	Model 11	Model 11-B	Model 12	Model 12-B	Model 13	Model 13-B	3-Year Hist Avg	4-Year Hist Avg
MAE	1.97	2.30	1.74	1.88	1.89	1.83	1.86	1.76	1.74	2.06	1.98
Model 1	-	47.37%	52.63%	47.37%	54.39%	50.88%	47.37%	54.39%	54.39%	45.61%	47.37%
Model 2	52.63%	-	61.40%	63.16%	59.65%	57.89%	61.40%	70.18%	57.89%	63.16%	61.40%
Model 7	47.37%	38.60%	-	45.61%	52.63%	40.35%	50.88%	49.12%	52.63%	43.86%	40.35%
Model 11	52.63%	36.84%	54.39%	-	52.63%	49.12%	52.63%	52.63%	56.14%	47.37%	50.88%
Model 11-B	45.61%	40.35%	47.37%	47.37%	-	47.37%	38.60%	49.12%	54.39%	49.12%	45.61%
Model 12	49.12%	42.11%	59.65%	50.88%	52.63%	-	49.12%	56.14%	57.89%	47.37%	45.61%
Model 12-B	52.63%	38.60%	49.12%	47.37%	61.40%	50.88%	-	52.63%	59.65%	49.12%	49.12%
Model 13	45.61%	29.82%	50.88%	47.37%	50.88%	43.86%	47.37%	-	45.61%	47.37%	47.37%
Model 13-B	45.61%	42.11%	47.37%	43.86%	45.61%	42.11%	40.35%	54.39%	-	49.12%	52.63%
3-Year Hist Avg	54.39%	36.84%	56.14%	52.63%	50.88%	52.63%	50.88%	52.63%	50.88%	-	54.39%
4-Year Hist Avg	52.63%	38.60%	59.65%	49.12%	54.39%	54.39%	50.88%	52.63%	47.37%	45.61%	-

Chapter 6 - Conclusions

In today's environment, developing a reliable expectation of what basis will be in the future is imperative for producers that utilize futures contracts as risk management tools or in derivation of price forecasts for any managerial purposes. With so many unknowns within a complex and intricate global market, many industry participants find themselves searching for the best performing methods for estimating basis.

This study began by comparing econometric models with in-sample estimations. In-sample testing provides the researcher with a foothold understanding the directional impacts that determinants of basis will possess and also which determinants of basis are statistically significant. Lagged basis, weight of the animals, corn futures price, and seasonality were consistently statistically significant across all econometric models. Additionally, choice-select spread, market ready cattle, beef and pork cold storage, and beef and pork retail prices were statistically significant in several of the models depending on the variables included. The inclusion of all variables in Model 11 proved to perform the best in-sample, but this could have been the result of over fitting the data and not true prediction power. We observed the poor performance Model 11 displayed during the out-of-sample testing.

For January 2003 through September 2016, basis averaged around \$0.37/cwt while the MAE for in-sample testing ranged from \$1.05/cwt to \$1.57/cwt. This means the in-sample models produced basis forecasts that were, on average, \$1.05/cwt to \$1.57/cwt different from actual basis. If the most accurate models that can be produced for in-sample estimations are over \$1.00 from actual basis, then the expectation is that involving more unknown values during out-of-sample testing will only diminish the performance of econometric models which is exactly what was observed.

As discussed earlier, the beef industry has undergone many changes over the past several decades. Consolidation of firms, demand growth, and decreases in cowherd size has clearly shown to impact our understanding of the determinants of basis. After conducting Bai-Perron structural change testing, we have attempted to capture some shifts in basis determinants.

The results of the BP tests determined that variables such as weights and corn futures price had less of an impact on basis in more recent years. After 2013, both weights and corn futures price had shifted from being statistical significant to statistically insignificant suggesting that variables impacting the supply of cattle to be less important when forecasting basis. On the contrary, choice-select spread proved to be statistically significant in regimes post 2013. Since the choice-select spread captures the price difference between high quality and low quality beef, this could suggest a growing importance of the impact high quality beef demand could have on basis.

In the models tested, lagged basis was consistently statistically significant after 2005. Lagged basis allows the model to capture the persistence and direction of fed cattle basis. Furthermore, the inclusion of lagged basis allows to model to capture how basis is being impacted by variables that are not included on the right hand side of the equation. More narrowly, the analyst can account for changes in basis levels without having to know specifically what directly caused the changes in basis. With a notable consistency in the statistical significance of lagged basis, we can conclude that the inclusion of lagged basis could be a reliable determinant of basis, especially during periods of high volatility and unpredictability. In recent years, seasonality has shown to be much more important when attempting to understand basis than it has in the past. Several of the regimes that include dates post 2013 data, resulted in large seasonality impacts. After 2013, the monthly variables for quarter 3 and 4 showed to be very negative relative to the default month January and were very statistically significant. As a results of the BP testing exhibited, lagged basis and seasonality showed to be consistent and statistically significant determinants of basis, especially over the past 2 to 3 years.

In-sample estimations outperformed the out-of-sample estimations for MAE and MSE diagnostic measures. For the MPE and MAPE diagnostic measures, the range of mean prediction errors for in-sample and out-of-sample estimations were very similar. Comparison of SSEs was not considered due to the fact that the out-of-sample models only estimated 4 years and 9 months of basis predictions while the in-sample estimated 13 years and 9 months of basis values. In line with our expectations, the in-sample models outperformed the out-of-sample estimations.

The out-of-sample econometric models outperformed the historical average models for all of the diagnostic measures that were examined; however, the prediction errors for the econometric models and the historical average models are not statistically different. Even though the mean errors of the econometric models were smaller than the historical average models, the standard errors for the models were so large that the confidence intervals overlapped; therefore, we can conclude that the simple historical average models are statistically the same as the more complex econometric models. If two models are statistically the same, then this suggests that a practitioner will be just as good off using a simple model rather than a complicated model. The time input to create and the necessary upkeep of an econometric model is not worth the effort if the implementation of the model does not prove a distinct advantage over less time consuming forecasting methods. In hindsight, one should keep in the mind that during this specific out-of-sample prediction period, the beef industry was experiencing some impactful changes. Herd expansion was creating a very tight supply of cattle which lead to record high cash and futures contract prices beyond anyone's expectations. Needless to say, this was a very difficult time period to predict for any price forecasting, especially fed cattle basis. What is apparent, is that there is plenty of room and need for future work in re-assessing use of econometric models to forecast basis.

6.1 Future Research

Due to the inclusion of several variables that are compiled monthly in publicly accessible data (cold storage, cattle on feed, retail meat prices), it would be very interesting to see how these models performed if applied using weekly data. Another factor to consider was that the market ready cattle variable was created using fixed average daily gain schedules which could not realistically capture feedlots' early or late marketings of cattle on feed. If weekly data were available, one should consider allowing for flex time of 4 to 8 weeks to create a more accurate variable to simulate the feedlot's ability to market cattle green, before they reach goal weight, or to hold on to their cattle longer in hope of better prices.

With a larger percentage of marketings using grid pricing, repeating this exercise or similar analyses with negotiated, dressed prices converted to live equivalents would be a worthwhile assessment. Additionally, you could possibly combine the negotiated live prices and negotiated dressed prices to construct a composite negotiated live price, then repeat a similar exercise to see how capturing more of total negotiated transactions impact conclusions drawn here with negotiated live prices.

Comparing national to regional results would provide valuable information for producers in different regions of the country. Since basis is the difference between local cash price and futures contract price, assessing how the models tested during these analyses would perform for different parts of the country would be valuable. These estimations could also be compared to examine how the utilization of negotiated live or negotiated dressed prices would differ across the country.

Within the out-of-sample testing, the forecasts for right hand side variables used only simple and composite lag values for forecast expectations. Focusing more time on producing alternative expectations for the future values used as regressors might improve the prediction accuracy of econometric models.

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Appendix A - Bai Perron SupF(l + 1|l) Results

Table A-1 Model 7 supF(l+1|l) Test

l	New Break	supF(l+1|l)	Pr > supF(l+1|l)
0	130	157.3788	<.0001
1	41	37.6725	0.0447
2	104	49.5156	0.0006
3	64	9.6472	1
4	0	.	<.0001
5	0	.	<.0001

Table A-2 Model 11 supF(l+1|l) Test

l	New Break	supF(l+1|l)	Pr > supF(l+1|l)
0	132	180.1743	<.0001
1	31	255.8743	<.0001
2	65	40.9291	0.3222
3	60	120.0492	<.0001
4	89	151.5027	<.0001
5	0	.	<.0001

Table A-3 Model 12 supF(l+1|l) Test

l	New Break	supF(l+1|l)	Pr > supF(l+1|l)
0	132	110.1974	<.0001
1	42	67.3903	<.0001
2	107	25.3052	0.9977
3	69	9.9568	1
4	85	18.4478	0.9999
5	0	.	<.0001

Table A-4 Model 13 supF(l+1|l) Test

l	New Break	supF(l+1|l)	Pr > supF(l+1|l)
0	131	131.9050	<.0001
1	31	175.8268	<.0001
2	104	21.5960	0.9999
3	59	68.2931	0.0002
4	84	13.7954	1
5	0	.	<.0001