Evaluating Structural Breaks and the Drivers of Structural Change in Live Cattle Basis

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Abstract

Live cattle basis witnessed incredible volatility in recent years leading to questions of structural change and the possibility of decreased hedging effectiveness. If fundamental drivers of live cattle cash and futures prices have changed, cattle feeders and beef packers alike may need to re-evaluate their business, marketing, and hedging plans. Structural breaks can be identified and confirmed using statistical methods while the drivers of those structural breaks can be evaluated using regression models. This research finds evidence that live cattle basis witnessed structural change near the beginning of 2014. Furthermore, results suggest that changes to the live cattle supply chain including regional cash market thinness and a trend towards higher quality beef are among the most important factors driving structural change.

Acknowledgements

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Dedication

I would like to dedicate this Thesis to my wife, Lizbeth Wilder, who constantly reminded me why I chose graduate school and encouraged me to finish strong.

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CHAPTER 1: INTRODUCTION

Since 2014, live cattle cash and futures markets have been extremely volatile leading to rising concerns about futures contract efficacy and broad discussion about current risk management practices. Several factors could be the reason for volatile prices including changes in the cash market structure, changes to Chicago Mercantile Exchange (CME) Live Cattle Futures contract delivery specifications, and the start of a new period of U.S. cattle inventory expansion. However, if a structural break in cattle markets has changed the way cash and futures price interact, basis – the difference between cash and futures prices – could continue to be unpredictable and volatile. A new era of higher basis risk could mean substantially less predictable profit margins for cattle feeders and beef packers across the United States.

Figure 1.1 shows the annual average of weekly nearby live cattle futures prices versus the annual average of weekly live cattle basis. Average basis rose sharply from -\$0.51/cwt in 2013 to \$2.72/cwt in 2014. Basis has remained high, even though futures prices have fallen from an all-time high annual average of \$151.59/cwt in 2014 to a more stable annual average of \$118.23 in 2017. This measure does not necessarily mean that basis will remain highly positive, but it does support the previous argument that underlying factors influencing basis may have changed.

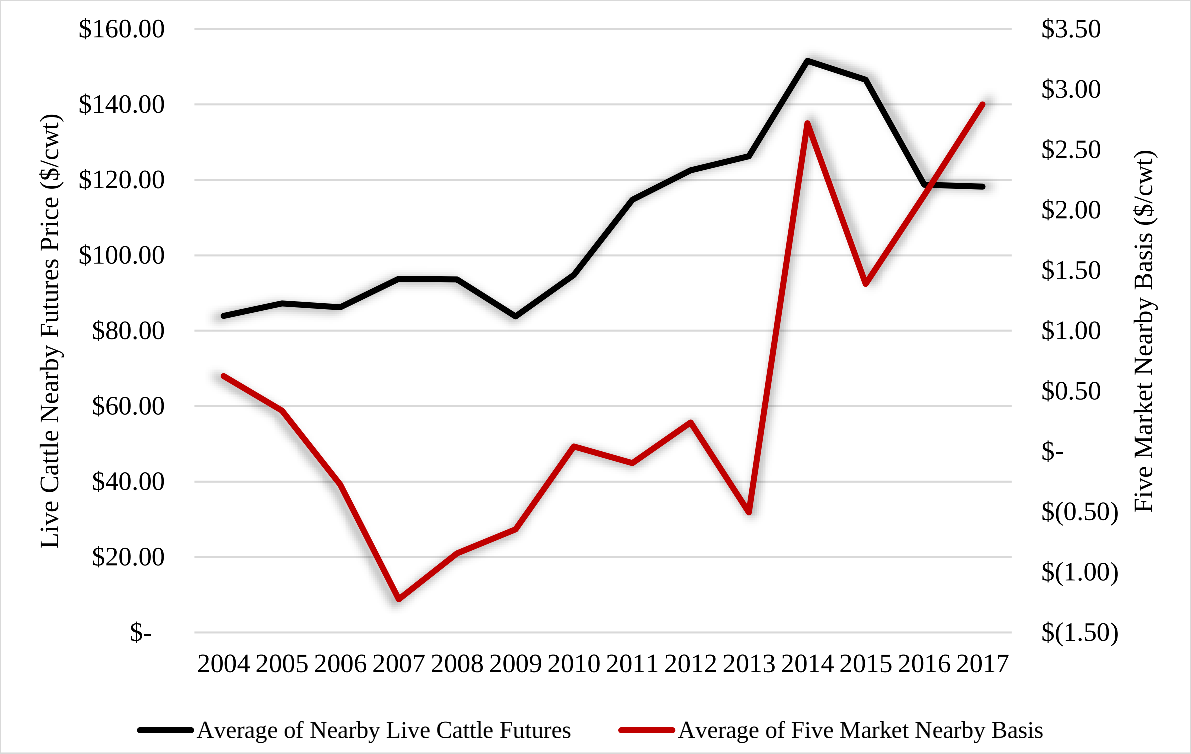

Figure 1.1 Average Annual Live Cattle Futures vs. Average Annual Nearby Live Cattle Basis

Still, the average basis level is less important to hedgers than basis predictability. A Wall Street Journal article (Gee, 2016) called livestock markets the “Meat Casino” due to the rapid rise and fall of futures prices between 2014 and 2016. However, as a percentage, basis has been even more volatile. Wilder, Tejeda and Johnson (2018) note that basis variance for the 2014-2017 period was more than 250% larger than basis variance during the 2004-2013 period. Cash and futures price variance were only 44% and 35% higher over the same period. This unprecedented basis variation (National Cattlemen’s Beef Association, 2016) is what raises the largest concern for commercial operations. If this concern is valid, then cash and futures prices may no longer move together.

Even if cash and futures prices still move together, a significant structural break could mean that important supply and demand factors now impact basis differently. In fact, timehonored assumptions about how important factors such as average slaughter weights and quality grades affect cattle and beef prices could now be up for debate. This study seeks to quantify changes to important supply factors before and after 2014 and discover the variables whose impact on basis has changed the most.

1.1 Objective

The objective of this study is two-fold: (1) to determine if structural changes to basis exist and (2) to evaluate the drivers of any structural change to basis. The results of these tests have both economic and practical implications. Economically it's important to understand how the live cattle market is changing. If structural break tests can identify a breakpoint in basis and estimation models can determine which variables are most likely to have caused the break, then further research can dive into why those influential factors are becoming so important to the cattle supply chain. Practically, a cattle feeder, beef packer or trader could take the results of this study and use them to adjust their personal marketing and hedging strategies, potentially improving their bottom-line.

1.2 Organization of Thesis

This thesis is comprised of six chapters, including the introduction. Chapter 2 outlines previous literature related to live cattle basis, structural break testing, and basis estimation. Chapter 3 discusses the theoretical models used to complete this research. Chapter 4 presents the data used for all analyses in this study and describes the empirical basis estimation models used to evaluate drivers of structural change. Chapter 5 includes a full report of results from structural break testing and basis estimation models. Finally, Chapter 6 brings forth conclusions and implications of this study along with suggestions for further research.

CHAPTER 2: LITERATURE REVIEW

In this chapter, previous literature that helped guide this study and that is vital for understanding the current status of live cattle basis research is reviewed. Foundational information about cash prices, futures prices and the cash-futures price relationship, especially as they relate to non-storable commodities, is discussed in Section 2.1. Section 2.2 is focused on issues relating to structural changes in live cattle markets and presents a definition for a structural break. Research attempting to estimate basis and sources of basis volatility is presented in Section 2.3. Lastly, the relevance of this work and its contribution to the literature is argued in Section 2.4.

2.1. The Cash-Futures Relationship

Discussion about basis, defined herein as the cash price minus the futures price, roots back to Keynes' (1923) theory of normal backwardation and Working's (1948, 1949, 1953) theories of price storage and inverse carrying charges. These early works rely on the concept of "carrying costs" which is essentially the cost associated with storing commodities. However, the non-storable nature of livestock commodities prevents the general application of these theories to live cattle markets (Naik and Leuthold, 1988). While there is not a generally agreed upon theory that explains price movements for non-storable commodities, the following presents an interpretation of basis as it relates to live cattle.

Cash price is a result of current demand and supply conditions (Leuthold, 1979). The futures price can be interpreted as the consensus of what traders expect the cash price to be at a particular time in the future, given currently available information (Leuthold, 1974). Thus, the difference between futures and cash prices is an indication of the expected movement in cash price over time, which will occur because of shifting demand and supply conditions

(Leuthold, 1979). As a result, live cattle basis can be positive or negative, depending upon whether cash prices are expected to rise or fall and should converge to zero during the delivery month (Leuthold, 1979).

This is important because understanding basis and the factors which affect its behavior are fundamental for successful commodity production and optimal marketing decisions (Garcia, Leuthold, and Sarhan, 1984). Commercial firms and traders who take position (buy or sell) in either the cash or futures market and reverse position (sell or buy) in the other market are called hedgers. Hedgers use the futures market to replace price risk, or the risk associated with price changes in the underlying cash (or futures) prices, with basis risk, which is the risk associated with changes in the price spread between cash and futures prices. The idea is that, since cash and futures prices should react similarly to supply and demand shocks and converge during the delivery month, basis risk should be smaller than price risk. Thus producers who hedge have greater confidence in the final prices they will receive for their commodities and end-users have greater confidence in the price they will pay for those same commodities. This in turn leads to greater confidence in profit margins for both groups of hedgers. However, unexpected changes in basis can create additional basis risk and make hedging less desirable (Garcia, Leuthold, and Sarhan, 1984). Therefore, a long-term move towards higher basis variability would directly equate to higher basis risk and lower hedging effectiveness.

A predictable hedging tool is vital to the success of commercial operations. When basis becomes highly variable, market participants more actively seek ways to reduce volatility. Unprecedented fed cattle basis variation in 2016 led the National Cattlemen’s Beef Association (NCBA) to raise concerns over the viability of the futures contract as a hedging tool (NCBA, 2016). Since then, researchers have taken several approaches to explaining the variation and providing solutions. Couleau, Serra and Garcia (2017) looked at high frequency trading as a cause of the variability. Ultimately, they agree with the notion that fundamentals were a driving factor of the increased variance in 2015. Coffey, Tonsor, and Schroeder (2018) evaluated changes to basis prediction error and studied how market factors affect the major cattle production regions differently. They find that the regional share of negotiated cash cattle trade and delivery costs are a primary driver of regional differences for basis prediction error, which has been higher since 2014. Thompson et. al. (2018) even presented a possible solution in the form of implementing a wholesale beef futures contract based on the boxed beef cutout value. Still, the best long-term solution for decreasing basis variability is not obvious. Instead of trying to solve the problem, this paper will focus on better understanding when and why basis became unstable.

2.2 Identifying and Evaluating Structural Change

Before addressing what caused basis instability to increase, it is necessary to pinpoint when basis levels became unstable. These levels can be determined by testing for a structural break. The existing body of literature is not explicit about what constitutes a structural break, but the most common definition is a significant change in regression parameters (Maddala and Kim, 1998). Structural breaks typically occur after meaningful change to the supply chain or demand structure of a commodity. Several fundamental changes in the fed cattle marketing chain have been addressed by research papers in the last year. This section presents an overview of those changes and pertinent research which helps determine how to test for a structural break.

2.2.1 Recent Fundamental Changes to Fed Cattle Markets

The most complete review of recent fundamental changes in the fed cattle market can be found in a report submitted by Schroeder and Coffey to the National Cattleman's Beef Association (NCBA) in 2018. A major topic is the declining volume of cash cattle trade. Negotiated cattle purchases represented 38% of total volume during 2005 but declined steadily to 11% by 2017 (USDA AMS, 2018). The report also notes a trend towards a greater percentage of cattle grading Choice or better and high live slaughter weights. They further hypothesize that regional differences in quality grade and slaughter weights may account for regional price differences. The live cattle futures contract has been amended to reflect both of these trends[1].

Subsequently, Schroeder, Tonsor and Coffey (2018) took a deeper look at recent shifts, focusing on the implications of thinner cash trade in the market. Their paper views basis error as the difference between current week basis and the historical three-year average basis for the same week, which was used as a proxy for expected basis. Using their methodology, basis error for most major regions more than doubled from 2013 to 2014 and has remained high. Their finding supports the notion of a structural break in basis variability.

Additionally, Schroeder, Tonsor and Coffey (2018) note that increased usage of branded beef programs and sales made using quality grade grid pricing increases commercial producers' exposure to increased basis risk from movement in the Choice/Select spread[2]. They are also the first authors to utilize the Commodity Futures Trading Commission's (CFTC) weekly disaggregated Commitment of Traders (COT) report to study live cattle

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[1] An overview of changes to the live cattle futures contract can be found online at https://www.uidaho.edu/-/media/UIdaho-Responsive/Files/cals/programs/idaho-agbiz/livestock-markets/live-cattle-delivery.pdf

[2] The Choice/Select Spread represents the premium offered for cattle graded USDA Choice versus USDA Select.

basis. The COT report provides a weekly breakdown of the types of traders holding positions in a select group of futures contracts. Disaggregated COT trader categories and descriptions can be viewed in Table 1.1. One conclusion they make is that only about 25% of long open interest in live cattle futures is responding to short-term market signals. Therefore, short hedgers (i.e. cattle feeders) may have a difficult time finding liquidity to exit their positions. These conclusions mean that changes in the Choice/Select spread and changes in the cumulative percentage of open interest held by commercial hedgers, non-reportables and other reportables could help explain additional basis estimation error.

Table 1.1 Description of Trader Categories in the CFTC Disaggregated COT report

1. Producer/Merchant/ Processor/User	An entity that predominantly engages in the production, processing, packing or handling of a physical commodity and uses the futures markets to manage or hedge risks associated with those activities.
2. Swap Dealer	An entity that deals primarily in swaps for a commodity and uses the futures markets to manage or hedge the risk associated with those swaps transactions. The swap dealer's counterparties may be speculative traders, like hedge funds, or traditional commercial clients that are managing risk arising from their dealings in the physical commodity.
3. Managed Money or "Money Manager"	A "money manager," for the purpose of this report, is a registered commodity trading advisor (CTA); a registered commodity pool operator (CPO); or an unregistered fund identified by CFTC. These traders are engaged in managing and conducting organized futures trading on behalf of clients.
4. Other Reportables	Every other reportable trader that is not placed into one of the above three categories is placed into the "other reportables" category.
5. Non-reportables	Traders whose holdings do meet the threshold for mandatory reporting. Generally small speculative traders.
	Source: United States Commodity Futures Trading Commission (CFTC)

The changes noted in these studies regarding the live cattle marketing system provide an argument a structural break has occurred. The remainder of this section is focused on outlining structural break and basis estimation tests that are available and which ones are best suited to this research.

2.2.2 Breaking Down Structural Break Tests

There are numerous statistical tests that can be used to evaluate structure change (Maddala and Kim, 1998), with the earliest tests for structural breaks in economic literature rooting back to Chow (1960). Still, the existing body of literature is not explicit about what constitutes a structural break. For this study, structural breaks are defined as a significant change in regression parameters. According to Maddala and Kim (1998), structural break tests can be grouped into four categories:

(i) Known break points versus unknown break points
(ii) Single break versus multiple breaks
(iii) Univariate versus multivariate relationships
(iv) Stationary versus nonstationary variables

Known break points exist when the exact point in time an event occurred is certain. A relevant example would be testing differences in the live cattle futures contract before and after a specific change in contract specifications. Break points are considered unknown when the exact point in time the break occurred is uncertain. Based on those definitions, literature about tests that account for an unknown break point is outlined in the following sections.

The difference between a single break and multiple breaks is straight forward. Has the data broken from its trend once or more than once? Usually this decision can be made based on visual appraisal but can also depend on how volatile the series in question is. For simplicity and because an aim of this paper is to determine whether higher basis variability is a long-term change, this research will primarily focus on tests with a single structural break.

Univariate versus multivariate tests is also a simple modeling decision. Does the research question involve a single variable or several? In this case, basis is a univariate series.

The most complex point is stationarity versus non-stationarity. A stationary time series is one whose properties do not depend on the time at which the series is observed

(Hyndman and Athanasopoulos, 2018). Further, if cash and futures prices are cointegrated, meaning a linear combination of the two series is stationary (Hyndman and Athanasopoulos, 2018), then basis is, by definition, stationary.

Multiple tests exist for determining stationarity of a time series. One of the simplest is testing for a unit root. If a unit root exists, then the series has a stochastic trend and is somewhat unpredictable. The two most common tests for a unit root are the Augmented Dickey-Fuller (ADF) (1979) and Phillips-Perron (PP) (1988) tests. These tests assume a null hypothesis that a unit root exists, meaning that a rejected null hypothesis points to stationarity. ADF tests are most often used in fed cattle literature. Coffey, Tonsor, and Schroeder (2018) use an ADF test to show that regional time series of basis prediction error are stationary, Parcell, Schroeder and Dhuyvetter (2000) use a Dickey-Fuller test to test basis stationarity and Goodwin and Schroeder (1991) use an ADF test to check for unit roots in regional fed cattle cash prices.

Another way to determine the existence of a unit root is to assume stationarity as the null hypothesis. The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (1992) assumes a null hypothesis of stationarity and looks for evidence that the null is false. The KPSS test can also help determine the appropriate number of differences required to achieve stationarity. An early indicator of possible structural change occurs when stationarity tests (Such as KPSS) and unit root tests (ADF, PP) lead to contradictory results (Iván and Zsolt, 2016). Therefore, it is common to run a KPSS test and an ADF test when checking for stationarity of a time series.

2.2.3 Testing for Structural Change

It is assumed that live cattle basis is stationary, univariate and has an unknown break point which motivates a review of structural break literature. Structural break tests root back to the Chow test (1960), which was developed to test the null hypothesis of parameter constancy against the null hypothesis of a known break point. The Chow test is taught in many introductory statistics courses as a relatively simple way to see if an economic relationship remains stable in two separate periods of time. In the same year, Quandt (1960) discussed testing the null hypothesis of constant coefficients more generally, where structural change occurred at some unknown time and the error variance is allowed to change.

Since the early tests by Chow (1960) and Quandt (1960), one of the most important advancements for testing structural breaks is the cumulative sum, or CUSUM, test. The CUSUM test is one of several classes of structural break tests that tests whether or not a break exists and identifies the location of the break (Maddala and Kim, 1998). Variations of the CUSUM test have become widely available for economists to study structural breaks. The common CUSUM test is for general alternatives including a single break and is mainly aimed at detecting systematic movement of coefficients. The CUSUM of squares test proposed by Brown, Durbin and Evans (1975) uses recursive residuals and is more widely applicable. Ploberger, Kramer, and Alt (1989) and Kramer, Ploberger and Alt (1988) made extensions to the test for models with lagged dependent variables and Kao and Ross (1992) made extensions for models with serially correlated distributions. Maddala and Kim (1998) notes that a drawback of the CUSUM tests is that they have asymptotically low power against the instability in the intercept, but not the entire coefficient vector. Ploberger, Kramer, and Kontrus (1989) address the CUSUM power problem and propose a fluctuation test based on successive parameter estimates rather than on recursive residuals. They derived the limiting distribution of the test statistic by Monte Carlo methods and show that their fluctuation test has nontrivial local power irrespective of the particular type of structural change. Later, Ploberger and Kramer (1992) extended the CUSUM test to OLS residuals making the test simpler to both execute and interpret.

Around the same time, Andrews (1993) improved upon the model introduced in Quandt (1960) by deriving the asymptotic distribution of the Quandt test for one-time structural change with an unknown change point, as well an analogous Wald and Lagrange Multiplier tests (Maddala and Kim, 1998). Andrews (1993) shows his Sup F test, or Max Chow test, has better power properties than the CUSUM test and the fluctuation test. The F test also allows for testing a structural break in non-linear models. Andrews and Ploberger (1994) expanded on the initial research, developing tests with stronger optimality properties than those in Andrews (1993). If the F test and OLS-based CUSUM test show the same results, a structural break has almost definitely taken place.

More recently, there has been a surge of interest in recovering the date of a shift if one has occurred or in methods which allow for several shifts at once (Zeileis et. al. 2003). Bai (1997) studied the least squares estimation of a change point in multiple regressions, then Bai and Perron (1998) developed a model to evaluate and test linear models with multiple structure change. Hawkins (2001) fitted multiple change point problems to data with differing statistical distributions and Sullivan (2002) attempted to detect multiple change points from clustering individual observations. Bai and Perron (2003) further developed on the literature, mainly their own test which originated in 1998, by addressing issues related to practical application of the test. Their adjusted test is well recognized and highly used in economics for both determining if there were multiple structural breaks and when they occurred.

By utilizing a combination of CUSUM-type tests, F tests and multiple structural break tests, this research will confirm to a high degree of certainty whether live cattle basis witnessed a structural break and when that break occurred.

2.3 Estimating Live Cattle Basis

Regardless of whether statistical tests reveal structural breaks in basis, it’s important to identify why live cattle basis has become more volatile. Knowing the fundamental drivers of basis can help hedgers, marketers and traders react to market conditions in a timely manner. If there actually has been a recent structural change, then fundamental drivers of basis may have changed. A second major goal of this study is to build estimation models for live cattle basis to identify variables whose impact has changed in recent years.

2.3.1 Previous Literature on Estimating Live Cattle Basis

The bulk of literature on live cattle basis estimation and forecasting roots back to Leuthold (1979) and Tomek (1980) who empirically confirm that supply variables have an impact on the predictability of live cattle basis. Their work formalized the early notion that basis is a function of the expected shift in supply. This review will evaluate the supply factors included in basis estimation models, which ones were found to be significant, and the methods used to create accurate estimates.

Leuthold (1979) attempted to estimate monthly basis for the nearby futures contract and the next three deferred futures contracts. The paper found basis was progressively easier to estimate farther into the future. Leuthold noted that effects from factors such as commercial slaughter volume were positive but insignificant, while cattle on feed reports and seasonal variables had mixed results. Corn, feeder steer and fat cattle prices were all significant explanatory variables. Tomek (1980) empirically confirms the model built in Leuthold (1979) while rebuilding the estimating equation to emphasize seasonality. Tomek (1980) further argued that cash prices and are not necessarily related to more distant futures contract prices. This can be interpreted to mean that nearby futures have the greatest explanatory power in estimation models. More recently, Parcell, Schroeder, and Dhuyvetter (2000) evaluated additional fundamental factors and determined that corn prices and changes in the Choice/Select spread affect basis, while changes in the level of captive supplies[3] had no statistical or economic impact. These papers have been heavily cited and are widely used as a baseline by researchers when looking at which variables to include in a fed cattle basis study.

Researchers have also used their ability to estimate nearby basis as a barometer for basis volatility. Liu et al (1994) found that a lagged futures spread and lagged basis have more predictive power than supply and demand factors[4] when evaluating nearby basis. A lagged futures spread refers to the difference between nearby futures and the deferred contract for the preceding period. Their study also notes open interest and delivery costs[5] as significant factors to include in the model. By studying various modeling options, Liu et al. (1994) broadened the scope of previous research.

A common producer practice is to use a historical average of basis as a quick estimate of expected basis. Tonsor, Dhuyvetter, and Mintert (2004) expanded on that process by using

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[3] Captive supplies were calculated as the quantity of cattle marketed through forward contract agreements as a percentage of total head marketed.

[4] This study used commercial beef slaughter volume, cattle on feed numbers, and prices of substitutes for supply and demand factors.

[5] The Consumer Price Index (CPI) was used as a proxy.

different length moving averages of historical basis as a predictor. They found that including current basis levels can improve estimate accuracy, especially with a short forecast horizon. This paper is particularly interesting because it requires no data other than historical basis and is relatively simple to implement.

Most recently, Coffey, Tonsor, and Schroeder (2018) proposed a framework to analyze basis prediction errors across the five major United States Department of Agriculture (USDA) Livestock Mandatory Reporting (LMR) regions[6]. Their model showed that delivery costs[7], changes in the share of negotiated cash trade, and a ratio of the live cattle price versus the corn price had an impact on regional basis. They also note the importance of considering price impacts to these regions separately due to the local nature of basis. This piece of literature is extremely important for several reasons. Primarily, it is the first major paper to utilize LMR data for live cattle basis estimation. Pendell and Schroeder (2006) found that regional fed cattle prices became more cointegrated following LMR. LMR is also responsible for providing broader availability of data that can be used both by market participants and academic researchers. Coffey, Tonsor, and Schroeder (2018) also establishes that regional differences impact the explanatory variables for fed cattle basis.

Beyond the raw forecastability of basis, researchers began to study basis risk itself in the 1980's. Garcia, Leuthold and Sarhan (1984) used a variate difference approach to evaluate the amount of non-systematic variation in basis. They used the CPI, a livestock cycle ratio, and seasonal and regional dummy variables to account for systematic risk. They found evidence of significant variability in the unsystematic basis component. Naik and

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[6] The five USDA LMR regions are: Colorado, Iowa/Minnesota, Kansas, Nebraska, and Texas/Oklahoma/New Mexico

[7] Average hourly earnings of employees in the trade, transportation, and utilities industry, as reported by the Bureau of Labor Statistics were used as a proxy

Leuthold (1988) also studied basis risk but adjusted their model to account for the fact that producers can choose both when to place[8] and when to market[9] cattle. More importantly, their study introduces maturity basis risk and a speculative component of maturity basis risk to the literature. They suggest that if the absolute value of a correlation coefficient between cash and futures prices for a particular futures contract is different during the maturity month than otherwise, then there is additional basis risk as the contract nears expiration. Further, they suggest that if a regression of cash prices against futures prices during the delivery month returns a correlation coefficient different than one, then speculative risk exists during the delivery month. Their empirical study showed that both maturity basis risk and a speculative component to maturity basis risk exist in cattle basis. Together, these seminal papers on basis risk helped shape future research on basis for non-storable commodities both by indicating the existence of unsystematic variability and laying a foundation for how to evaluate it.

Also relevant to the discussion on basis estimation are a few problems associated with the cash and futures prices themselves. Even though LMR has greatly improved the available cash data, cash price reporting can still be inconsistent as the majority of negotiated cash sales take place on Wednesday, Friday or Saturday (USDA AMS). This affects the price discovery process as futures contracts are negotiated and traded every weekday. Additionally, live cattle futures have been found to be inefficient by several researchers. Most notably, Sanders, Garcia and Manfredo (2008) found that deferred futures contracts provide declining amounts of unique information at the two, four, six, eight, and ten-month horizon and no new information at the twelve-month horizon. More recently, Kristoufek and

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[8] "Placing" cattle refers to placing them on a feedlot.
[9] "Marketing" cattle refers to selling them for slaughter.

Vosvrda (2014) studied 25 different commodity futures prices between 2000 and 2013 and found live cattle and feeder cattle futures to be the least efficient using their proposed Efficiency Index (see Kristoufek and Vosvrda [2014] for details). With this information, we can conclude that fed cattle markets are complex and there will be limitations to even the best estimation models.

2.3.2 Time Series Methods

Before developing an estimation model, it is important to evaluate the most commonly used models in live cattle basis research against the alternatives. Most research to date, as described in the previous section, has utilized Ordinary Least Squares (OLS) regression or simple moving average (SMA) methods. While these are lauded for their relative simplicity, this section explores other econometric methods which could be a better choice.

In a recent thesis, Linnell (2017) evaluated the fed cattle basis forecast performance of Box-Jenkins autoregressive integrated moving average (ARIMA), vector autoregressive (VAR) and vector error correction (VEC) models. Linnell (2017) concluded that simpler models provide the most accurate forecasts with ARIMA and VAR models consistently outperforming at nearby horizons. Together, these methodologies are considered an extremely rigorous set of forecasting and estimation tools.

ARIMA methods provide accurate estimates based on the series itself by incorporating autoregressive (AR) and moving average (MA) techniques. Alone, an AR model estimates the variable of interest using a linear combination of past values of that same variable (Hyndman and Athanasopoulos, 2018). An MA model uses past errors in a regression-like model to predict future values. An ARIMA model combines the two methods and adds differencing to address the series' unit root and obtain a potentially more reliable estimate. Unfortunately, ARIMA models are univariate and would not allow for the study of how a set of variables affect changes in basis. Therefore, it cannot be used for the current research.

VAR and VEC methods solve that problem by incorporating an entire vector of predictive variables. A traditional OLS regression is unidirectional, meaning the dependent variable is influenced by the independent variables, but not vice versa (Hyndman and Athanasopoulos, 2018). In a VAR or VEC model, all variables are treated as if they are endogenous and influence each other equally. This is useful in the case where all variables affect each other. A VAR model requires that time series included in the vector are stationary, while a VEC model can handle time series that are non-stationary, but cointegrated. While these methods may provide very accurate estimates, they are not appropriate when attempting to determine a unidirectional impact.

Since ARIMA, MA, VAR, and VEC models are not appropriate, traditional OLS regression is a better option. However, OLS regressions present a major drawback for time series models that have autocorrelation, which is the linear relationship between lagged values of a time series (Hyndman and Athanasopoulos, 2018). The existence of autocorrelation can result in estimates that are not minimum variance and can be identified using a Durbin-Watson test or Ljung-Box Q test. Autocorrelation can also be determined using autocorrelation function (ACF) plots known as a correlogram (Hyndman and Athanasopoulos, 2018). The simplest to use of the three autocorrelation tests, and the one used in a recent study of live cattle basis (Coffey, Tonsor and Schroeder, 2018), is the Durbin-Watson test. If autocorrelation is found, a sufficient solution is to use a Generalized

Least Squares (GLS) model. However, if autocorrelation is not found, OLS is still the best, linear, unbiased estimator (BLUE).

After considering the existence of autocorrelation, the next question is whether basis in one region has a direct impact on basis in other regions. If this presumption is a valid concern, it can be addressed by estimating each region basis equation collectively in a system. The groundwork for such combined modeling roots back to Zellner (1962) with the concept of Seemingly Unrelated Regression (SUR) methods. In the procedures outlined by Zellner, "regression coefficients […] are estimated simultaneously by applying Aiken's generalized least squares to the whole system of equations" (1962, p. 348). Since the Aitken estimator differs from the OLS estimator, Zellner argues that "it must be the case that the Aitken estimator is more efficient" (1962, p. 353).

2.4 Contribution to the Literature

While previous literature about live cattle basis is expansive, this paper provides insightful contributions to the discussion. In addition to including an updated chronology of major live cattle basis research, this is the first study to address the notion of structural change in basis by applying statistical methods. Alone, the confirmation or dismissal of a true structural change provides clarity to the broader discussion of how market participants should react to current market conditions. Beyond determining a structural break, this research also evaluates major supply factors in an attempt to identify the variables which led to rapid change in basis levels. Other researchers in the past two years provided valuable input by identifying changing trends such as a larger percent of U.S. cattle grading Choice or better and defining the percentage of liquid long positions in live cattle futures. This study expands on those contributions by including them in estimation models and drawing meaningful conclusions about their impacts to live cattle basis. Moreover, this is the first study to investigate regional basis values applying the SUR model. The results of both the structural break tests and estimation models can assit producers, merchants and traders alike to re-evaluate their business, marketing and hedging plans.

CHAPTER 3: METHODOLOGY

This methodology chapter describes theoretical models used to complete this research. The framework for live cattle basis structural break testing is laid out in Section 3.1 while the framework for estimating live cattle basis is described in Section 3.2.

3.1 Structural Break Testing

As described in the literature review, there are a variety of ways to test for a structural break. For rigor, this paper evaluates structural change in five major ways. First by testing for stationarity in each basis time series and looking for discrepancies between unit root and stationarity tests. Second by looking at cointegration of cash and futures variables. The last three tests may provide strong economic evidence of a structural break and if significant, determine the most likely breakpoints. The tests applied are:

1. The OLS-CUSUM based Fluctuation test (Ploberger and Kramer, 1992)
2. The F Test (Andrews 1993; Andrews and Ploberger 1994)
3. The Multiple Structural Break test (Bai and Perron, 1998; 2003)

3.1.1 Stationarity Tests

This study will first check for stationarity in basis series using Augmented Dickey Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. According to Maddala and Kim (1998), the augmented Dickey-Fuller (ADF) test tests for the null hypothesis of a unit root while the KPSS test assumes stationarity as the null hypothesis. Since the break is expected to occur at or near the start of 2014, stationarity will be checked for the full period and pre- and post-2014 timeframes separately. If stationarity is rejected in the long run, but it exists in both shorter periods, the case for a structural break is made stronger.

3.1.2 Cointegration Tests

The second test in this study is to confirm results of cointegration between live cattle futures and all different market cash prices. Cointegration was first defined by Granger (1981) and further developed upon by Engle and Granger (1987). Johansen (1988; 1991) expanded on the original model allowing applications to Vector Autoregressive (VAR) models. There is a significant amount of literature which uses cointegration to examine the relationship between futures and cash prices including Chowdhury (1991), Fortenbery and Zapata (1993), Lien (1996) and Bekiros and Diks (2008). Cointegration tests are also commonly used in fed cattle literature to evaluate regional cash price differences as evidenced by Goodwin and Schroeder (1991) and Pendell and Schroeder (2006).

This paper follows the methodology developed by Johansen (1988, 1991) and Johansen and Julius (1990). Ultimately, if the test statistic is larger than the one percent critical value, the null hypothesis of no cointegration is rejected. Conversely, if cointegration is rejected, then it is possible that cash and futures prices do not respond to the same information and that basis risk could be larger than price risk. It is important to note this test is done following the previous one because two time series can be non-stationary and not cointegrated, but for this case cannot fail to be cointegrated and non-stationary.

3.1.3 Framework for Structural Break Testing

Next, this paper follows structural break testing procedures as outlined by Zelies, Kleiber, Kramer and Hornik (2003). They note that, in general, structural break testing is "concerned with testing the hypothesis that the regression coefficients remain constant

$$H_0: \beta_i = \beta_0 \quad \forall \quad (i = 1, \dots, n)$$

against the alternative hypothesis that at least one coefficient varies over time." (2003).

Zelies, Kleiber, Kramer and Hornik (2003) outline two primary frameworks for testing structural change: (i) fluctuation tests that do not assume a particular pattern of deviation from the null hypothesis and (ii) *F* statistics that are designed for a specific alternative.

The generalized fluctuation testing techniques proposed by Zelies, Kleiber, Kramer and Hornik (2003) include formal significance tests yet are designed to present results graphically. Graphic representation allows fluctuation test results to be easily interpreted by an audience rather than limiting understanding to individuals trained in statistical methods. Such graphical representation is possible because the standard linear model developed by Zelies, Kleiber, Kramer and Hornik "is fitted to the data and an empirical process is derived that captures the fluctuation either in residuals or in parameter estimates." (p. 3, 2003)

In addition, Zelies, Kleiber, Kramer and Hornik (2003) provide a formal interpretation of the fluctuation tests hypotheses used in their statistical software package:

> *"Under the null hypothesis these [structural break tests] are governed by functional central limit theorems (see Kuan and Hornik, 1995) and therefore boundaries can be found that are crossed by the corresponding limiting processes with fixed probability under the null hypothesis. Under the alternative hypothesis, fluctuation in the process is in general increased. Also, the trajectory of the process often sheds light on the type of deviation from the null hypothesis such as the dating of structural breaks." (p. 3,2003).*

Zelies, Kleiber, Kramer and Hornik (2003) discuss three main versions of the fluctuation test have been established following the initial groundwork laid with the classical CUSUM test (Brown, Durbin, and Evans, 1975). First, the recursive estimates test (Ploberger, Kramer, and Kontrus, 1989) which solved the parameter power problem of the original test. Next the OLS-based CUSUM test was established by Ploberger and Kramer (1992) after discovering the test also worked using OLS residuals. Last and most recently, the MOSUM (moving sum) and moving estimates tests developed by Chu, Hornik and Kuan (1995).

The OLS-based CUSUM test (Ploberger and Kramer, 1992) and the *F* statistics (Andrews 1993; Andrews and Ploberger 1994) test against a single-shift alternative of unknown timing will be used in this research to determine whether or not a break occurred. Test procedures follow Zelies, Kleiber, Kramer and Hornik (2003).

Although the OLS-based CUSUM test presents a general location for where the break occurred, an additional measure is required to confirm the timing of changepoints. Structural break dating methods proposed by Bai and Perron (2003) are used here for expediency. They present a dynamic programming algorithm for pure and partial structural change in the context of an OLS regression. This algorithm finds the “optimal” structural break point by minimizing the Bayesian Information Criterion, or BIC. The BIC was developed by Gideon Schwarz (1978) to solve the problem of choosing the appropriate dimensionality of a model that will fit a given set of observations. Here it is used to confirm, with some degree of certainty, when structural break in live cattle basis most likely took place. See Schwarz (1978) for more detail on the BIC or Zelies, Kleiber, Kramer and Hornik (2003) for more detail on the general structural break testing procedures used in this paper.

3.2 Basis Estimation

The literature review presents a sound argument for using Ordinary Least Squares (OLS) or conversely, Seemingly Unrelated Regression (SUR) modeling procedures for basis estimation. The basic OLS model is

$$\boldsymbol{Y} = \boldsymbol{X\beta} + \boldsymbol{e}$$

where $\boldsymbol{Y}$ is a n^{10} x 1 matrix of dependent variables, $\boldsymbol{X}$ is an n x k^{11} matrix of explanatory variables, $\boldsymbol{\beta}$ is a k x 1 matrix of parameters and $\boldsymbol{e}$ is a n x 1 matrix of error terms. Under the Gauss-Markov Theorem (Griffiths, Hill and Judge, 1993), the OLS regression equation will be the best linear unbiased estimator of $\boldsymbol{Y}$ if under the following assumptions:

1. $E[\boldsymbol{e}] = 0$; The error terms are unbiased.
2. $E[\boldsymbol{ee}'] = \sigma^2 I$; The variance of regression estimates is the same as actual sample variance. If this is true, or if the variance of regression estimates is the smallest compared to all other alternatives, then OLS is the best estimator.
3. *No exact linear relationship exists among X_i's.* In other words, the matrix is invertible and the regression is mathematically possible.
4. $\boldsymbol{Y} = \boldsymbol{X\beta} + \boldsymbol{e}$. A linear model is assumed.

Many previous articles estimating live cattle basis found autocorrelation in the error terms. In other words, error terms influence each other causing assumption 2 to be violated. If this is true, then the OLS estimator is no longer best. Autocorrelation can traditionally be found using the Durbin-Watson test statistic (see Durbin and Watson, 1950; 1951). However,

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[10] n refers to the number of rows in the matrix
[11] k refers to the number of columns in the matrix

the study's explanatory variables include a lagged dependent variable, so the Durbin H test (Durbin, 1970) must be used instead. That equation is:

$$h = \hat{\rho}\sqrt{\frac{n}{1 - n \cdot var(b_1)}} \sim N(0,1)$$

Where b_1 is the parameter estimate corresponding to the lagged dependent variable, $\hat{\rho}$ is an estimated serial correlation coefficient, and n is the number of observations in the sample. This test cannot be calculated if $n \cdot var(b_1) > 1$. For this case, Durbin suggests an asymptotically equivalent test which involves regressing the least squares residuals on their lags and the X matrix which includes the lagged dependent variable (for more, see Durbin, 1970). If the least squares alternative is applied the main focus is on whether or not the lagged dependent variable has a statistically significant coefficient. When the coefficient is significant, autocorrelation is likely to exist.

Assuming there is no autocorrelation in the models after incorporating a lagged dependent variable, and assuming that basis in one region impacts basis in another region, the SUR model is more appropriate. The SUR procedures in the paper follow the outline provided by Henningsen and Hamann (2007). Here, a system of *G* equations is considered, where the *i*th equation is of the form

$$y_i = X_i\beta_i + e_i, i = 1,2, \dots, G,$$

where y_i is a vector of the dependent variable, X_i is a matrix of the exogenous variables, β_i is the coefficient vector and e_i is a vector of the disturbance terms of the *i*th equation (Henningsen and Hamann, 2007). Therefore, the stacked system can be shown as:

$$\begin{bmatrix} y_1 \\ \vdots \\ y_G \end{bmatrix} = \begin{bmatrix} X_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & X_G \end{bmatrix} \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_G \end{bmatrix} \begin{bmatrix} e_1 \\ \vdots \\ e_G \end{bmatrix}$$

This stacked model comes with several additional assumptions as outlined in Henningsen and Hamann (2007):

1. It is assumed that there is no correlation of the disturbance terms across observations, so that

$$E\left[e_{it}e_{js}\right] = 0 \ \forall \ t \neq s$$

where *i* and *j* indicate the equation number and *t* and *s* denote the observation number and the number of observations is the same for all equations (Henningsen and Hamann, 2007).

2. The model however, explicitly allows for contemporaneous correlation, i.e.,

$$E\left[e_{it}e_{jt}\right] = \sigma_{ij}$$

3. Therefore, “the covariance matrix of all disturbances is

$$E[ee^T] = \Omega = \Sigma \otimes I_T$$

where $\Sigma = \sigma_{ij}$ is the (contemporaneous) disturbance covariance matrix, $\otimes$ is the Kronecker product, I_T is an identity matrix of dimension T , and T is the number of observations in each equation” (Henningsen and Hamann, 2007, p. 3). For more details, see Henningsen and Hamann (2007).

Used together, the structural break tests presented in Section 3.1 and the least squares procedures outlined in Section 3.2 will allow for a thorough interpretation of current live cattle basis conditions. More importantly, there can be a high level of confidence in results finding (or not finding) a structural break and its subsequent implications, by using these methods.

CHAPTER 4: DATA

This chapter is divided into two sections. The data used for testing structural breaks of live cattle is provided in Section 4.1 while the data used for estimating live cattle basis is described in Section 4.2.

Both the structural break tests and estimation models focus on basis between nearby live cattle futures and six different cash series. Weekly cash data are obtained from the Livestock Marketing Information Center (LMIC), who compiled the data from USDA AMS. Nearby futures prices are acquired from a Bloomberg Terminal. Friday closing prices for the "Generic 1st Live Cattle Futures Contract[12]" are used. The cash series are:

1. The LMR Five-Market Weighted Average Cash Price
2. Cash prices for each individual LMR market
    a. Texas/Oklahoma/New Mexico
    b. Colorado
    c. Nebraska
    d. Iowa/Minnesota
    e. Kansas

4.1 Data for Structural Break Testing

The purpose of structural break tests in this paper is to determine if live cattle nearby basis or live cattle basis variance has significantly changed in recent years. To accomplish this goal, live cattle cash and futures data is needed.

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[12] On a Bloomberg Terminal, this series can be found using the ticker symbol "LC1 Cmdty."

All cash price data were obtained from USDA Agricultural Marketing Service (AMS) via LMIC and all futures data were acquired from Bloomberg. Cash prices are weekly averages. Since most cash live cattle sales occur on Friday and Saturday (USDA AMS), Friday closing prices are used for live cattle futures. Descriptive statistics for the original series are included in Table 4.1 below.

Table 4.1 Descriptive Statistics of Weekly Data, 2004-2017

Variable	Units	Mean	Median	St Dev	Min	Max
Nearby Live Cattle Futures	$/cwt	108.75	102.48	23.10	73.85	170.90
Five Market Cash Price	$/cwt	109.23	101.85	23.97	74.49	171.38
TX/OK/NM Cash Price	$/cwt	109.36	102.88	23.81	73.91	172.00
Colorado Cash Price	$/cwt	109.52	102.33	24.32	74.65	173.27
Nebraska Cash Price	$/cwt	109.19	101.53	24.26	74.80	172.06
IA/MN Cash Price	$/cwt	108.70	100.79	24.13	76.95	169.93
Kansas Cash Price	$/cwt	109.27	101.97	23.91	74.06	172.94

Notes: N = 730 for all variables.

4.2 Basis Estimation and Empirical Methods

The purpose of regression models in this paper is to find drivers of changing basis after a structural break, which will be presented later and found to occur at the start of 2014. This section will be broken into two subsections. The first will present the data used in regression models while the second will outline the empirical models tested.

4.2.1 Data for Basis Estimation

The dependent variables listed in Table 4.2 (below) are major basis series for cattle sold on a live basis. Each basis series uses weekly average cash prices and weekly closing nearby live cattle futures prices. Since the modeling procedures include a lagged variable, the first observation of each new period (where the lag would be from a different contract) are excluded.

Table 4.2 Dependent Variables for Live Cattle Basis Regression

Variables	Description
FMNB	Five Market Nearby Basis
TXOKNMNB	Texas/Oklahoma/New Mexico Nearby Basis
CONB	Colorado Nearby Basis
NENB	Nebraska Nearby Basis
IAMNNB	Iowa/Minnesota Nearby Basis
KSNB	Kansas Nearby Basis

A set of variables was chosen to help explain the causes of structural change taken from previous literature. These explanatory variables are described in the Table 4.3.

Table 4.3 Explanatory Variables for Live Cattle Basis Regression*

Variables	Description
Lagged Basis	The relevant cash price minus the nearby live cattle futures price from the previous week
Weight	The average live steer slaughter weight for the relevant region
Head	The total head of steers slaughtered on a live basis in the given region
NegShare	The negotiated cash sales occurring in a given region as a percentage of all sales in each of the five major LMR reporting regions
CornRatio	Ratio of the nearby corn futures price in cents/bu to the nearby live cattle futures price in $/cwt
PCOB	Percent of cattle which graded Choice or better in the given week
CSSpread	The Choice/Select Spread, which is the difference between Choice and Select cutout values
PLLOI	Percent Liquid Long Open Interest in Live Cattle futures (all contracts) as outlined by (Schroeder, Tonsor, and Coffey, 2018)
RSI	A 14-day Relative Strength Index for nearby live cattle futures. This is a commonly used measure of market momentum

*All data is weekly

Some of the variables listed are not necessarily relevant for each regression. Along with providing descriptive statistics, Table 4.4 separates the variables based on the dependent variables they were used to estimate.

Table 4.4 Descriptive Statistics of Weekly Data, 2006-2017

Region/Series	Variable	Units	Mean	Median	St Dev	Min	Max
Five Market Weighted Average	Basis	$/cwt	0.47	-0.19	3.21	-7.70	16.30
	Weight	lbs	1365.02	1356.00	54.41	1241.00	1504.00
	Head	#	35663.80	33461.50	15015.53	7837.00	88053.00
Texas/Oklahoma/ New Mexico	Basis	$/cwt	0.60	-0.01	3.04	-8.12	16.14
	Weight	lbs	1284.51	1276.75	42.82	1175.50	1457.70
	Head	#	8643.38	5696.50	8348.67	77.00	38844.00
	NegShare	%	0.20	0.18	0.14	0.00	0.54
Colorado	Basis	$/cwt	0.81	0.10	3.41	-7.21	18.05
	Weight	lbs	1377.91	1371.25	56.20	1221.50	1556.10
	Head	#	2265.06	2010.50	1526.36	65.00	8395.00
	NegShare	%	0.06	0.06	0.04	0.00	0.30
Nebraska	Basis	$/cwt	0.46	-0.28	3.43	-7.19	16.58
	Weight	lbs	1409.19	1409.90	50.21	1267.30	1530.90
	Head	#	8319.52	7350.00	4060.50	529.00	29907.00
	NegShare	%	0.26	0.22	0.12	0.04	0.63
Iowa/Minnesota	Basis	$/cwt	-0.07	-0.95	3.71	-8.67	15.47
	Weight	lbs	1411.39	1405.55	50.17	1297.30	1542.50
	Head	#	5392.96	4825.50	2934.87	435.00	17319.00
	NegShare	%	0.17	0.14	0.10	0.02	0.62
Kansas	Basis	$/cwt	0.49	-0.17	3.10	-8.36	16.43
	Weight	lbs	1344.43	1341.70	42.04	1228.60	1493.80
	Head	#	11042.88	10578.50	5377.50	118.00	29317.00
	NegShare	%	0.31	0.31	0.09	0.01	0.68
All	CornRatio	bu/cwt	4.16	3.98	1.31	1.99	7.66
	PCOB	%	0.66	0.66	0.08	0.00	0.81
	CSSpread	$/cwt	8.73	7.79	5.31	-0.13	30.38
	PLLOI	%	0.31	0.31	0.07	0.19	0.51
	RSI	%	52.20	52.06	9.80	22.64	82.10

Notes: N = 533 for all variables. The first variables in the set are for the week ending 6/24/2006. The last variables in the set are for the week ending 12/30/2017.

Lagged Basis is expected to be relatively close to 0 for all periods, since basis should ultimately converge to 0. The variable is included to capture current basis levels.

The average weight (or dressed weight) is included as a proxy for total quantity of beef sold as noted in Parcell, Schroeder and Dhuyvetter (2000). As the average weight increases it is expected that cash price will decline, so it should be negatively correlated with basis.

The total head of steers (live or dressed) slaughtered is also included to estimate total supply of beef. It is expected that as total head increases, cash price should decline. Therefore, total head slaughtered should have a negative relationship with basis.

NegShare is included only for the regional markets. As noted by Coffey, Tonsor and Schroeder (2018), this proportion could increase or decrease independent of aggregate supply conditions and is a proxy for shifts in live cattle marketing - either toward or away from negotiated sales. If NegShare is statistically significant, it could mean that market thinness impacts basis.

CornRatio is included to capture current market conditions. As noted in Coffey, Tonsor and Schroeder (2018), this ratio is a proxy for the marginal benefit feeders receive from adding a pound to live cattle before slaughter.

It is well documented that the percentage of slaughter cattle grading Choice or better has been trending upward. Since Choice beef generally receives a premium to select beef, it is expected that a higher PCOB should have a positive impact on cash prices and therefore a positive impact on basis.

The Choice/Select Spread measures the premium that Choice beef receives over Select beef in each period. This is expected to have a varied effect depending on the quality of cattle supplied. As established by Parcell, Schroeder and Dhuyvetter (2000), when the

Choice-to-Select price spread widens, it is hypothesized that locations with higher (lower) quality cattle should receive a premium (discount) and basis should strengthen (weaken).

Schroeder, Tonsor, and Coffey (2018) determine that only long futures positions held by commercial hedgers, other reportable traders and non-reportable traders are liquid enough to allow short hedgers to offset their position. They indicate that if PLLOI is too low, then short hedgers could have problems finding enough liquidity to exit their positions, ultimately being forced to accept higher prices, and decreasing traders' individual basis. If this holds true, an increase in PLLOI should have a positive impact on basis.

The RSI is included as measure of momentum and could be positive or negative. Coffey, Tonsor and Schroeder (2018) used a stochastic oscillator, the RSI is another commonly used alternative.

4.2.2 Empirical Basis Estimation Models

Since it is possible that basis in each regional market impacts basis in other regional markets, a SUR model will be used to evaluate individual regions. These results can be compared to the OLS model for the five-market region aggregate basis. The first empirical model uses OLS to estimate basis for the Five Market average and is specified as

$$\begin{aligned} Basis_t = {} & \beta_0 + \beta_1 Basis_{t-1} + \beta_2 Weight_t + \beta_3 Head_t + \beta_4 CornRatio_t + \beta_5 PCOB_t \\ & + \beta_6 CSSpread_t + \beta_7 PLLOI_t + \beta_8 RSI_t + \beta_9 Feb + \beta_{10} Apr + \beta_{11} Aug \\ & + \beta_{12} Oct + \beta_{13} Dec + \varepsilon_t \end{aligned}$$

where *t* represents the given week and *Weight* and *Head* use Five Market averages.

The base equations for the SUR model are similar but add the NegShare variable and uses regional values for basis, *NegShare*, *Weight* and *Head*. These empirical models are specified as

$$\begin{aligned} Basis_{t,r} = {} & \beta_0 + \beta_1 Basis_{t-1,r} + \beta_2 Weight_{t,r} + \beta_3 Head_{t,r} + \beta_4 CornRatio_t + \beta_5 PCOB_t \\ & + \beta_6 CSSpread_t + \beta_7 PLLOI_t + \beta_8 RSI_t + \beta_9 NegShare_{t,r} + \beta_{10} Feb \\ & + \beta_{11} Apr + \beta_{12} Aug + \beta_{13} Oct + \beta_{14} Dec + \varepsilon_t \end{aligned}$$

where *t* represents the given week and *r* represents the given region.

The SUR model itself is applied using the R package *systemfit* developed by Henningsen and Hamann (2007). A separate SUR is completed for both the pre- and post-break time periods (see Henningsen and Hamann, 2007 for code).

For all three models, a positive value for a β coefficient suggests that as the related explanatory increases, so does basis. A negative value for a β coefficient suggests that as the related explanatory increases, basis decreases. If β coefficient’s changing meaningfully from the pre- to post-break periods, they may be primary drivers of structural change in basis.

CHAPTER 5: RESULTS AND DISCUSSION

This chapter is divided into two sections. The results for live cattle basis structural break, stationarity and cointegration tests are laid out in Section 5.1. The results show a break in live cattle basis in all regions. The results for both OLS and SUR based live cattle basis estimation models are described in Section 5.2. Results of the 22 regression models point to the changes in the percentage of cattle grading Choice or better as a primary driver of the break.

5.1 Structural Break Test Results

Several tests were required to thoroughly evaluate structural breaks in basis and the results and discussion have been broken into three subsections. Section 5.1.1 includes details on results of the stationarity tests, Section 5.1.2 includes results for cointegration tests, and Section 5.1.3 covers results and interpretations of the structural break tests.

5.1.1 Stationarity Test Results

Results of the ADF unit roots tests KPSS stationarity tests were conflicting when evaluating the full 2004-2017 period. When ADF and KPSS tests were ran for observations before and after the suspected breakpoint (the first week of 2014), both tests showed stationarity. Test statistics and results are outlined in Tables 5.1 and 5.2.

Table 5.1 Augmented Dickey-Fuller Unit Root Test Results, Nearby Basis

	2004-2013		2014-2017		2004-2017	
Series	Test Statistic	Stationary? (Yes/No)	Test Statistic	Stationary? (Yes/No)	Test Statistic	Stationary? (Yes/No)
Five Market Avg.	-8.2008	Yes	-4.1265	Yes	-8.5253	Yes
TX/OK/NM	-8.8087	Yes	-4.5651	Yes	-9.3104	Yes
Colorado	-8.299	Yes	-3.9449	Yes	-8.353	Yes
Nebraska	-7.6857	Yes	-4.0574	Yes	-8.2509	Yes
Iowa/Minnesota	-6.6503	Yes	-4.1718	Yes	-7.8581	Yes
Kansas	-8.624	Yes	-4.3884	Yes	-9.0528	Yes

Note: 1% critical value = -2.58, 5% critical value = -1.95, 10% critical value = -1.62

Table 5.2 KPSS Stationarity Test Results, Nearby Basis

	2004-2013		2014-2017		2004-2017	
Series	Test Statistic	Stationary? (Yes/No)	Test Statistic	Stationary? (Yes/No)	Test Statistic	Stationary? (Yes/No)
Five Market Avg.	0.1757	Yes	0.1765	Yes	1.4642	No
TX/OK/NM	0.1858	Yes	0.1177	Yes	1.5094	No
Colorado	0.2747	Yes	0.2543	Yes	2.2201	No
Nebraska	0.2796	Yes	0.229	Yes	1.8786	No
Iowa/Minnesota	0.2586	Yes	0.2048	Yes	1.1167	No
Kansas	0.2817	Yes	0.1328	Yes	1.6217	No

Note: 1% critical value = 0.739, 5% critical value = 0.574, 10% critical value = 0.347

As noted in the previous chapter, an indicator of possible structural change occurs when stationarity tests (e.g. KPSS) and unit root tests (e.g. ADF) lead to contradictory results (Iván and Zsolt, 2016). The conflicting results in the ADF and KPSS tests when evaluating stationarity for the full timeframe of 2004-2017 point to structural change in live cattle basis at the start of 2014. The fact that basis was stationary in both of the shorter timeframes, however, indicates that cash and futures prices should still move together in the short run.

5.1.2 Cointegration Tests Results

Each of the six cash series versus nearby live cattle futures from 2004-2017 was tested for cointegration during the full period. Since the previous section already shows stationarity for periods pre and post 2014 (the suspected breakpoint), the cointegration tests (applicable to non-stationary series 2004-2017) tell whether basis risk should still be smaller than price risk. Results are shown in Table 5.3. Cointegration procedures follow Johansen (1988, 1991). In all instances, the null hypothesis of no cointegration (r = 0) is rejected and the alternative hypothesis of cointegration (r <= 1) shows inadequate evidence for rejection.

Table 5.3 Johansen Cointegration Test Results

	2004-2017	
Series	Test Statistic (r = 0)	Cointegrated ? (Yes/No)
Five Market Cash Price vs. Nearby Futures	76.29***	Yes
TX/OK/NM Cash Price vs. Nearby Futures	90.4***	Yes
Colorado Cash Price vs. Nearby Futures	83.55***	Yes
Nebraska Cash Price vs. Nearby Futures	76.44***	Yes
Iowa/Minnesota Cash Price vs. Nearby Futures	62.71***	Yes
Kansas Cash Price vs. Nearby Futures	84.6***	Yes

The results show cointegration between cash and futures prices with 99 percent confidence for all regions and time periods. In general, these results lead us to believe that basis risk should still be smaller than price risk following the expected 2014 breakpoint. However, smaller test statistics could be correlated with wider ranges of basis. In fact, Wilder, Tejeda and Johnson (2018) show that there were several times where the range of basis was larger than the range of futures prices during the last two months of contract expiration from 2004-2017. Therefore, it is still important to consider if a structural break occurred.

Result of the stationarity and cointegration tests both point to change within the cash-futures price relationship near the start of 2014. Using more sophisticated test procedures in Section 5.1.3 the break, and the timing of the breakpoint, can be identified with a high level of certainty.

5.1.3 Structural Break Test Results

While it has been heavily hypothesized that live cattle basis witnessed a structural break near the start of 2014, the results of the following tests represent the first statistical evidence in academic literature.

Table 5.4 Structural Breaks of Basis Time Series

	Break? (Yes/No)	
	OLS-CUSUM	F Test
Five Market Basis	Yes***	Yes***
	(4.494)	(114.18)
TX/OK/NM Basis	Yes***	Yes***
	(4.586)	(121.66)
Colorado Basis	Yes***	Yes***
	(5.126)	(155.42)
Nebraska Basis	Yes***	Yes***
	(4.728)	(128.10)
Iowa/Minnesota Basis	Yes***	Yes***
	(3.866)	(67.32)
Kansas Basis	Yes***	Yes***
	(4.867)	(138.64)

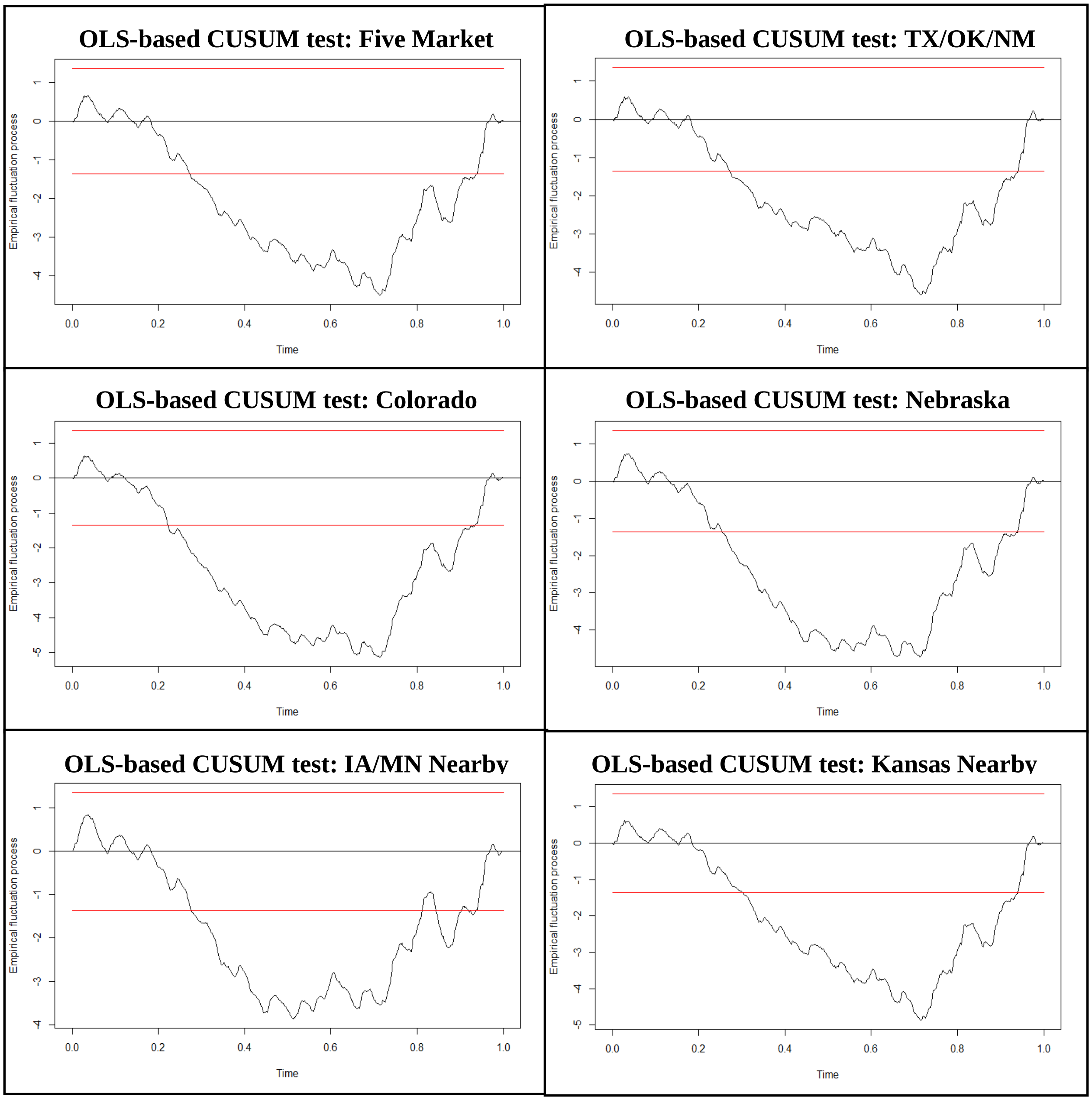
Note: Numbers in parentheses are test statistics. For the OLS-CUSUM Test, these are the values of S_e*. For the F Test, these are the values of the supplemental F statistic.* $*p<0.10$, $**p<0.05$, $***p<0.01$

Table 5.4 shows the largest test statistic values in the entire period and empirically confirms whether each basis time series witnessed a structural break.

As helpful as the empirical results are, charting the test statistics over time can be more intuitive. In OLS-based CUSUM test charts (Figures 2 & 3), the two red lines represent the normal range of the test statistic. When the value of the statistic goes above the higher bound or below the lower bound of the normal range, a structural break has occurred. The strength of the break can be noted by the size of the test statistic relative to the range. In other words, the peak, or the largest test statistic in terms of absolute value, will correspond to the values in the table above and can also be interpretted as the timing of the break.

Charting the F Statistic is similar. If the F Statistic becomes sufficiently large to cross its boundary, the red line drawn on the chart, representing the null hypothesis of no structural change is rejected. The larger the F Statistic, the more confident one can be that structural change occurred. As before the peak, or highest value of the test statistic, is shown in the Table 5.4 above.

Based on the emperical tests and the graphical considerations, it is clear there are structural breaks in all regions. However, the rate at which both the OLS-based CUSUM test statistic and F Statistics accellerated and declined differ drastically across regions, providing evidence that each regional cash price has a unique relationship with the live cattle futures price. When looking at the OLS-based CUSUM test statistics over time for live markets, it also appears there may have been multiple structural breaks in some markets, particularly in the Iowa/Minnesota region. This chart, in combination with less significant cointegration results, leads to a potential assumption that producers in the Iowa/Minnesota region may have the largest exposure to basis risk at this time. Further consideration of this issue is outside of the scope of this project.



OLS-based CUSUM test: Five Market

OLS-based CUSUM test: TX/OK/NM

OLS-based CUSUM test: Colorado

OLS-based CUSUM test: Nebraska

OLS-based CUSUM test: IA/MN Nearby

OLS-based CUSUM test: Kansas Nearby

Figure 5.1 OLS-based CUSUM Test statistics for Nearby Basis in Live Cattle

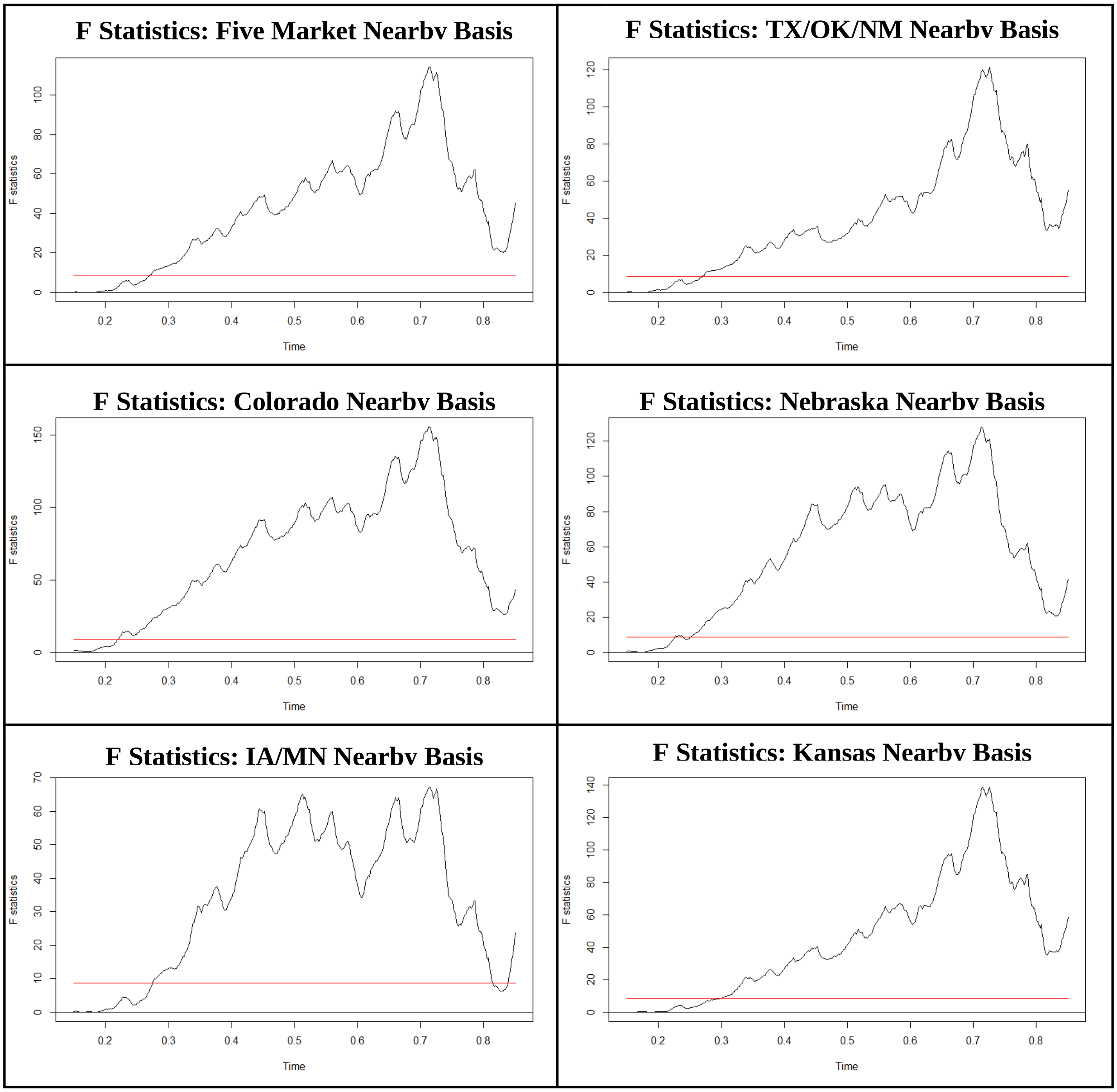


Figure 5.2 F Statistics for Nearby Basis in Live Cattle Markets

In addition to confirming the existence of a break, results of the Bai-Perron multiple structural break test show where the optimal number of structural breaks occur for each series by minimizing the BIC. The result of the test for a “best-fit” model which reduces the BIC are shown in Table 5.5. Results for a single break model are shown in Table 5.6

Table 5.5 Bai-Perron Test Results for Nearby Basis, Best Fit Model

	Potential breakpoints by observation number (Week)	BIC
Five Market Basis	127, 247, 521	3634
TX/OK/NM Basis	530	3547
Colorado Basis	127, 324, 522	3676
Nebraska Basis	127, 324, 531	3714
Iowa/Minnesota Basis	127, 324, 530	3889
Kansas Basis	127, 522	3552

Results for nearby basis show between one and three potential breaks when the Bai-Perron test attempts to minimze the BIC. Five series show a possible break at week 127. Week 127 is the week ending 6/10/2006, which is both the month live cattle serial futures[13] were delisted from the CME[14] and the first month data is available from the U.S. Commodity Futures Trading Commision (CFTC) Dissagreggated Commitment of Traders (COT) report[15]. Together, these two points create questions about the data before of June 2006, since there are fewer contracts, but more information, available afterwards. Therefore, the basis estimation models in Section 5.2 use data only after June 2006.

Week 247 (week ending 9/27/2008) showed up once as a possible breakpoint. This single instance was with five market weighted average basis and mostly likely shows up due to general noise generated by the market recession and greater overall market volatility in 2008-2009. Week 324 (week ending 3/20/2010) shows up three times. These instances

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[13] From 2003 to 2006, serial futures were available for live cattle futures. This means there was a contract for each of the twelve calendar months.

[14] One can find a complete list of live cattle futures changes at: https://www.uidaho.edu/-/media/UIdaho-Responsive/Files/cals/programs/idaho-agbiz/livestock-markets/live-cattle-delivery.pdf

[15] Further information on the COT report can be found at: https://www.cftc.gov/MarketReports/CommitmentsofTraders/DisaggregatedExplanatoryNotes/index.htm

cannot be explained by CME specification changes, but they do correspond with the start of a four year period of greater dissapearance than production of U.S. beef (USDA ERS).

All series broke at some point between week 521 (week ending 12/28/2013) and week 531 (week ending 3/8/2014). This is a strong indicator that the largest break took place at the start of 2014. Table 5.6 shows results of the Bai-Perron test for a single break point only.

Table 5.6 Bai-Perron Test Results for Nearby Basis, Single Break Case

	Potential breakpoint by observation number (Week)	BIC
Five Market Basis	521	3635
TX/OK/NM Basis	530	3547
Colorado Basis	521	3690
Nebraska Basis	520	3732
Iowa/Minnesota Basis	522	3907
Kansas Basis	530	3558

Looking at just a single-break model, all series witnessed change at some point between week 520 (week ending 12/21/2013) and week 530 (week ending 3/1/2014). This strengthens the premise that the structural break occurred somehwere at the beginning of 2014. With these results, the basis estimation results in the following section will be used to hone in on probable drivers of these structural breaks.

5.2 Basis Estimation Results

The results in Section 5.1 show a clear structural break in basis, quantitatively confirming suspicions that the series themselves have experienced change. The most common timing for structural breaks is found to occur during the first months of 2014. The goal of this section is to determine the drivers of that structural break by evaluating how the relationship of major fundamental factors and live cattle basis change from pre- to post-break periods. Section 4.2 in the previous chapter outlines the use of OLS and SUR estimation modelling procedures, assuming there is no autocorrelation in the original OLS regressions. No or very little evidence of autocorrelation was found in any region using the auxiliary regressions (substitute for the Durbin H test) described in Chapter 3. Results of those auxiliary regressions can be found in Appendix A.

All regressions were separated by pre-break (2006-2013), and post-break (2014-2017) periods. Seasonal dummy variables were added for each futures contract with June as the constant. The explanatory variables included in each regression differ from region-to-region. Since each cattle feeding region responds differently to supply and demand factors, any future research should pay special attention to regional results. All OLS regression tables are at the end of the document in Appendix B, and SUR tables are in Appendix C.

Given that the Five-Market weighted basis is a representation of the broader market, its basis equation was estimated using OLS regression procedures rather than as part of the SUR. The results for the Five-Market equation are not adequate to make assumptions about any individual region but do foreshadow a few of the changes found between periods in regional regressions. The only constants before and after the break are: (i) lagged nearby basis was significant and positive, (ii) the RSI was significant and negative, (iii) and the average live weight, Choice/Select Spread, Corn Ratio and October and December seasonal variables were not significant in either period. Items (i) and (ii) are found to be true throughout most of the SUR results as well. Item (iii), which discusses the estimated coefficients not significant in estimating the Five-Market basis equation, houses a surprisingly large number of explanatory variables. SUR results (Appendix C) show that most of these variables are useful in determining basis across different regions. Only the estimated coefficient for the Corn Ratio, made popular by research based in Kansas, was found to never be significant.

Most interesting to the Five-Market comparison is that the percent of cattle grading Choice or better each week was significant and positive pre-break and significant and negative post-break. This phenomenon holds true across all 22 regression equations in Appendices B & C. This means that after 2014 a higher percentage of cattle grading Choice or better in a given week had a negative impact on cash prices and therefore a negative impact on basis. This seems counter-intuitive. However, Wilder, Tejeda and Johnson (2018) note that the percentage of cattle grading Choice or better in the U.S. climbed steadily until 2016 and has now leveled off. Today, over 80 percent of all cattle in the U.S. grade Choice or better as opposed to around 60 percent in 2006. These numbers support the assertion by John Stika, President of Certified Angus Beef, that the U.S. cattle industry is headed to a point where Choice beef is the new market expectation (Stika, 2018). The changes to the percent of cattle grading Choice or better showed the largest changes across all estimation equations and is what this research finds to be the largest contributor to the structural break in basis.

Regional estimates add an additional variable, the share of negotiated cash sales taking place in each region in a given week, an additional variable which likely helps to compound the break. Both in regular OLS regressions and the SUR, three regions found the average live weight variable to be significant and negative pre-break, while only one region found it significant (and also negative) post-break. The OLS regressions (which had estimates with consistently higher R^2 values as compared to SUR estimates) showed the Head variable to be insignificant in all pre-break estimates and significant and positive in all post-break models. This result, combined with less significance in the Weight variable, means that the number of head slaughtered each week may now be the best proxy for amount of beef on the market versus the average weight variable, which was made popular in previous literature.

The Choice/Select spread variable was positive when significant, in both OLS and SUR estimates. Both estimation methods found the spread to be significant in two additional regions post-break as opposed to pre-break. If Choice really is the new “normal,” then the premium given to Choice beef will likely continue to have a large impact on cash prices and therefore on basis.

The measure of the percentage of liquid long open interest (PLLOI) became much more significant post-break. OLS estimation procedures found PLLOI significant once pre-break and three times post-break while SUR estimation procedures found PLLOI significant twice pre-break and in all five regions post-break. In all instance PLLOI was negative where significant, meaning as the futures contacts become more liquid, there is a negative impact on basis. This has interesting implications because it means that as short-term traders become more involved (as a percentage of total long futures), basis weakens. This is potential evidence that active trading impacts the ability of cattle producers (and other short hedgers) to have certainty in profit margins when hedging. If PLLOI, as outlined by Schroeder, Tonsor, and Coffey (2018) distorts the ability of cattlemen to hedge, it warrants further research.

The NegShare variable, which focused on the percentage of negotiated cash sales taking place in each region, was not found to be as important as in other recent literature. In fact, when using SUR estimation methods, which assume basis in each region has an impact on basis in other regions, the NegShare variable was significant (and positive) only once pre-break in the Iowa/Minnesota region. Using OLS estimation methods, the variable also shows as significant and positive in one region (Kansas) pre-break, but also shows NegShare as significant and negative in three regions post-break. These conflicting results between methods provide evidence to dispute the idea that thin cash trade may be the primary factor of the structural break. However, the fact the sign changed from positive to negative between pre- and post-break estimates when significant does support the idea that too much cash trade in one region can potentially lead to lower regional cash prices. The reverse could also be true; relative cash thinness in a particular region could lead to a regional cash market premium. Conflicting results relative to recent literature also lead to a belief that the current five regions outlined by USDA AMS may not be representative of the full U.S. cattle market.

Last, the OLS and SUR estimates show changes to seasonality. Post-break, the October and December Contracts seem to have a negative impact on basis (compared to June) across most regions. The estimation equations also pinpoint regional differences in seasonality. For example, the April contact appears to have a positive impact on basis in the Iowa/Minnesota region. No other region found the April contract to be significant at any point in time.

As a whole, this research finds evidence that changes to the percentage of cattle grading Choice or better, the Choice/Select spread, the percentage of liquid long open interest, and the share of negotiated cash trade in each region contributed to the break in basis. This research also finds that the number of head slaughtered in a given week is a better proxy for total beef on the market than average live weight at slaughter. Further, this research shows that the Corn Ratio is not typically effective in estimating live cattle basis. The estimation equations also show lagged basis and a measure of momentum as helpful estimation tools. Last, a large takeaway from these results is to use regional cash price when building a personal estimation or forecast model as regional differences have a significant impact on basis.

CHAPTER 6: CONCLUSION

Basis is a moving target and will continue to change over time. This research confirms structural change and evaluates major supply factors across several major cattle producing regions and valuation methods. Ultimately, this study presents a new way to look at live cattle basis changes and provides an interpretation of the fundamental drivers which market participants can use to update their current business strategies.

Chapter 2 presented a comprehensive review of previous literature on live cattle basis, structural break testing and basis estimation. Since 2016 and given the ample discussion of volatile livestock futures by popular press, there has been a large amount of new research attempting to either resolve or evaluate current market issues. This research was able to build on several of those studies and incorporate new variables of interest, such as the percent of cattle grading Choice or better and the percent of long open interest liquid enough for short hedgers to offset their positions.

Many structural break tests are available in the literature, so several tests were applied in this study to provide a greater level of certainty about the results. Similar results could be found using other methods, but results show a structural break in 2014 by applying the OLS-based CUSUM test, *F* statistics, and the Bai-Perron structural break test. The Bai-Perron test uses a dating algorithm for the basis series being tested, the results of which are difficult to refute. This has interesting implications. Regardless of factors influencing basis, it can now be expected to be more volatile (less stable). For hedgers, this means both greater risk and greater opportunities when participating in the futures market. In other words, sound risk management practices and well thought out marketing plans are now more important than before.

The OLS and SUR regression results provide an excellent place to start understanding why basis is changing. If one can understand why basis is changing, hedgers may be able to make more timely business decisions when there are shocks to relevant market factors. This study finds significant changes to (i) the percent of cattle grading Choice or better, (ii) the regional share of negotiated cash sales, and (iii) the percent of liquid long open live cattle futures interest, all of which impact basis across the board. Moreover, the Choice/Select cutout spread was found to have much more explanatory power post-2014. Also interesting is that the number of head sold seems to now be a better proxy for total beef supply than the average weight of cattle sold. In addition, the impact of seasonality differs greatly across all regions. Together these results can be used to better understand how day-to-day changes in supply factors can impact basis. Still, it is important to note that factors respond differently across regions and cash valuation methods. Any attempt to use these results in a practical sense should pay special attention to the cash price (and basis series) which is most applicable to them.

While the estimation models allow an interpretation of the drivers of structural changes, there are limitations. While explanatory variables were chosen based on previous literature and widely discussed factors of interest, important variables which help explain basis could have been omitted. By moving to a monthly, quarterly, or even annual model, research could also include supply and disappearance measures, delivery costs variables and supply variables for competing proteins. In addition, it is possible that measurement error could bias the results. Weekly average cash prices were used and Friday nearby futures closing prices were used to calculate basis. It is possible that a weekly average of daily closing futures prices could provide a more efficient result, even though the majority of negotiated cash cattle sales take place on Friday and Saturday. In addition, not all movement of futures prices is explained by the nearby contract. Futures research could seek to incorporate deferred contracts to the explanatory model.

Although any attempt to use this information in a practical sense should be done at a market participant’s own risk, this study provides meaningful contributions and interpretations to a relevant, timely issue. Studies addressing to livestock markets are made complex by the non-storable nature of the commodities in question. By confirming the existence of a structural break and using a weekly estimation model to evaluate the drivers of changing basis, this research provides actionable interpretations which could help cattle feeders, packers and end-users alike make improved business decisions.

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APPENDIX A: Auxiliary Autocorrelation Regression Results and R Code

Table A.1 Five-Market Auxiliary Regression for Autocorrelation

```
> summary(FMauto)

Call:
lm(formula = resid(FMols)[1:601] ~ FMlaggede + FMNBL[1:601] + 
    FMALW[1:601] + FMHD[1:601] + CornRatio[1:601] + PCOB[1:601] + 
    CSSpread[1:601] + PLLOI[1:601] + LC1RSI14D[1:601] + Feb[1:601] + 
    Apr[1:601] + Aug[1:601] + Oct[1:601] + Dec[1:601])

Residuals:
    Min      1Q  Median      3Q     Max 
-5.7219 -1.4031 -0.2036  1.2658  5.9679 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)      -1.536e-01  1.198e+01  -0.013    0.990
FMlaggede        -3.102e-02  1.181e-01  -0.263    0.793
FMNBL[1:601]      1.936e-03  5.991e-02   0.032    0.974
FMALW[1:601]      8.184e-05  8.485e-03   0.010    0.992
FMHD[1:601]      -3.155e-07  2.021e-05  -0.016    0.988
CornRatio[1:601]  8.251e-04  5.120e-01   0.002    0.999
PCOB[1:601]       5.106e-02  7.036e+00   0.007    0.994
CSSpread[1:601]   1.639e-03  3.937e-02   0.042    0.967
PLLOI[1:601]     -3.151e-02  3.331e+00  -0.009    0.992
LC1RSI14D[1:601] -2.734e-04  2.511e-02  -0.011    0.991
Feb[1:601]       -4.115e-04  8.566e-01   0.000    1.000
Apr[1:601]        1.734e-02  6.816e-01   0.025    0.980
Aug[1:601]       -5.810e-03  6.928e-01  -0.008    0.993
Oct[1:601]        4.023e-03  8.617e-01   0.005    0.996
Dec[1:601]       -3.088e-03  8.539e-01  -0.004    0.997

Residual standard error: 2.078 on 170 degrees of freedom
  (416 observations deleted due to missingness)
Multiple R-squared:  0.0004059,	Adjusted R-squared:  -0.08191 
F-statistic: 0.004931 on 14 and 170 DF,  p-value: 1
```

Table A.2 Texas/Oklahoma/New Mexico Auxiliary Regression for Autocorrelation

```
> summary(TXOKNMauto)

Call:
lm(formula = resid(FMols)[1:601] ~ TXOKNMlaggede + TXOKNMNBL[1:601] + 
    TXOKNMALW[1:601] + TXOKNMHD[1:601] + CornRatio[1:601] + PCOB[1:601] + 
    CSSpread[1:601] + PLLOI[1:601] + LC1RSI14D[1:601] + TXOKNMPCT[1:601] + 
    Feb[1:601] + Apr[1:601] + Aug[1:601] + Oct[1:601] + Dec[1:601])

Residuals:
    Min      1Q  Median      3Q     Max 
-5.6085 -1.0661 -0.0582  0.8301  8.0541 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)    
(Intercept)       1.250e+01  3.264e+00   3.830 0.000144 ***
TXOKNMlaggede    -2.121e-02  4.220e-02  -0.503 0.615518    
TXOKNMNBL[1:601] -6.737e-02  3.330e-02  -2.023 0.043560 *  
TXOKNMALW[1:601] -8.573e-03  2.446e-03  -3.505 0.000496 ***
TXOKNMHD[1:601]  -2.307e-05  2.415e-05  -0.955 0.339870    
CornRatio[1:601] -9.509e-02  7.444e-02  -1.278 0.201998    
PCOB[1:601]       3.777e-01  1.394e+00   0.271 0.786586    
CSSpread[1:601]   3.624e-03  1.879e-02   0.193 0.847128    
PLLOI[1:601]     -7.229e-01  1.593e+00  -0.454 0.650228    
LC1RSI14D[1:601] -1.569e-02  1.083e-02  -1.449 0.148083    
TXOKNMPCT[1:601] -3.882e-01  1.556e+00  -0.250 0.803051    
Feb[1:601]       -6.132e-02  3.314e-01  -0.185 0.853278    
Apr[1:601]        1.333e-02  3.254e-01   0.041 0.967353    
Aug[1:601]       -3.280e-02  3.054e-01  -0.107 0.914529    
Oct[1:601]        7.027e-02  3.226e-01   0.218 0.827627    
Dec[1:601]       -2.836e-02  3.074e-01  -0.092 0.926541    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1 

Residual standard error: 1.734 on 516 degrees of freedom
  (69 observations deleted due to missingness)
Multiple R-squared:  0.03699,	Adjusted R-squared:  0.008994 
F-statistic: 1.321 on 15 and 516 DF,  p-value: 0.1841
```

Table A.3 Colorado Auxiliary Regression for Autocorrelation

```
> summary(COauto)

Call:
lm(formula = resid(FMols)[1:601] ~ COlaggede + CONBL[1:601] + 
    COALW[1:601] + COHD[1:601] + CornRatio[1:601] + PCOB[1:601] + 
    CSSpread[1:601] + PLLOI[1:601] + LC1RSI14D[1:601] + COPCT[1:601] + 
    Feb[1:601] + Apr[1:601] + Aug[1:601] + Oct[1:601] + Dec[1:601])

Residuals:
    Min      1Q  Median      3Q     Max 
-5.9211 -0.9910 -0.0967  0.9301  8.3463 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)  
(Intercept)       3.961e+00  2.625e+00   1.509    0.132  
COlaggede        -6.406e-02  4.247e-02  -1.508    0.132  
CONBL[1:601]      3.163e-02  2.963e-02   1.068    0.286  
COALW[1:601]     -3.462e-03  2.076e-03  -1.668    0.096 .
COHD[1:601]      -1.857e-05  8.524e-05  -0.218    0.828  
CornRatio[1:601]  1.046e-03  7.049e-02   0.015    0.988  
PCOB[1:601]       5.602e-01  1.298e+00   0.432    0.666  
CSSpread[1:601]  -7.400e-03  1.891e-02  -0.391    0.696  
PLLOI[1:601]      1.042e+00  1.519e+00   0.686    0.493  
LC1RSI14D[1:601]  4.059e-03  9.675e-03   0.420    0.675  
COPCT[1:601]     -3.706e+00  3.335e+00  -1.111    0.267  
Feb[1:601]        3.546e-01  3.539e-01   1.002    0.317  
Apr[1:601]        2.298e-02  3.157e-01   0.073    0.942  
Aug[1:601]        2.397e-01  3.020e-01   0.794    0.428  
Oct[1:601]        2.925e-01  3.303e-01   0.886    0.376  
Dec[1:601]        3.202e-01  3.252e-01   0.984    0.325  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1 

Residual standard error: 1.748 on 516 degrees of freedom
  (69 observations deleted due to missingness)
Multiple R-squared:  0.0213,  Adjusted R-squared:  -0.007147 
F-statistic: 0.7488 on 15 and 516 DF,  p-value: 0.7346 
```

Table A.4 Nebraska Auxiliary Regression for Autocorrelation

```
> summary(NEauto)

Call:
lm(formula = resid(FMols)[1:601] ~ NElaggede + NENBL[1:601] + 
    NEALW[1:601] + NEHD[1:601] + CornRatio[1:601] + PCOB[1:601] + 
    CSSpread[1:601] + PLLOI[1:601] + LC1RSI14D[1:601] + NEPCT[1:601] + 
    Feb[1:601] + Apr[1:601] + Aug[1:601] + Oct[1:601] + Dec[1:601])

Residuals:
    Min      1Q  Median      3Q     Max 
-5.8543 -1.0400 -0.0594  0.8855  8.7610 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)   
(Intercept)       8.881e-01  3.600e+00   0.247  0.80525   
NElaggede        -1.200e-01  4.406e-02  -2.723  0.00668 **
NENBL[1:601]      5.205e-02  3.058e-02   1.702  0.08928 . 
NEALW[1:601]     -1.565e-03  2.959e-03  -0.529  0.59725   
NEHD[1:601]       2.667e-05  2.652e-05   1.006  0.31490   
CornRatio[1:601]  1.115e-02  7.131e-02   0.156  0.87577   
PCOB[1:601]       3.348e-01  1.394e+00   0.240  0.81038   
CSSpread[1:601]  -1.268e-02  1.898e-02  -0.668  0.50423   
PLLOI[1:601]      1.767e+00  1.581e+00   1.118  0.26427   
LC1RSI14D[1:601]  9.516e-03  9.837e-03   0.967  0.33379   
NEPCT[1:601]     -1.313e+00  1.122e+00  -1.170  0.24253   
Feb[1:601]        1.895e-01  4.000e-01   0.474  0.63595   
Apr[1:601]        2.456e-02  3.314e-01   0.074  0.94096   
Aug[1:601]        1.802e-01  3.194e-01   0.564  0.57282   
Oct[1:601]        3.563e-01  3.800e-01   0.938  0.34889   
Dec[1:601]        3.781e-01  3.800e-01   0.995  0.32015   
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1 

Residual standard error: 1.748 on 516 degrees of freedom
  (69 observations deleted due to missingness)
Multiple R-squared:  0.02147,	Adjusted R-squared:  -0.006978 
F-statistic: 0.7547 on 15 and 516 DF,  p-value: 0.7282
```

Table A.5 Iowa/Minnesota Auxiliary Regression for Autocorrelation

```
> summary(IAMNauto)

Call:
lm(formula = resid(FMols)[1:601] ~ IAMNlaggede + IAMNNBL[1:601] + 
    IAMNALW[1:601] + IAMNHD[1:601] + CornRatio[1:601] + PCOB[1:601] + 
    CSSpread[1:601] + PLLOI[1:601] + LC1RSI14D[1:601] + IAMNPCT[1:601] + 
    Feb[1:601] + Apr[1:601] + Aug[1:601] + Oct[1:601] + Dec[1:601])

Residuals:
    Min      1Q  Median      3Q     Max 
-5.9077 -1.0667 -0.0478  0.8857  7.8326 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)   
(Intercept)      -5.558e+00  4.150e+00  -1.339  0.18106   
IAMNlaggede      -7.307e-02  4.336e-02  -1.685  0.09255 . 
IAMNNBL[1:601]    1.230e-02  2.907e-02   0.423  0.67248   
IAMNALW[1:601]    4.412e-03  3.429e-03   1.287  0.19883   
IAMNHD[1:601]     1.122e-04  3.964e-05   2.830  0.00483 **
CornRatio[1:601]  3.467e-02  6.943e-02   0.499  0.61774   
PCOB[1:601]      -1.005e+00  1.332e+00  -0.754  0.45099   
CSSpread[1:601]  -7.822e-03  1.941e-02  -0.403  0.68718   
PLLOI[1:601]     -5.107e-01  1.681e+00  -0.304  0.76143   
LC1RSI14D[1:601] -3.723e-03  1.031e-02  -0.361  0.71805   
IAMNPCT[1:601]   -7.721e-01  1.238e+00  -0.624  0.53310   
Feb[1:601]       -1.637e-01  4.012e-01  -0.408  0.68344   
Apr[1:601]        1.416e-02  3.389e-01   0.042  0.96669   
Aug[1:601]       -3.433e-01  3.143e-01  -1.092  0.27527   
Oct[1:601]       -4.394e-01  4.067e-01  -1.080  0.28051   
Dec[1:601]       -1.972e-01  3.980e-01  -0.496  0.62040   
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1 

Residual standard error: 1.742 on 516 degrees of freedom
  (69 observations deleted due to missingness)
Multiple R-squared:  0.02886,	Adjusted R-squared:  0.0006267 
F-statistic: 1.022 on 15 and 516 DF,  p-value: 0.4301 
```

Table A.6 Kansas Auxiliary Regression for Autocorrelation

```
> summary(KSauto)

Call:
lm(formula = resid(FMols)[1:601] ~ KSlaggede + KSNBL[1:601] + 
    KSALW[1:601] + KSHD[1:601] + CornRatio[1:601] + PCOB[1:601] + 
    CSSpread[1:601] + PLLOI[1:601] + LC1RSI14D[1:601] + KSPCT[1:601] + 
    Feb[1:601] + Apr[1:601] + Aug[1:601] + Oct[1:601] + Dec[1:601])

Residuals:
    Min      1Q  Median      3Q     Max 
-5.7928 -1.0462 -0.0778  0.9268  8.4517 

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)  
(Intercept)       9.646e+00  4.307e+00   2.239   0.0256 *
KSlaggede        -3.666e-02  4.452e-02  -0.823   0.4106  
KSNBL[1:601]     -2.105e-02  3.323e-02  -0.633   0.5268  
KSALW[1:601]     -8.516e-03  3.512e-03  -2.425   0.0157 *
KSHD[1:601]      -1.032e-05  2.167e-05  -0.476   0.6342  
CornRatio[1:601] -1.089e-01  7.926e-02  -1.373   0.1702  
PCOB[1:601]       1.958e+00  1.377e+00   1.422   0.1556  
CSSpread[1:601]  -5.028e-03  1.898e-02  -0.265   0.7911  
PLLOI[1:601]      1.166e+00  1.613e+00   0.723   0.4700  
LC1RSI14D[1:601] -3.019e-04  1.002e-02  -0.030   0.9760  
KSPCT[1:601]      2.332e+00  1.200e+00   1.944   0.0525 .
Feb[1:601]       -5.784e-02  3.327e-01  -0.174   0.8620  
Apr[1:601]       -2.423e-01  3.226e-01  -0.751   0.4529  
Aug[1:601]        1.614e-01  3.111e-01   0.519   0.6041  
Oct[1:601]        3.218e-01  3.443e-01   0.935   0.3504  
Dec[1:601]        1.388e-01  3.217e-01   0.431   0.6663  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1 

Residual standard error: 1.752 on 516 degrees of freedom
  (69 observations deleted due to missingness)
Multiple R-squared:  0.01759,  Adjusted R-squared:  -0.01097 
F-statistic: 0.6159 on 15 and 516 DF,  p-value: 0.8629
```

APPENDIX B: Ordinary Least Squares (OLS) Regressions and Code

Table B.1 Five-Market Pre-Break (2006-2013) OLS Basis Estimation Regression

```
> summary(FMlm1)

Call:
lm(formula = yFM1 ~ xFM1)

Residuals:
    Min      1Q  Median      3Q     Max 
-5.3679 -0.8821 -0.0606  0.7557  6.5199 

Coefficients:
                Estimate Std. Error t value Pr(>|t|)    
(Intercept)    3.794e+00  5.352e+00   0.709 0.478939    
xFM1FMNBL      5.252e-01  4.734e-02  11.095  < 2e-16 ***
xFM1FMALW     -3.394e-03  4.418e-03  -0.768 0.442894    
xFM1FMHD       4.213e-06  7.404e-06   0.569 0.569769    
xFM1PCOB       5.466e+00  1.485e+00   3.680 0.000271 ***
xFM1CSSpread   3.006e-02  2.213e-02   1.358 0.175334    
xFM1CornRatio -3.860e-02  8.153e-02  -0.473 0.636212    
xFM1PLLOI     -1.755e+00  2.030e+00  -0.864 0.388002    
xFM1LC1RSI14D -4.012e-02  1.159e-02  -3.463 0.000604 ***
xFM1Feb       -9.040e-01  3.579e-01  -2.526 0.012012 *  
xFM1Apr       -2.975e-02  3.360e-01  -0.089 0.929518    
xFM1Aug       -7.093e-01  3.502e-01  -2.025 0.043639 *  
xFM1Oct       -3.285e-01  3.991e-01  -0.823 0.411039    
xFM1Dec       -5.511e-01  3.630e-01  -1.518 0.129872    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.431 on 334 degrees of freedom
Multiple R-squared:   0.57,	Adjusted R-squared:  0.5532 
F-statistic: 34.05 on 13 and 334 DF,  p-value: < 2.2e-16
```

Table B.2 Texas/Oklahoma/New Mexico Pre-Break (2006-2013) OLS Basis Estimation Regression

```
> summary(TXOKNMlm1)

Call:
lm(formula = yTXOKNM1 ~ xTXOKNM1)

Residuals:
    Min      1Q  Median      3Q     Max 
-5.4306 -0.8160 -0.0178  0.7506  5.9926 

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)    
(Intercept)        1.357e+01  4.814e+00   2.818  0.00512 ** 
xTXOKNM1TXOKNMNBL  4.344e-01  5.008e-02   8.674  < 2e-16 ***
xTXOKNM1TXOKNMALW -8.029e-03  3.640e-03  -2.206  0.02808 *  
xTXOKNM1TXOKNMHD   1.398e-05  2.169e-05   0.644  0.51989    
xTXOKNM1PCOB       3.906e+00  1.501e+00   2.603  0.00965 ** 
xTXOKNM1CSSpread   3.665e-03  2.288e-02   0.160  0.87283    
xTXOKNM1CornRatio -7.979e-02  8.290e-02  -0.963  0.33648    
xTXOKNM1PLLOI     -5.628e+00  1.846e+00  -3.048  0.00249 ** 
xTXOKNM1LC1RSI14D -5.990e-02  1.216e-02  -4.926 1.33e-06 ***
xTXOKNM1TXOKNMPCT -1.863e+00  1.474e+00  -1.264  0.20713    
xTXOKNM1Feb       -8.969e-01  3.434e-01  -2.612  0.00941 ** 
xTXOKNM1Apr       -1.912e-01  3.451e-01  -0.554  0.57996    
xTXOKNM1Aug       -9.237e-01  3.398e-01  -2.718  0.00691 ** 
xTXOKNM1Oct       -1.648e-01  3.495e-01  -0.471  0.63760    
xTXOKNM1Dec       -3.493e-01  3.211e-01  -1.088  0.27751    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.443 on 333 degrees of freedom
Multiple R-squared:  0.5268,   Adjusted R-squared:  0.5069 
F-statistic: 26.48 on 14 and 333 DF,  p-value: < 2.2e-16
```

Table B.3 Colorado Pre-Break (2006-2013) OLS Basis Estimation Regression

```
> summary(COlm1)

Call:
lm(formula = yCO1 ~ xCO1)

Residuals:
    Min      1Q  Median      3Q     Max 
-5.3767 -0.9277 -0.1091  0.9630  6.7689 

Coefficients:
                Estimate Std. Error t value Pr(>|t|)    
(Intercept)    5.512e+00  3.456e+00   1.595   0.1117    
xCO1CONBL      5.665e-01  4.466e-02  12.685  < 2e-16 ***
xCO1COALW     -6.051e-03  2.765e-03  -2.189   0.0293 *  
xCO1COHD       7.754e-05  9.841e-05   0.788   0.4313    
xCO1CornRatio -3.795e-03  8.728e-02  -0.043   0.9653    
xCO1PCOB       6.585e+00  1.565e+00   4.208 3.32e-05 ***
xCO1CSSpread   3.011e-02  2.370e-02   1.270   0.2049    
xCO1PLLOI     -2.973e-01  1.860e+00  -0.160   0.8731    
xCO1LC1RSI14D -2.549e-02  1.167e-02  -2.184   0.0297 *  
xCO1COPCT     -3.563e+00  4.446e+00  -0.802   0.4234    
xCO1Feb       -8.807e-01  3.941e-01  -2.235   0.0261 *  
xCO1Apr        9.118e-02  3.538e-01   0.258   0.7968    
xCO1Aug       -3.937e-01  3.484e-01  -1.130   0.2592    
xCO1Oct        1.390e-02  3.669e-01   0.038   0.9698    
xCO1Dec       -3.362e-01  3.592e-01  -0.936   0.3499    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.534 on 333 degrees of freedom
Multiple R-squared:  0.5903,	Adjusted R-squared:  0.5731 
F-statistic: 34.28 on 14 and 333 DF,  p-value: < 2.2e-16
```

Table B.4 Nebraska Pre-Break (2006-2013) OLS Basis Estimation Regression

```
> summary(NElm1)

Call:
lm(formula = yNE1 ~ xNE1)

Residuals:
    Min      1Q  Median      3Q     Max 
-5.0170 -0.9460 -0.0779  0.8526  6.8766 

Coefficients:
                Estimate Std. Error t value Pr(>|t|)    
(Intercept)    4.171e+00  4.364e+00   0.956  0.33989    
xNE1NENBL      5.976e-01  4.410e-02  13.552  < 2e-16 ***
xNE1NEALW     -5.132e-03  3.494e-03  -1.469  0.14278    
xNE1NEHD       2.451e-05  3.944e-05   0.621  0.53474    
xNE1CornRatio  1.213e-02  8.561e-02   0.142  0.88741    
xNE1PCOB       5.874e+00  1.532e+00   3.835  0.00015 ***
xNE1CSSpread   3.005e-02  2.324e-02   1.293  0.19695    
xNE1PLLOI      8.165e-01  1.982e+00   0.412  0.68061    
xNE1LC1RSI14D -2.347e-02  1.167e-02  -2.011  0.04508 *  
xNE1NEPCT     -1.028e+00  1.610e+00  -0.639  0.52348    
xNE1Feb       -6.763e-01  4.422e-01  -1.529  0.12714    
xNE1Apr        3.671e-01  3.559e-01   1.031  0.30307    
xNE1Aug       -3.386e-01  3.543e-01  -0.956  0.33996    
xNE1Oct        1.358e-02  4.144e-01   0.033  0.97387    
xNE1Dec       -2.660e-01  4.144e-01  -0.642  0.52142    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.496 on 333 degrees of freedom
Multiple R-squared:  0.6217,	Adjusted R-squared:  0.6058 
F-statistic: 39.08 on 14 and 333 DF,  p-value: < 2.2e-16
```

Table B.5 Iowa/Minnesota Pre-Break (2006-2013) OLS Basis Estimation Regression

```
> summary(IAMNlm1)

Call:
lm(formula = yIAMN1 ~ xIAMN1)

Residuals:
    Min      1Q  Median      3Q     Max 
-4.9827 -1.0105 -0.0351  0.9986  6.2770 

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)    
(Intercept)      7.335e+00  5.146e+00   1.426 0.154943    
xIAMN1IAMNNBL    5.742e-01  4.283e-02  13.406  < 2e-16 ***
xIAMN1IAMNALW   -6.350e-03  4.154e-03  -1.529 0.127311    
xIAMN1IAMNHD     7.498e-05  4.910e-05   1.527 0.127658    
xIAMN1CornRatio -5.941e-03  9.051e-02  -0.066 0.947707    
xIAMN1PCOB       5.201e+00  1.595e+00   3.260 0.001230 ** 
xIAMN1CSSpread   6.409e-02  2.561e-02   2.503 0.012802 *  
xIAMN1PLLOI     -1.888e+00  2.154e+00  -0.877 0.381350    
xIAMN1LC1RSI14D -4.855e-02  1.268e-02  -3.830 0.000153 ***
xIAMN1IAMNPCT    3.103e+00  2.159e+00   1.437 0.151683    
xIAMN1Feb       -4.256e-01  4.567e-01  -0.932 0.352041    
xIAMN1Apr        9.103e-01  3.983e-01   2.285 0.022914 *  
xIAMN1Aug       -8.090e-01  3.765e-01  -2.149 0.032367 *  
xIAMN1Oct       -9.704e-01  4.775e-01  -2.032 0.042909 *  
xIAMN1Dec       -3.077e-01  4.530e-01  -0.679 0.497366    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.596 on 333 degrees of freedom
Multiple R-squared:  0.672,	Adjusted R-squared:  0.6582 
F-statistic: 48.74 on 14 and 333 DF,  p-value: < 2.2e-16
```

Table B.6 Kansas Pre-Break (2006-2013) OLS Basis Estimation Regression

```
> summary(KSlm1)

Call:
lm(formula = yKS1 ~ xKS1)

Residuals:
    Min      1Q  Median      3Q     Max 
-5.3185 -0.8127 -0.0395  0.7460  6.8782 

Coefficients:
                Estimate Std. Error t value Pr(>|t|)    
(Intercept)    1.281e+01  5.844e+00   2.191  0.02911 *  
xKS1KSNBL      4.858e-01  4.755e-02  10.216  < 2e-16 ***
xKS1KSALW     -1.055e-02  4.612e-03  -2.287  0.02280 *  
xKS1KSHD       2.697e-05  2.205e-05   1.223  0.22217    
xKS1CornRatio -7.484e-02  8.363e-02  -0.895  0.37154    
xKS1PCOB       4.401e+00  1.464e+00   3.007  0.00284 ** 
xKS1CSSpread   1.336e-02  2.321e-02   0.576  0.56533    
xKS1PLLOI     -6.103e-01  1.831e+00  -0.333  0.73907    
xKS1LC1RSI14D -4.703e-02  1.121e-02  -4.194 3.52e-05 ***
xKS1KSPCT      3.350e+00  1.406e+00   2.383  0.01772 *  
xKS1Feb       -8.301e-01  3.396e-01  -2.445  0.01502 *  
xKS1Apr       -2.414e-01  3.552e-01  -0.680  0.49720    
xKS1Aug       -6.204e-01  3.393e-01  -1.829  0.06836 .  
xKS1Oct        1.833e-01  3.736e-01   0.491  0.62401    
xKS1Dec       -4.140e-01  3.398e-01  -1.218  0.22397    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.442 on 333 degrees of freedom
Multiple R-squared:  0.5373,	Adjusted R-squared:  0.5179 
F-statistic: 27.62 on 14 and 333 DF,  p-value: < 2.2e-16
```

Table B.7 Five-Market Post-Break (2014-2017) OLS Basis Estimation Regression

```
> summary(FMlm2)

Call:
lm(formula = yFM2 ~ xFM2)

Residuals:
    Min      1Q  Median      3Q     Max 
-5.7048 -1.3787 -0.2136  1.3300  5.9382 

Coefficients:
                Estimate Std. Error t value Pr(>|t|)    
(Intercept)    3.434e+01  1.193e+01   2.879  0.00450 ** 
xFM2FMNBL      5.680e-01  5.929e-02   9.581  < 2e-16 ***
xFM2FMALW     -1.010e-02  8.456e-03  -1.194  0.23408    
xFM2FMHD       8.359e-05  2.012e-05   4.154 5.15e-05 ***
xFM2PCOB      -1.984e+01  7.015e+00  -2.828  0.00525 ** 
xFM2CSSpread   5.479e-02  3.877e-02   1.413  0.15938    
xFM2CornRatio -5.144e-01  5.106e-01  -1.007  0.31516    
xFM2PLLOI     -6.200e+00  3.320e+00  -1.867  0.06354 .  
xFM2LC1RSI14D -8.203e-02  2.502e-02  -3.279  0.00126 ** 
xFM2Feb        1.963e+00  8.542e-01   2.297  0.02281 *  
xFM2Apr        1.192e+00  6.766e-01   1.761  0.07999 .  
xFM2Aug        2.896e-01  6.905e-01   0.419  0.67545    
xFM2Oct       -8.979e-01  8.592e-01  -1.045  0.29746    
xFM2Dec       -1.390e-01  8.515e-01  -0.163  0.87055    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.073 on 171 degrees of freedom
Multiple R-squared:  0.7169,	Adjusted R-squared:  0.6954 
F-statistic: 33.32 on 13 and 171 DF,  p-value: < 2.2e-16
```

Table B.8 Texas/Oklahoma/New Mexico Post-Break (2014-2017) OLS Basis Estimation Regression

```
> summary(TXOKNMlm2)

Call:
lm(formula = yTXOKNM2 ~ xTXOKNM2)

Residuals:
    Min      1Q  Median      3Q     Max 
-6.6776 -1.5040 -0.0528  1.3644  5.6905 

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)    
(Intercept)        3.239e+01  8.018e+00   4.040 8.08e-05 ***
xTXOKNM2TXOKNMNBL  4.614e-01  6.452e-02   7.152 2.43e-11 ***
xTXOKNM2TXOKNMALW -6.279e-03  4.683e-03  -1.341 0.181774    
xTXOKNM2TXOKNMHD   5.933e-04  1.923e-04   3.086 0.002369 ** 
xTXOKNM2PCOB      -2.201e+01  8.052e+00  -2.734 0.006923 ** 
xTXOKNM2CSSpread   1.210e-01  4.399e-02   2.750 0.006603 ** 
xTXOKNM2CornRatio -4.707e-01  5.218e-01  -0.902 0.368303    
xTXOKNM2PLLOI     -6.562e+00  3.478e+00  -1.887 0.060883 .  
xTXOKNM2LC1RSI14D -9.918e-02  2.736e-02  -3.624 0.000382 ***
xTXOKNM2TXOKNMPCT -9.052e+00  6.985e+00  -1.296 0.196725    
xTXOKNM2Feb        1.837e+00  9.088e-01   2.021 0.044811 *  
xTXOKNM2Apr        4.116e-01  7.976e-01   0.516 0.606498    
xTXOKNM2Aug        5.528e-01  7.181e-01   0.770 0.442419    
xTXOKNM2Oct       -1.312e+00  7.540e-01  -1.740 0.083675 .  
xTXOKNM2Dec       -1.334e+00  7.573e-01  -1.761 0.080028 .  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.321 on 170 degrees of freedom
Multiple R-squared:  0.6022,	Adjusted R-squared:  0.5694 
F-statistic: 18.38 on 14 and 170 DF,  p-value: < 2.2e-16
```

Table B.9 Colorado Post-Break (2014-2017) OLS Basis Estimation Regression

```
> summary(COlm2)

Call:
lm(formula = yCO2 ~ xCO2)

Residuals:
    Min      1Q  Median      3Q     Max 
-4.9622 -1.4114  0.0482  1.3479  6.5309 

Coefficients:
                Estimate Std. Error t value Pr(>|t|)    
(Intercept)    1.708e+01  8.360e+00   2.043  0.04262 *  
xCO2CONBL      5.210e-01  6.173e-02   8.439 1.35e-14 ***
xCO2COALW     -1.948e-03  4.031e-03  -0.483  0.62957    
xCO2COHD       4.752e-04  2.468e-04   1.925  0.05587 .  
xCO2CornRatio  4.110e-01  5.179e-01   0.794  0.42858    
xCO2PCOB      -1.477e+01  7.830e+00  -1.886  0.06096 .  
xCO2CSSpread   8.599e-02  4.253e-02   2.022  0.04474 *  
xCO2PLLOI     -6.408e+00  3.413e+00  -1.877  0.06218 .  
xCO2LC1RSI14D -3.258e-02  2.730e-02  -1.193  0.23437    
xCO2COPCT     -1.861e+01  6.601e+00  -2.820  0.00538 ** 
xCO2Feb        1.003e+00  9.302e-01   1.078  0.28251    
xCO2Apr        7.236e-01  7.640e-01   0.947  0.34492    
xCO2Aug        7.095e-01  7.186e-01   0.987  0.32487    
xCO2Oct       -1.323e+00  7.878e-01  -1.680  0.09482 .  
xCO2Dec       -1.097e+00  8.043e-01  -1.364  0.17438    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.311 on 170 degrees of freedom
Multiple R-squared:  0.6492,	Adjusted R-squared:  0.6204 
F-statistic: 22.48 on 14 and 170 DF,  p-value: < 2.2e-16
```

Table B.10 Nebraska Post-Break (2014-2017) OLS Basis Estimation Regression

```
> summary(NElm2)

Call:
lm(formula = yNE2 ~ xNE2)

Residuals:
    Min      1Q  Median      3Q     Max 
-5.1030 -1.6476 -0.1079  1.2465  6.9016 

Coefficients:
                Estimate Std. Error t value Pr(>|t|)    
(Intercept)    2.019e+01  9.259e+00   2.180 0.030616 *  
xNE2NENBL      6.006e-01  5.950e-02  10.094  < 2e-16 ***
xNE2NEALW      1.533e-03  6.654e-03   0.230 0.818047    
xNE2NEHD       1.769e-04  5.269e-05   3.357 0.000972 ***
xNE2CornRatio  2.255e-03  5.049e-01   0.004 0.996441    
xNE2PCOB      -2.114e+01  7.716e+00  -2.740 0.006793 ** 
xNE2CSSpread   4.553e-02  4.078e-02   1.116 0.265862    
xNE2PLLOI     -7.758e+00  3.423e+00  -2.266 0.024693 *  
xNE2LC1RSI14D -5.490e-02  2.598e-02  -2.114 0.036002 *  
xNE2NEPCT     -7.389e+00  2.154e+00  -3.431 0.000755 ***
xNE2Feb        1.048e+00  9.188e-01   1.140 0.255783    
xNE2Apr        8.903e-01  7.486e-01   1.189 0.235957    
xNE2Aug        1.567e-01  7.053e-01   0.222 0.824486    
xNE2Oct       -1.421e+00  8.264e-01  -1.720 0.087297 .  
xNE2Dec       -8.661e-01  8.784e-01  -0.986 0.325546    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.188 on 170 degrees of freedom
Multiple R-squared:  0.7021,  Adjusted R-squared:  0.6776 
F-statistic: 28.62 on 14 and 170 DF,  p-value: < 2.2e-16
```

Table B.11 Iowa/Minnesota Post-Break (2014-2017) OLS Basis Estimation Regression

```
> summary(IAMNlm2)

Call:
lm(formula = yIAMN2 ~ xIAMN2)

Residuals:
    Min      1Q  Median      3Q     Max 
-7.1113 -1.2029 -0.0492  1.3076  5.4376 

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)    
(Intercept)      1.207e+01  1.225e+01   0.985 0.326166    
xIAMN2IAMNNBL    6.044e-01  6.221e-02   9.715  < 2e-16 ***
xIAMN2IAMNALW    4.065e-03  8.387e-03   0.485 0.628542    
xIAMN2IAMNHD     3.218e-04  8.726e-05   3.688 0.000304 ***
xIAMN2CornRatio  4.266e-01  5.721e-01   0.746 0.456897    
xIAMN2PCOB      -1.536e+01  7.544e+00  -2.037 0.043239 *  
xIAMN2CSSpread   6.920e-02  4.031e-02   1.717 0.087869 .  
xIAMN2PLLOI     -1.251e+01  3.771e+00  -3.318 0.001110 ** 
xIAMN2LC1RSI14D -8.104e-02  2.699e-02  -3.002 0.003085 ** 
xIAMN2IAMNPCT   -4.427e+00  2.581e+00  -1.715 0.088168 .  
xIAMN2Feb        9.405e-01  9.976e-01   0.943 0.347131    
xIAMN2Apr        1.232e+00  7.524e-01   1.637 0.103406    
xIAMN2Aug       -6.766e-01  7.120e-01  -0.950 0.343293    
xIAMN2Oct       -2.517e+00  9.331e-01  -2.698 0.007678 ** 
xIAMN2Dec       -1.483e+00  9.765e-01  -1.518 0.130825    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.184 on 170 degrees of freedom
Multiple R-squared:  0.7705,	Adjusted R-squared:  0.7516 
F-statistic: 40.76 on 14 and 170 DF,  p-value: < 2.2e-16
```

Table B.12 Kansas Post-Break (2014-2017) OLS Basis Estimation Regression

```
> summary(KSlm2)

Call:
lm(formula = yKS2 ~ xKS2)

Residuals:
    Min      1Q  Median      3Q     Max 
-6.0702 -1.3086 -0.0542  1.4496  5.5204 

Coefficients:
                Estimate Std. Error t value Pr(>|t|)    
(Intercept)    4.602e+01  9.734e+00   4.728 4.73e-06 ***
xKS2KSNBL      5.058e-01  5.999e-02   8.433 1.40e-14 ***
xKS2KSALW     -1.963e-02  7.037e-03  -2.789 0.005889 ** 
xKS2KSHD       3.678e-04  7.578e-05   4.853 2.73e-06 ***
xKS2CornRatio -6.385e-01  4.766e-01  -1.340 0.182159    
xKS2PCOB      -1.724e+01  7.211e+00  -2.390 0.017940 *  
xKS2CSSpread   5.951e-02  4.015e-02   1.482 0.140154    
xKS2PLLOI     -4.500e+00  3.372e+00  -1.335 0.183813    
xKS2LC1RSI14D -8.494e-02  2.518e-02  -3.373 0.000922 ***
xKS2KSPCT     -4.304e+00  2.665e+00  -1.615 0.108092    
xKS2Feb        1.736e+00  8.263e-01   2.101 0.037107 *  
xKS2Apr        5.320e-01  6.954e-01   0.765 0.445372    
xKS2Aug        7.050e-01  6.867e-01   1.027 0.306106    
xKS2Oct       -6.546e-01  7.232e-01  -0.905 0.366704    
xKS2Dec       -3.016e-01  7.104e-01  -0.425 0.671668    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.11 on 170 degrees of freedom
Multiple R-squared:  0.6644,	Adjusted R-squared:  0.6367 
F-statistic: 24.04 on 14 and 170 DF,  p-value: < 2.2e-16
```

APPENDIX C: Seemingly Unrelated Regression (SUR) Estimation Results and Code

Table C.1 Pre-Break (2006-2013) SUR initial results

```
> summary(FMsur1)

systemfit results
method: SUR

          N   DF     SSR  detRCov   OLS-R2 McElroy-R2
system 1740 1665 3905.33 0.014707 0.585901   0.524115

            N  DF     SSR     MSE    RMSE       R2   Adj R2
TXOKNMeq1 348 333 710.534 2.13374 1.46073 0.515084 0.494698
COeq1     348 333 814.895 2.44713 1.56433 0.573814 0.555896
NEeq1     348 333 771.633 2.31722 1.52224 0.608315 0.591848
IAMNeq1   348 333 886.557 2.66233 1.63167 0.657201 0.642789
KSeq1     348 333 721.715 2.16731 1.47218 0.517990 0.497725

The covariance matrix of the residuals used for estimation
          TXOKNMeq1   COeq1   NEeq1 IAMNeq1   KSeq1
TXOKNMeq1   2.08207 1.92336 1.85238 1.82345 1.95445
COeq1       1.92336 2.35221 2.12877 1.98827 1.97369
NEeq1       1.85238 2.12877 2.23823 2.07015 1.91723
IAMNeq1     1.82345 1.98827 2.07015 2.54725 1.85054
KSeq1       1.95445 1.97369 1.91723 1.85054 2.08037

The covariance matrix of the residuals
          TXOKNMeq1   COeq1   NEeq1 IAMNeq1   KSeq1
TXOKNMeq1   2.13374 2.05546 1.97634 1.96302 2.07258
COeq1       2.05546 2.44713 2.24760 2.17451 2.10485
NEeq1       1.97634 2.24760 2.31722 2.23000 2.03124
IAMNeq1     1.96302 2.17451 2.23000 2.66233 2.01240
KSeq1       2.07258 2.10485 2.03124 2.01240 2.16731

The correlations of the residuals
          TXOKNMeq1    COeq1    NEeq1  IAMNeq1    KSeq1
TXOKNMeq1  1.000000 0.899517 0.888811 0.823615 0.963784
COeq1      0.899517 1.000000 0.943860 0.851925 0.913971
NEeq1      0.888811 0.943860 1.000000 0.897822 0.906396
IAMNeq1    0.823615 0.851925 0.897822 1.000000 0.837763
KSeq1      0.963784 0.913971 0.906396 0.837763 1.000000
```

Table C.2 Texas/Oklahoma/New Mexico SUR Pre-Break (2006-2013) Regression

```
SUR estimates for 'TXOKNMeq1' (equation 1)
Model Formula: yTXOKNM1 ~ xTXOKNM1

                      Estimate   Std. Error  t value   Pr(>|t|)    
(Intercept)        3.71263e+00  1.90964e+00  1.94415 0.05271911 .  
xTXOKNM1TXOKNMNBL  4.26137e-01  2.95085e-02 14.44115 < 2.22e-16 ***
xTXOKNM1TXOKNMALW -1.47311e-03  1.23372e-03 -1.19404 0.23331150    
xTXOKNM1TXOKNMHD  -9.18064e-06  9.71855e-06 -0.94465 0.34552177    
xTXOKNM1PCOB       4.78969e+00  1.39142e+00  3.44231 0.00065033 ***
xTXOKNM1CSSpread   2.09084e-02  2.20997e-02  0.94609 0.34478738    
xTXOKNM1CornRatio -6.58817e-02  7.97019e-02 -0.82660 0.40905492    
xTXOKNM1PLLOI     -5.41211e+00  1.59356e+00 -3.39624 0.00076585 ***
xTXOKNM1LC1RSI14D -5.17996e-02  1.08417e-02 -4.77781 2.6618e-06 ***
xTXOKNM1TXOKNMPCT  8.57971e-01  5.49213e-01  1.56218 0.11919469    
xTXOKNM1Feb       -1.07267e+00  3.18206e-01 -3.37098 0.00083707 ***
xTXOKNM1Apr       -3.15339e-01  3.30762e-01 -0.95337 0.34109367    
xTXOKNM1Aug       -1.09447e+00  2.99265e-01 -3.65719 0.00029627 ***
xTXOKNM1Oct       -4.67139e-01  3.05209e-01 -1.53056 0.12682859    
xTXOKNM1Dec       -5.98724e-01  2.95163e-01 -2.02845 0.04331004 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.460731 on 333 degrees of freedom
Number of observations: 348 Degrees of Freedom: 333 
SSR: 710.533783 MSE: 2.133735 Root MSE: 1.460731 
Multiple R-Squared: 0.515084 Adjusted R-Squared: 0.494698 
```

Table C.3 Colorado SUR Pre-Break (2006-2013) Regression

```
SUR estimates for 'COeq1' (equation 2)
Model Formula: yCO1 ~ xCO1

                  Estimate   Std. Error  t value   Pr(>|t|)    
(Intercept)    4.51926e-02  1.58326e+00  0.02854  0.9772454    
xCO1CONBL      4.47633e-01  2.65490e-02 16.86063 < 2.22e-16 ***
xCO1COALW     -9.15447e-04  9.57707e-04 -0.95587  0.3398296    
xCO1COHD       1.59199e-05  4.57470e-05  0.34800  0.7280601    
xCO1CornRatio -2.26947e-02  8.45449e-02 -0.26843  0.7885320    
xCO1PCOB       6.68092e+00  1.47567e+00  4.52738 8.3267e-06 ***
xCO1CSSpread   4.13241e-02  2.34396e-02  1.76300  0.0788174 .  
xCO1PLLOI     -2.54027e+00  1.66943e+00 -1.52164  0.1290481    
xCO1LC1RSI14D -3.67383e-02  1.12694e-02 -3.26001  0.0012292 ** 
xCO1COPCT      9.51966e-01  1.85946e+00  0.51196  0.6090185    
xCO1Feb       -1.69313e+00  3.45496e-01 -4.90058 1.4948e-06 ***
xCO1Apr       -8.72912e-02  3.49287e-01 -0.24991  0.8028089    
xCO1Aug       -1.00267e+00  3.12800e-01 -3.20547  0.0014790 ** 
xCO1Oct       -6.04726e-01  3.22634e-01 -1.87434  0.0617584 .  
xCO1Dec       -9.13768e-01  3.15785e-01 -2.89364  0.0040589 ** 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.564331 on 333 degrees of freedom
Number of observations: 348 Degrees of Freedom: 333 
SSR: 814.89472 MSE: 2.447131 Root MSE: 1.564331 
Multiple R-Squared: 0.573814 Adjusted R-Squared: 0.555896 
```

Table C.4 Nebraska SUR Pre-Break (2006-2013) Regression

```
SUR estimates for 'NEeq1' (equation 3)
Model Formula: yNE1 ~ xNE1

                  Estimate   Std. Error  t value   Pr(>|t|)
(Intercept)    1.56506e+00  1.72208e+00  0.90882  0.3641039
xNE1NENBL      4.63469e-01  2.56080e-02 18.09860 < 2.22e-16 ***
xNE1NEALW     -2.21055e-03  1.11656e-03 -1.97979  0.0485499 *
xNE1NEHD      -8.16150e-06  1.69917e-05 -0.48032  0.6313128
xNE1CornRatio -6.30612e-03  8.23801e-02 -0.07655  0.9390282
xNE1PCOB       6.11786e+00  1.43648e+00  4.25893 2.6757e-05 ***
xNE1CSSpread   4.06667e-02  2.29121e-02  1.77490  0.0768284 .
xNE1PLLOI     -1.42434e+00  1.65472e+00 -0.86078  0.3899798
xNE1LC1RSI14D -3.37766e-02  1.09984e-02 -3.07106  0.0023086 **
xNE1NEPCT      3.82047e-01  6.31433e-01  0.60505  0.5455596
xNE1Feb       -1.49461e+00  3.43553e-01 -4.35045 1.8089e-05 ***
xNE1Apr        9.98541e-02  3.41489e-01  0.29241  0.7701572
xNE1Aug       -9.39926e-01  3.06114e-01 -3.07050  0.0023128 **
xNE1Oct       -7.12511e-01  3.22437e-01 -2.20977  0.0278011 *
xNE1Dec       -9.29677e-01  3.16735e-01 -2.93519  0.0035651 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.52224 on 333 degrees of freedom
Number of observations: 348 Degrees of Freedom: 333
SSR: 771.632866 MSE: 2.317216 Root MSE: 1.52224
Multiple R-Squared: 0.608315 Adjusted R-Squared: 0.591848
```

Table C.5 Iowa/Minnesota SUR Pre-Break (2006-2013) Regression

```
SUR estimates for 'IAMNeq1' (equation 4)
Model Formula: yIAMN1 ~ xIAMN1

                    Estimate   Std. Error  t value   Pr(>|t|)
(Intercept)      1.43591e+01  2.74377e+00  5.23334 2.9525e-07 ***
xIAMN1IAMNNBL    5.14880e-01  2.79187e-02 18.44215 < 2.22e-16 ***
xIAMN1IAMNALW   -1.22104e-02  2.07343e-03 -5.88900 9.4967e-09 ***
xIAMN1IAMNHD    -5.00543e-05  2.79238e-05 -1.79253 0.07395540 .
xIAMN1CornRatio  1.37986e-02  8.82401e-02  0.15638 0.87583199
xIAMN1PCOB       6.18715e+00  1.53591e+00  4.02832 6.9638e-05 ***
xIAMN1CSSpread   8.31198e-02  2.48155e-02  3.34951 0.00090237 ***
xIAMN1PLLOI     -9.01794e-01  1.83902e+00 -0.49037 0.62419822
xIAMN1LC1RSI14D -4.07084e-02  1.18943e-02 -3.42251 0.00069783 ***
xIAMN1IAMNPCT    3.67283e+00  1.16854e+00  3.14310 0.00182196 **
xIAMN1Feb       -4.39870e-01  3.75346e-01 -1.17191 0.24207287
xIAMN1Apr        8.30302e-01  3.70989e-01  2.23807 0.02587686 *
xIAMN1Aug       -6.32767e-01  3.33174e-01 -1.89921 0.05840130 .
xIAMN1Oct       -7.04526e-01  3.74128e-01 -1.88311 0.06055632 .
xIAMN1Dec       -2.33103e-01  3.58863e-01 -0.64956 0.51642523
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.631666 on 333 degrees of freedom
Number of observations: 348 Degrees of Freedom: 333
SSR: 886.557251 MSE: 2.662334 Root MSE: 1.631666
Multiple R-Squared: 0.657201 Adjusted R-Squared: 0.642789
```

Table C.6 Kansas SUR Pre-Break (2006-2013) Regression

```
SUR estimates for 'KSeq1' (equation 5)
Model Formula: yKS1 ~ xKS1

                  Estimate   Std. Error  t value   Pr(>|t|)
(Intercept)    5.74230e+00  2.03754e+00  2.81826  0.0051171 **
xKS1KSNBL      4.40254e-01  2.77433e-02 15.86883 < 2.22e-16 ***
xKS1KSALW     -3.41881e-03  1.40477e-03 -2.43371  0.0154702 *
xKS1KSHD       3.17606e-06  9.49761e-06  0.33441  0.7382837
xKS1CornRatio -8.15740e-02  7.96973e-02 -1.02355  0.3067921
xKS1PCOB       4.53928e+00  1.37999e+00  3.28936  0.0011115 **
xKS1CSSpread   1.99077e-02  2.20945e-02  0.90102  0.3682271
xKS1PLLOI     -3.35415e+00  1.58503e+00 -2.11615  0.0350742 *
xKS1LC1RSI14D -5.09779e-02  1.07118e-02 -4.75903 2.9043e-06 ***
xKS1KSPCT      4.05289e-01  5.03411e-01  0.80509  0.4213443
xKS1Feb       -1.01566e+00  3.16590e-01 -3.20812  0.0014659 **
xKS1Apr       -1.44499e-01  3.30475e-01 -0.43725  0.6622163
xKS1Aug       -9.42322e-01  2.96189e-01 -3.18149  0.0016031 **
xKS1Oct       -3.25250e-01  3.04431e-01 -1.06839  0.2861204
xKS1Dec       -7.34692e-01  2.96189e-01 -2.48048  0.0136142 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.472179 on 333 degrees of freedom
Number of observations: 348 Degrees of Freedom: 333
SSR: 721.715048 MSE: 2.167312 Root MSE: 1.472179
Multiple R-Squared: 0.51799 Adjusted R-Squared: 0.497725
```

Table C.7 Post-Break (2014-2017) SUR initial results

```
> summary(FMsur2)

systemfit results
method: SUR

         N  DF     SSR detRCov   OLS-R2 McElroy-R2
system 925 850 4794.91 2.24442 0.642464   0.477922

             N  DF      SSR     MSE    RMSE       R2   Adj R2
TXOKNMeq2 185 170 1014.492 5.96760 2.44287 0.559451 0.523171
COeq2     185 170 1019.083 5.99460 2.44839 0.606276 0.573851
NEeq2     185 170  943.145 5.54791 2.35540 0.654968 0.626553
IAMNeq2   185 170  920.593 5.41525 2.32707 0.739344 0.717879
KSeq2     185 170  897.592 5.27995 2.29781 0.601873 0.569086

The covariance matrix of the residuals used for estimation
          TXOKNMeq2   COeq2   NEeq2 IAMNeq2   KSeq2
TXOKNMeq2   5.38845 4.16361 4.03428 3.88222 4.22166
COeq2       4.16361 5.34034 4.23269 3.77325 4.09454
NEeq2       4.03428 4.23269 4.78937 4.02937 3.82518
IAMNeq2     3.88222 3.77325 4.02937 4.76887 3.68066
KSeq2       4.22166 4.09454 3.82518 3.68066 4.45106

The covariance matrix of the residuals
          TXOKNMeq2   COeq2   NEeq2 IAMNeq2   KSeq2
TXOKNMeq2   5.96760 5.07404 5.04124 4.80110 5.29975
COeq2       5.07404 5.99461 5.23707 4.75130 5.09819
NEeq2       5.04124 5.23707 5.54791 4.99730 4.91486
IAMNeq2     4.80110 4.75130 4.99730 5.41525 4.64903
KSeq2       5.29975 5.09819 4.91486 4.64903 5.27995

The correlations of the residuals
          TXOKNMeq2    COeq2    NEeq2  IAMNeq2    KSeq2
TXOKNMeq2  1.000000 0.848348 0.876138 0.844562 0.944148
COeq2      0.848348 1.000000 0.908120 0.833918 0.906192
NEeq2      0.876138 0.908120 1.000000 0.911719 0.908095
IAMNeq2    0.844562 0.833918 0.911719 1.000000 0.869437
KSeq2      0.944148 0.906192 0.908095 0.869437 1.000000
```

Table C.8 Texas/Oklahoma/New Mexico SUR Post-Break (2014-2017) Regression

```
SUR estimates for 'TXOKNMeq2' (equation 1)
Model Formula: yTXOKNM2 ~ xTXOKNM2

                      Estimate   Std. Error  t value   Pr(>|t|)    
(Intercept)        1.85237e+01  6.60734e+00  2.80350 0.00564318 ** 
xTXOKNM2TXOKNMNBL  3.07002e-01  4.62635e-02  6.63596 4.1395e-10 ***
xTXOKNM2TXOKNMALW  1.88279e-03  2.25937e-03  0.83332 0.40583122    
xTXOKNM2TXOKNMHD   8.18788e-05  1.06507e-04  0.76876 0.44310192    
xTXOKNM2PCOB      -1.71089e+01  7.02755e+00 -2.43455 0.01594459 *  
xTXOKNM2CSSpread   1.61545e-01  4.21752e-02  3.83034 0.00017976 ***
xTXOKNM2CornRatio  2.92821e-02  4.97085e-01  0.05891 0.95309482    
xTXOKNM2PLLOI     -1.12723e+01  3.30213e+00 -3.41365 0.00080138 ***
xTXOKNM2LC1RSI14D -8.50492e-02  2.61003e-02 -3.25856 0.00135235 ** 
xTXOKNM2TXOKNMPCT -1.32369e+00  3.64189e+00 -0.36346 0.71671063    
xTXOKNM2Feb        1.78517e+00  8.99196e-01  1.98529 0.04872002 *  
xTXOKNM2Apr        6.34668e-01  7.56948e-01  0.83846 0.40295162    
xTXOKNM2Aug        1.81960e-01  7.12061e-01  0.25554 0.79861546    
xTXOKNM2Oct       -2.09144e+00  7.08508e-01 -2.95190 0.00360479 ** 
xTXOKNM2Dec       -2.47941e+00  7.01613e-01 -3.53387 0.00052756 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.442867 on 170 degrees of freedom
Number of observations: 185 Degrees of Freedom: 170 
SSR: 1014.492135 MSE: 5.967601 Root MSE: 2.442867 
Multiple R-Squared: 0.559451 Adjusted R-Squared: 0.523171 
```

Table C.9 Colorado SUR Post-Break (2014-2017) Regression

```
SUR estimates for 'COeq2' (equation 2)
Model Formula: yCO2 ~ xCO2

                  Estimate   Std. Error  t value   Pr(>|t|)    
(Intercept)    2.14190e+01  6.71614e+00  3.18919  0.0016989 ** 
xCO2CONBL      3.06600e-01  4.41201e-02  6.94921 7.5023e-11 ***
xCO2COALW     -1.88807e-03  1.95642e-03 -0.96506  0.3358846    
xCO2COHD      -3.61986e-05  1.33535e-04 -0.27108  0.7866587    
xCO2CornRatio  6.92822e-01  4.94717e-01  1.40044  0.1632043    
xCO2PCOB      -1.86683e+01  6.98848e+00 -2.67129  0.0082904 ** 
xCO2CSSpread   1.33888e-01  4.15033e-02  3.22597  0.0015060 ** 
xCO2PLLOI     -1.07695e+01  3.28702e+00 -3.27637  0.0012746 ** 
xCO2LC1RSI14D -4.21502e-02  2.59188e-02 -1.62624  0.1057512    
xCO2COPCT      6.34693e-01  3.54647e+00  0.17896  0.8581786    
xCO2Feb        8.03570e-01  9.00831e-01  0.89203  0.3736369    
xCO2Apr        7.05759e-01  7.46450e-01  0.94549  0.3457523    
xCO2Aug        5.49678e-01  7.09053e-01  0.77523  0.4392815    
xCO2Oct       -2.24016e+00  7.16717e-01 -3.12559  0.0020873 ** 
xCO2Dec       -2.29780e+00  7.08110e-01 -3.24497  0.0014145 ** 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.448388 on 170 degrees of freedom
Number of observations: 185 Degrees of Freedom: 170 
SSR: 1019.082908 MSE: 5.994605 Root MSE: 2.448388 
Multiple R-Squared: 0.606276 Adjusted R-Squared: 0.573851 
```

Table C.10 Nebraska SUR Post-Break (2014-2017) Regression

```
SUR estimates for 'NEeq2' (equation 3)
Model Formula: yNE2 ~ xNE2

                  Estimate   Std. Error  t value   Pr(>|t|)    
(Intercept)    2.38170e+01  6.59721e+00  3.61016 0.00040238 ***
xNE2NENBL      3.41145e-01  4.07956e-02  8.36230 2.1316e-14 ***
xNE2NEALW     -4.55243e-03  2.90718e-03 -1.56593 0.11922566    
xNE2NEHD       1.51050e-05  2.73221e-05  0.55285 0.58109207    
xNE2CornRatio  5.63007e-01  4.72083e-01  1.19260 0.23468663    
xNE2PCOB      -1.54607e+01  6.63357e+00 -2.33067 0.02094489 *  
xNE2CSSpread   1.00603e-01  3.92131e-02  2.56556 0.01116438 *  
xNE2PLLOI     -1.10097e+01  3.15820e+00 -3.48608 0.00062375 ***
xNE2LC1RSI14D -5.02719e-02  2.45270e-02 -2.04965 0.04193454 *  
xNE2NEPCT     -7.77588e-01  1.02210e+00 -0.76078 0.44784462    
xNE2Feb        9.78017e-01  8.59773e-01  1.13753 0.25691798    
xNE2Apr        9.35859e-01  7.11442e-01  1.31544 0.19013366    
xNE2Aug        3.14432e-01  6.76524e-01  0.46478 0.64268665    
xNE2Oct       -2.40127e+00  6.95992e-01 -3.45014 0.00070667 ***
xNE2Dec       -2.18957e+00  6.96808e-01 -3.14228 0.00197806 ** 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.355401 on 170 degrees of freedom
Number of observations: 185 Degrees of Freedom: 170 
SSR: 943.145256 MSE: 5.547913 Root MSE: 2.355401 
Multiple R-Squared: 0.654968 Adjusted R-Squared: 0.626553 
```

Table C.11 Iowa/Minnesota SUR Post-Break (2014-2017) Regression

```
SUR estimates for 'IAMNeq2' (equation 4)
Model Formula: yIAMN2 ~ xIAMN2

                    Estimate   Std. Error  t value   Pr(>|t|)    
(Intercept)      3.13645e+01  8.02650e+00  3.90763 0.00013436 ***
xIAMN2IAMNNBL    3.66835e-01  4.42915e-02  8.28228 3.4417e-14 ***
xIAMN2IAMNALW   -9.39560e-03  4.30155e-03 -2.18424 0.03031425 *  
xIAMN2IAMNHD     4.39448e-05  5.03749e-05  0.87236 0.38424492    
xIAMN2CornRatio  5.64522e-01  4.93318e-01  1.14434 0.25409231    
xIAMN2PCOB      -1.23606e+01  6.63543e+00 -1.86281 0.06421417 .  
xIAMN2CSSpread   1.12120e-01  3.91987e-02  2.86031 0.00476321 ** 
xIAMN2PLLOI     -1.69179e+01  3.34334e+00 -5.06019 1.0788e-06 ***
xIAMN2LC1RSI14D -8.80454e-02  2.51381e-02 -3.50246 0.00058905 ***
xIAMN2IAMNPCT    7.43479e-01  1.42158e+00  0.52299 0.60165983    
xIAMN2Feb        1.20231e+00  8.86238e-01  1.35664 0.17669364    
xIAMN2Apr        1.40759e+00  7.15802e-01  1.96646 0.05087390 .  
xIAMN2Aug       -1.75023e-01  6.81514e-01 -0.25681 0.79763223    
xIAMN2Oct       -2.87049e+00  7.47354e-01 -3.84087 0.00017282 ***
xIAMN2Dec       -2.12303e+00  7.48823e-01 -2.83515 0.00513617 ** 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.32707 on 170 degrees of freedom
Number of observations: 185 Degrees of Freedom: 170 
SSR: 920.593188 MSE: 5.415254 Root MSE: 2.32707 
Multiple R-Squared: 0.739344 Adjusted R-Squared: 0.717879 
```

Table C.12 Kansas SUR Post-Break (2014-2017) Regression

```
SUR estimates for 'KSeq2' (equation 5)
Model Formula: yKS2 ~ xKS2

                  Estimate   Std. Error  t value   Pr(>|t|)
(Intercept)    2.03974e+01  6.46838e+00  3.15340 0.00190826 **
xKS2KSNBL      3.33310e-01  4.09771e-02  8.13406 8.3489e-14 ***
xKS2KSALW     -1.22719e-03  2.89975e-03 -0.42321 0.67267972
xKS2KSHD       5.36127e-05  3.76915e-05  1.42241 0.15674008
xKS2CornRatio  7.35338e-02  4.51763e-01  0.16277 0.87089243
xKS2PCOB      -1.60215e+01  6.29190e+00 -2.54637 0.01177263 *
xKS2CSSpread   1.35145e-01  3.81781e-02  3.53986 0.00051654 ***
xKS2PLLOI     -1.00349e+01  3.03639e+00 -3.30488 0.00115889 **
xKS2LC1RSI14D -6.89507e-02  2.37042e-02 -2.90879 0.00411334 **
xKS2KSPCT      1.39350e-01  1.19842e+00  0.11628 0.90756903
xKS2Feb        1.41400e+00  8.16509e-01  1.73176 0.08512948 .
xKS2Apr        3.75484e-01  6.79700e-01  0.55243 0.58138172
xKS2Aug        2.90016e-01  6.52890e-01  0.44420 0.65745987
xKS2Oct       -2.11868e+00  6.50312e-01 -3.25794 0.00135511 **
xKS2Dec       -2.17873e+00  6.36881e-01 -3.42094 0.00078155 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.297815 on 170 degrees of freedom
Number of observations: 185 Degrees of Freedom: 170
SSR: 897.592216 MSE: 5.279954 Root MSE: 2.297815
Multiple R-Squared: 0.601873 Adjusted R-Squared: 0.569086
```