Essays on Feeder Cattle Market Dynamics

by

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B. Agric., Obafemi Awolowo University, 2008
M.S., Kansas State University, 2013
M.A., Kansas State University, 2015

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
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Abstract

The United State has experienced a downward trend in cattle and calves marketing over the last decade. The gross income from cattle sales has been in the opposite direction of inventory recorded during this period. With changes in the cattle income over the years, it is expected that the market will be changing over time. This dissertation contains three related essays on feeder cattle market dynamics. The first essay explores spatial arbitrage opportunities in the feeder cattle markets across the United States. The second essay examines the time variation in the feeder cattle spatial market connectedness. The third essay examine the impact of the 2005 energy policy on the feeder cattle markets through a time-varying analysis.

The objective of the first essay is to determine the frequency of price differences in spatial feeder cattle markets offer profitable arbitrage? The study further investigates factors determining spatial arbitrage opportunities between pairs of markets. Arbitrage opportunities are at the lowest during the winter in the higher weight categories. The higher the number of cattle head the higher the size of arbitrage opportunities available between spatial markets. This study is the first to use a time-varying transaction cost in the feeder cattle market spatial analysis. The arbitrage information here will serve as a guideline for potential investors in the feeder cattle market. The major study limitation is that livestock is not a truly homogenous product, and there are always at least minor differences in animal prices within a market.

The second essay examines the degree of connectedness of the feeder cattle markets in the United States over time. Spillover index measure are applied to capture the impact of price shocks within selected feeder cattle markets on market connectedness. The essay further evaluates the influence of spatiotemporal factors that may impact the degree of market connectedness over the same period, and the impact of drought on periodic price transmission

between markets. This is the first study to apply a time-varying approach to study feeder cattle market linkages at the auction level and factors influencing the variation in market connectedness. Seven major auction markets across five states are selected, three markets within the state of Kansas and four markets outside Kansas. There is variation in the level of market connectedness over the study period. Long term drought severity accounts for some of the dynamics in the feeder cattle market.

The third essay examines the time path and magnitude of volatility translation across major agricultural commodities and energy markets and compares the causal relationships between pre-ethanol boom and post-ethanol boom periods. Results reveal strong evidence for time variation in the implied volatility spillover between the feeder cattle market and the energy market. Despite a high correlation between crude oil and feeder cattle volatilities in the post-ethanol boom period, the linkage between the two commodities' volatilities is only for a short term.

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Dedication

To Almighty God, my family - Joecy Lou Apos Ajewole, Oluwaseyi Edward Ajewole, my Dad, Mom, brothers, mother-in-law and all my wonderful friends.

Chapter 1 - Introduction

US cattle industry overview

The United States cattle industry accounted for over $78 billion in cash receipts in 2015, which is about 21 percent of all the agricultural commodities (USDA) [1]. Figures 1.1 and 1.2 show an overview of the United States Cattle industry over the years. There has been a downward trend in cattle and calves marketing over the last decade. Since 1990, cattle volume was at a peak around 2000 (Figure 1). The gross income from cattle sales has been in the opposite direction of inventory recorded during this period. The income from cattle and calves topped $80 billion around 2015. The continued increase in the income received from the cattle industry is due to an increase in prices. For instance, the average price per hundredweight of calves is over $250 around 2015, which is the peak price for the last two decades (Figure 2). With changes in the cattle income over the years, it is expected that the market will be changing over time. The objective of this dissertation is to examine the dynamics in the feeder cattle market over the last two decades.

Feeder cattle is one of the essential parts of the U.S. cattle industry. Feeder cattle operations are located across the United States. Feeder cattle serves as a stage (input) in the production process of the beef and dairy cattle industries. Feeder cattle are classified into steers, bulls, and heifers. A steer is a male feeder that has been castrated; a bull is a mature male that is used in the breeding program, while a heifer is a female animal that has never been involved in breeding. Heifer turns to cow after having a calf.

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[1] https://www.ers.usda.gov/topics/animal-products/cattle-beef/sector-at-a-glance/

Studying feeder cattle market relationships is a complex task. Price discovery of feeder cattle is associated with many factors external to the feeder cattle market. For instance, one of the factors affecting feeder cattle market prices is the expected market performance of live cattle, in terms of average daily gain and the feed-to-gain, including carcass characteristics (Dhuyvetter and Schroeder, 2000). Tonsor and Mollohan (2017) also confirmed that live cattle price has a high impact on feeder cattle prices. Tonsor and Mollohan (2017) noted that live cattle price expectations play three or more times larger impact than the comparable impact corn prices play on feeder cattle prices.

Apart from the aforementioned factors, the feeder cattle price is highly dependent on the weight of the animal. Prices are mostly reported by weight categories in feeder cattle transaction records. Dhuyvetter and Schroeder (2000) accentuated the importance of the relationship between price and weight by emphasizing weight has an essential role in the determination of prices in the cattle industry. It is also essential to note feeder cattle weight impacts the number of days to slaughter and the expected cost of feeding to the desired weight. Buyers purchase different weight categories of feeder cattle based on the nearest future need. Because of the importance of weight in price discovery and to have a direct comparison between markets, analyses are carried out using feeder cattle prices from same weight groups.

Demand and supply are other critical factors in the feeder cattle price discovery. Lot size at a particular day may influence the feeder cattle prices. Bailey et. al. (1993) found out that an increase in the buyer concentration at the auction depresses feeder cattle prices. Volume transacted in a given day may be a factor of several unforeseen demand and supply dynamics. While many factors affect feeder cattle market price dynamics, our study focuses on the information about the market price transmission, level of market connectedness, price leadership, and the law of one price (LOP), in the selected feeder cattle markets in great plains area of the United States.

This dissertation is presented in three major related essays on the feeder cattle market and price dynamics over the last two decades. Essay 1, “Livestock Spatial Arbitrage: Missed Opportunities in the Feeder Cattle Auctions,” assesses arbitrage opportunities between pairs of selected spatially separated markets. The essay further examines factors influencing arbitrage opportunities. The second essay, “Shocks Transmission “TO” and “FROM” Kansas Feeder Cattle Markets: A Rolling Sample Analysis,” examines the degree of feeder cattle market connectedness for the last two decades. The second essay also examines factors influencing spatial market integration over time. The third essay, “Does Energy Transmit Shocks to the Feeder Cattle Market? A Time-Varying Analysis” examines the time path and magnitude of volatility translation across the major agricultural commodities and the energy markets. The focus in the third essay is to assess time variation in the relationship between energy and feeder cattle markets.

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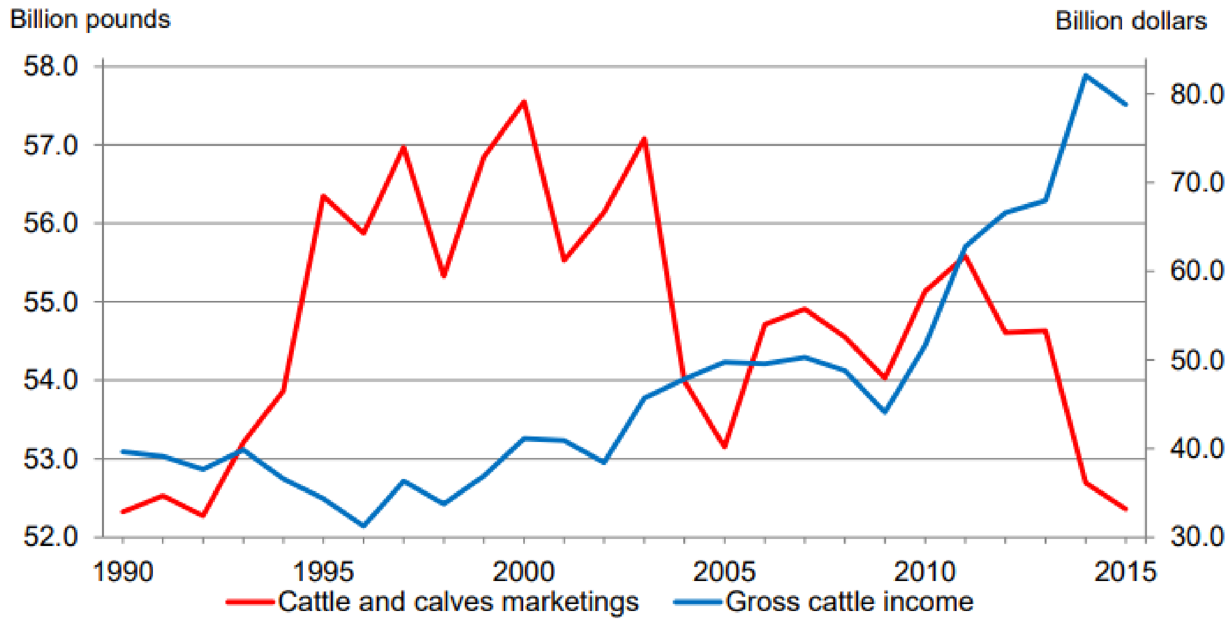

Figure 1.1 The United States Cattle and Calves Marketing and Gross Income by Year.

Source: USDA, National Agricultural Statistics Service, Overview of the United States Cattle Industry (June 2016)

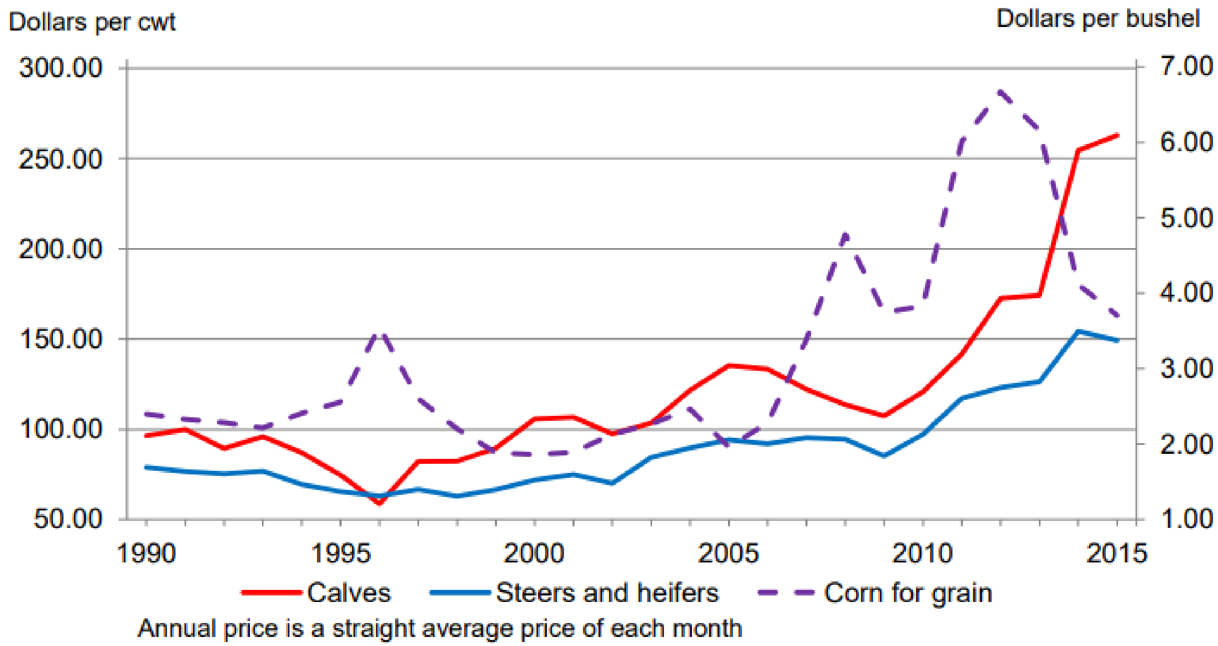

Figure 1.2 Prices Received by Farmers by Year – United States.

Source: USDA, National Agricultural Statistics Service, Overview of the United States Cattle Industry (June 2016)

Chapter 2 - Livestock Spatial Arbitrage: Missed Opportunities in the Feeder Cattle Auctions

Lack of arbitrage opportunities between spatially separated markets indicates market information efficiency. Although there is regular price reporting in the livestock industry, there is still the presence of price differential between geographically separated markets. An important question is if these price differences can lead to arbitrage activities in the physically traded markets. Considering the high risk involve in livestock arbitrgae, arbitrage in this study is examined through feedlots as the major arbitragers in the current feeder cattle market system.

In livestock studies, arbitrage has been mostly discussed in term of market integration. One of the most prominent studies on livestock market linkage is Goodwin and Schroeder (1991) where they evaluated prices co-integration between regional cattle markets. It is now widely known that using market integration to assess market efficiency without the consideration of transfer cost between markets would not give accurate price information on the spatially separated markets (Fackler and Goodwin 2001; Barrett and Li 2002). This study is the first to assess arbitrage opportunities in the livestock markets using a time-varying transaction cost. Furthermore, the impact of transportation cost and other variables on arbitrage opportunities are also examined using a binary dependent model and linear fixed effect panel model.

Feeder cattle auction markets are spread all over the United States with the major concentration lying in the Great Plains region. It is essential to know the level of arbitrage opportunities in the markets. Spatial arbitrage and the law of one price have been extensively discussed in several economic studies. Arbitrage is most common in the securities markets. There is always a potential for price differences across feeder cattle auctions markets, and an important question is; how often are these price differences offering profitable arbitrage?

Sometimes the differences in prices between markets are because of transaction cost. Arbitrage can only occur when price differences between spatially separated markets are bigger than the transaction cost between the markets.

When analyzing arbitrage opportunities in feeder cattle markets, it is imperative to understand the nature of the markets. There are many factors affecting spatially separated markets that can pose limits to arbitrage. First, feeder cattle markets operate at different days. For arbitrage to occur between markets, a market where the arbitrageur is willing to buy from (a market with lower prices) must operate same day or day(s) earlier before a market he is willing to sell. If the markets operate more than a day apart from each other, there is going to be an additional cost of keeping the animals before selling. The second reason for probable limits to arbitrage is lack of information about prices at the selling market ahead of time unless an arbitrageur knows price leadership information between the markets.

In this study, I access arbitrage opportunities between feeder cattle markets in the Great Plains region of the United States. This study uses data on weekly transactions that took place in the markets between 2000 and 2016. Whether arbitrage occurs or not, it is important to know if there are arbitrage opportunities in these markets. For an accurate measure of spatial arbitrage opportunities, this study only uses the prices from the livestock physical auction markets. This is because participants in these markets are physically present rather than through the video as it is done in the cattle satellite video auctions. There are significant differences between the two medium (satellite video auction and physical auction) of livestock auctions; satellite video auctions are national markets which can easily be accessed from different locations and could serve as a valuable source of market information (Bailey et. al, 1991), while the physical market limits the information between markets because of physical presence requirement. The inadequacy of information in the physical livestock markets provides a great opportunity for arbitrage.

Transaction cost between markets is significant when evaluating arbitrage opportunities. Assuming that transaction cost is fixed between two trading locations, Park et. al. (2002) stated that three possible trade and price outcomes could occur:

a. Autarky: If the price difference between the two locations is less than the transaction cost and trade would not occur.

b. Arbitrage: The price difference between the two locations equals the transaction cost and trade occurs.

c. Failed arbitrage: Price difference is bigger than the transaction cost between the two locations and trade does not occur.

Most of the past literature used a constant transaction cost to identified arbitrage opportunities. For instance, Suarez (2005) and Ghadhab and Hellara (2015) find arbitrage opportunity to occur when the price deviation is strictly above the constant measure of transaction cost. With useful information on transaction cost, there is a high possibility of getting an accurate markets relationship. This study makes a major contribution to literature by being the first to use a time-varying transaction cost in examining arbitrage opportunities in the livestock markets.

Why are spatial arbitrage opportunities available?

Fackler and Goodwin (2001) defined arbitrage as "the simultaneous purchase and sale of the same, or essentially similar, security in two different markets for advantageously different prices." Because of the complexity of the feeder cattle markets, we do not expect a high volume of arbitrage to be taking place between the markets. The most common form of arbitrage comes from a cattle feeder or stocker choosing between two markets for best price opportunities. In a broader context, selecting one market over another can also be considered a form of arbitrage. Even with or without trade between two markets, any changes in market integration will be reflected in prices because the divergence of price indicates the potential for arbitrage (Parsley and Wei, 2003).

Although there has not been much reported arbitrage taking place in the livestock auction markets, it is very informative to examine the availability of arbitrage opportunities in these markets. Transportation of animals from one place to another and lack of price information between markets are some of the most significant barriers to arbitrage opportunities. In this study, I look at arbitrage opportunities as when a buyer/seller choose to buy/sell from/to a market over another in order to take advantage of the price differences between the markets after transportation cost has been factored in. After accounting for the difference in the transfer cost, arbitrage opportunities exist if the price in location i is lower or higher than the price in location j.

Arbitrage in the livestock market is different from that of the financial securities. In the feeder cattle market, feedlots serve as the major arbitrager in the market. The feedlot chooses from different feeder cattle auctions to purchase from. For example, a contracted feeder cattle procurement personnel for a feedlot in Iowa may want to take advantage of the price difference between Kansas and Texas by deciding to buy an extra head from Amarillo, Texas instead of Pratt, Kansas at a profitable price, after accounting for differences in transaction cost. If after including all necessary transaction cost, the prices are the same, then we can say the LOP price holds.

This study provides a piece of novel information about the feeder cattle auctions prices to the stakeholders in the feeder cattle industry. Good knowledge of price relationship between markets can serve as a tool for both buyers and the sellers. Information on arbitrage opportunity also assesses spatial market efficiency in the US feeder cattle market. Another uniqueness of this study is the analysis of the feeder cattle markets using precise local market prices rather than using the average prices for each state or region. The precise location allows us to calculate the precise distance between the markets. Distances between markets and the estimated transportation costs will serve as the measure of the transaction cost, which can influence the opportunities for arbitrage between markets.

Background

One significant limit to market efficiency is the geographical gap between markets, i.e., spatial distance to be covered to complete a trade between two markets. The presence of this barrier can serve as an opportunity for arbitrageurs. With the presence of a spatial barrier between markets, the use of price dispersion as a measure of market efficiency may be inadequate. The cost of a transaction between two spatial markets can create a price difference between the markets. The magnitude of this price dispersion after factoring in the cost of trade between the two markets will be a good measure of market efficiency.

Arbitrage has been studied across economics and finance fields. In finance, arbitrage is referred to as the simultaneous purchase and sale of a homogenous product in two different markets with the aim of taking advantage of the price differential between the markets (Sharpe, Alexander and Bailey 1998). Arbitrage is vital in a spatial market analysis because it is crucial in determining market efficiency in spatially separated markets (Shleifer and Vishny 1997). In the presence of substantial price dispersion, higher than transaction cost, an investor can buy a live animal in one market and sell in another market to take advantage of the price difference. After a series of arbitrage activities, the spatially separated market will converge to a level where the price difference will be below the transaction cost, leading to a reduction in arbitrage profit (Barrett and Li 2002).

In agriculture, arbitrage usually takes place in the futures and derivative markets. Distance and lack of current price information form a significant limit to arbitrage in the spatial cash market. Aside from the price differential between spatially separated markets, the high price spread within a market (individual market price standard deviation) makes the risk involved in arbitraging the market higher. When the price difference between two spatially separated markets for a homogenous good equals the transaction cost, the market is said to be integrated (Goodwin and Schroeder 1991) and the law of one price holds between the two spatially separated markets (Carter & Hamilton, 1989; Goodwin et. al., 1990; Sexton et. al., 1991). Spatial arbitrage behavior is difficult to trace because it does not frequently occur even when spatial arbitrage occurs between markets, there is no or only a few records of the activities. Because of a lack of arbitrage record, price dispersion is a good measure of spatial arbitrage opportunities between markets (Overby and Clarke 2012).

As mentioned earlier, one major barrier to the estimation of spatial price efficiency is inadequate information on transaction cost. The inclusion of trade cost in market integration analysis has provided support for the LOP (Crouhy-veyrac et. al,1982; Goodwin, 1992; Michael et. al., 1994; Fackler and Goodwin 2001). Agriculture commodities, especially livestock, are costly to transport from one market to another because of the long spatial distance between the markets. Unlike testing price co-movement as a means of determining market efficiency, many recent studies have included transaction cost associated with trading between location as part of a measure of market efficiency (e.g., Baulch, 1997; Overby & Clarke, 2012).

When there are opportunities to arbitrage between spatial markets, there are markets and geographical factors that may cause price dispersion between the markets. I apply the dynamic random effect probit model to capture factors that influence the presence of arbitrage opportunities between spatial markets. The common econometric issues with nonlinear dynamic panel data models are the unobserved heterogeneity and the initial condition (Stewart 2007; Wooldridge 2005). The problem occurs due to a lack of knowledge of stochastic process before the observation period (Akay 2012). Wooldridge (2005) provided an approach to the non-linear dynamic panel data models that account for the unobserved heterogeneity and solve the initial condition problem.

Conceptual Framework

Spatial arbitrage analysis is also a test for the law of one price (LOP) between geographically separated markets. When LOP holds, it means that the market is efficient. The test for LOP between feeder cattle markets will ascertain if markets are spatially pricing efficient. Since feeder cattle markets span geographical space, this study will follow a definition of spatial market efficiency defined by Fackler and Goodwin (2001) as "no opportunities for certain arbitrage profits have been left unexploited by spatial traders." In this study context, spatial market efficiency occurs when a potential trade between two markets will lead to the same prices between the markets, after factoring in transaction cost.

In a given two feeder cattle market i and j, without trade, prices at the two markets can be represented in reduce form equations as:

$$\boldsymbol{P_{it} = d_{it} + u_{it}} \qquad \textbf{Equation 1}$$

$$P_{jt} = d_{jt} + u_{jt} \quad \textbf{Equation 2}$$

where d_{it} and d_{jt} are non-stochastic elements of prices influenced by demand and supply in an individual market, and u_{it} and u_{jt} are the random shocks to individual market supply and demand. In a free market within a nation, the third arbitrage situation described by Park et al. (2002) will be ruled out. The inclusion of transaction cost determines if two markets are unified (equilibrium). In this study, using the definition of LOP, arbitrage (accounting for transaction cost) occurs when there is an opportunity for a buyer to take advantage of a price differential between two locations. For instance, a feedlot could travel further distance away from a nearby livestock market to purchase feeder cattle in order to take advantage of a price difference. A feedlot will purchase feeder cattle from location j instead of location i at time t if

$$p_{it} - p_{jt} \leq \tau_t \quad \textbf{Equation 3}$$

where p_{it} is the price of the commodity at the location i, P_{jt} is the price of the commodity at location j. τ_t represents the transaction cost between the two locations. This situation is similar to one discussed in Goodwin and Piggott (2001), where they described market integration from a perspective of a widely dispersed grain producers evaluating price conditions among several terminal markets and decide to sell at a market that will give the highest margin, above the cost of transaction. In this case, markets are said to be efficient if the differences in market prices does not surpass the differences in the costs of selling in one market versus another. In the case of feeder cattle auction markets, we consider a situation where there is an individual (e.g. a feedlot, contractor) at location k making a purchasing decision between two feeder cattle auction markets i and j, the two markets are at equilibrium if the

$$p_{it} - p_{jt} = T_{jkt} - T_{ikt} \quad \textbf{Equation 4}$$

where T_{ikt} and T_{jkt} are the transaction cost of moving the purchased feeder cattle from location i to k, and location j to k, respectively. This means that $\tau_t = T_{jkt} - T_{ikt}$. In this case, the market exhibits LOP if the differences in prices equals the differences in the cost of purchasing in one market versus the other. Here, there is LOP where there is no opportunity to gain or loss money if one market is choosing over another.

In this study, an estimated weekly transfer cost[2] between markets is employed, i.e., transaction cost is modeled as a random variable with expected component T_c and a stochastic term v_t:

$$\boldsymbol{T_{jkt} = T_{cjt} + v_{jt}}$$ **Equation 5**

$$\boldsymbol{T_{ikt} = T_{cit} + v_{it}}$$ **Equation 6**

The stochastic term v_t is normally distributed as $\mathrm{E}v_t = 0$ and $Ev_t^2 = \sigma_v$. For easier representation, the difference in the transportation cost is represented as $T_t = T_{jkt} - T_{ikt}$, and T_t is modeled as a random variable:

$$\boldsymbol{T_t = \tau_t + v_t}$$ **Equation 7**

Spatial arbitrage opportunity only occurs if the absolute market prices between two locations are higher than the difference in the transaction cost. The probability of successful arbitrage occurs if and only if;

$$\boldsymbol{|p_{it}(1-\eta) - p_{jt}| > T_t}$$ **Equation 8**

$$\Rightarrow \quad \boldsymbol{|p_{it} - p_{jt}| > T_t + p_{it}\eta}$$ **Equation 9**

[2] I use time varying transaction cost just like Cirera and Arndt (2008)

where η is the depreciation on the animal quality after being transported from one location to another, and it ranges between zero and one. In this case, spatial markets exhibit LOP if differences in prices equal the differences in the cost of purchasing in one market versus another. One important criterium here; due to lack of information and financial risk involved, the presence of arbitrage opportunity does not give assurance that it will lead to successful arbitrage. Many factors can hinder arbitrage success between spatial markets.

For robustness check, several thresholds for the transaction cost are used to examine spatial arbitrage opportunities — first, only the transportation cost, $TC.$ Arbitrage will occur when the price deviation is above the transportation cost, $TC.$ Second, multiple thresholds of transportation cost (2TC and 3TC) is applied to cover for any unobserved risk involves in transaction between two markets. The other thresholds are 2TC and 3TC. The thresholds represent two and three multiples of the transportation cost, respectively. The market is spatially efficient when there are less than 5% arbitrage opportunities between the two markets.

Study assumptions:

1. There is a length of time to ship animals from market to destination.
2. There is a risk-neutral arbitrageur that have full information about the two markets before the open of the markets. He only arbitrages when he knows that the difference in transaction cost between two markets is less than the price difference between the two markets.
3. The live animal being transported will depreciate after spending some time on the road. The longer the distance between the markets the higher the depreciated value of the animal. The depreciation on the animal value is covered by the transaction cost thresholds (TC_i).

4. The difference in the demand curve for steers and heifers from one market to another intercepted at zero. In the presence of adequate information about the markets, arbitrageurs will be willing to participate in the market if the differences in prices are more than the transaction cost (majorly transportation cost), which means it is profitable. The slope of the demand curve depends on the differences in inventory at both markets involved.
5. The magnitude of profit (through gain from price differential) will determine the level of risk the arbitrageur is willing to take.
6. There is a finite volume of cattle an arbitrageur will be willing to transact. Instead of using full truck capacity, we will be using marginal transportation cost. The transportation company will charge in a way that does not include expected opportunity for a backhaul. Transportation of the live animals between two locations will also lead to a depreciation in their value. The transportation cost thresholds will cover depreciation. The depreciation technically translates to a proportion of animal value because of the differences in the transportation cost across weight groups and higher valued (priced) animals depreciate at greater rates.
7. Arbitrage only occur within the same period, precisely a week in our study. In a situation where the market is on Thursday or Friday, and it will take waiting over the weekend to buy in another market, which will lead to rewriting Equation 9 as;

$$\boldsymbol{T_{jkt} - T_{ik(t+1)} \leq \; p_{i(t+1)}(1 - \eta) - p_{jt}} \qquad \textbf{Equation 10}$$

Constructing the Transaction Cost

Transaction cost is crucial in determining arbitrage opportunity. The price spread must be larger than the cost of the transaction between two markets before arbitrage can take place. An appropriate measure of transaction cost will be a construction of proxy variable or primary data transportation, if available (Hobbs, 1997). There is currently no extensive data on cattle transported in the United States (Swanson and Morrow-Tesch 2001). Since there is no regular data for the cost of arbitrage between markets, a proxy is created for the transaction cost. The cattle hauling fees is an excellent proxy to estimate the cost of transferring cattle between two markets. This study uses the truck distance[3] between markets (Table 2.1) and the average freight cost to estimate the cost of transportation between two locations. The average transportation cost across each market pairs and the cattle head are shown in Table 2.2.

Since transportation is set as a proxy for transaction cost between markets, when modeling transportation cost, care must be taken. Cattle hauling involves both a fixed cost and a variable cost. These two types of cost must be appropriately accounted for in constructing cost of transportation between two locations. Transportation cost has been model for many agricultural products, including vegetable (Beilock and Shonkwiler 1983), refrigerated foods (Ward and Farris 1990) and grain truck transport (Adcock, Welch and Ellis 2015). During the development of this study, there is no access to a time series data on cattle hauling cost (none available that is known to the author). Many sources are employed to derive a nearest to exact transportation cost between locations. An average per mile cattle hauling fees are collected from the custom rate survey from the Kansas Department of Agriculture (2018). The cattle hauling fee is then

[3] http://www.truckmiles.com/

converted to per hundredweight cost across different weight groups. The conversion is performed with freight calculator by CattleRange (2019). The calculation is compared to quotes from other websites that provide information and/or services on cattle hauling[4].

The data is across multiple years, so I assume that there is a continuous change in the transportation cost across the study period. To estimate this variation in transportation cost across the year, I construct a time series transportation cost using the average U.S. quarterly truck rates from the United States Department of Agriculture Agricultural Marketing Services[5] (Figure 2.A1) as a cost index. Using the historic agricultural commodity truck freight cost will give more accurate cost than using the U.S. Bureau of Labor Statistics (2018) national truck services index (Figure 2.A2).

Transfer cost between markets is an unobservable variable. After generating the transportation cost across the study period, the predicted cost is used with other variables to estimate the transfer cost between markets. The estimation includes variables that can affect the cost of transportation, such as, seasonality, diesel price, e.t.c.

$$\boldsymbol{TC_t = \alpha + \theta T_t + X_t \beta + \epsilon_t} \qquad \textbf{Equation 11}$$

where T_t is the absolute difference in the transportation cost, $|T_{jkt} - T_{ikt}|$ and X_t is the covariate of other variables influencing transfer cost. The random shock, ϵ_t, is assumed to be normally distributed with mean zero and standard deviation σ_ϵ.

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[4] https://www.griesstrucking.com/rates
https://www.comcapfactoring.com/blog/cost-per-mile-calculator-trucking/
https://careertrend.com/how-7467256-calculate-trucking-rates.html

[5] https://www.ams.usda.gov/services/transportation-analysis/agricultural-refrigerated-truck-quarterly-datasets

Econometric Analyses

Analyses are based on different weight categories and sex of the animals. This study hypothesized that the market should link within the select markets since much of the demand for the feeder cattle are the feedlots in the Mid-West (most extensive concentration of the feeding lots).

Determinants of spatial arbitrage opportunity

Frequency and probabilities of spatial arbitrage of the feeder cattle markets are manually calculated. After analyzing the frequency and probabilities of spatial, I then investigate the factors determining spatial arbitrage opportunities between a pair of markets. As mentioned earlier, it takes a high price disparity between locations for spatial arbitrage to occur. What factors are the primary driver of price disparity exceeding the transfer cost? It is expected of a market to readjust after arbitrage opportunities have been exploited. During the periods of disparity exceeding the transaction cost, I examine what led to the disparity in prices. Two approaches are employed in examining the determinants of arbitrage opportunities: a binary choice panel model and a fixed effect panel regression. I classify the binary options as a period of arbitrage opportunity and otherwise, represented as 1 and 0, respectively. The second approach involves using an arbitrage price difference (absolute markets price dispersion minus the transportation cost) in a panel fixed effect model.

Dynamic panel probit model

To elicit the effect of the selected variables on the availability of arbitrage opportunity, I apply Dynamic panel probit model with unobserved heterogeneity. I avoid using a pooled probit model because of the unobserved heterogeneity across the market pairs, which cannot be accounted for in a pooled probit model. Generally, for a random draw i from the population and time $t = 1, 2, . . . , T$, the dynamic model takes this format:

$$\boldsymbol{y_{it}^* = \alpha y_{i,t-1} + X_{it}\delta + c_i + u_{it}} \quad \textbf{Equation 12}$$

$$\boldsymbol{y_{it} = 1[y_{it}^* > 0]} \quad \textbf{Equation 13}$$

Where $y_{it}^* = 1$ if price disparity between markets exceeds transfer cost ($Y_t = p_{it}(1 - \eta) - p_{jt} > T_t$) , i.e., there is an opportunity for arbitrage, otherwise $y_{it}^* = 0$. X_{it} are the strictly independent variables that can influence the probability of arbitrage opportunity. c_i represents the unobserved effects in the model. The choice probability is stated as:

$$\boldsymbol{P(y_{it} = 1 | y_{i,t-1}, \ldots, y_{i0}, X_i, c_i) = \Phi(\alpha y_{i,t-1} + X_{it}\delta + c_i)} \quad \textbf{Equation 14}$$

The following assumptions are made for the model:

1. Apart from other factors affecting arbitrage opportunity, I assume the present outcome is affected by past outcomes. When there is price disparity in the market, the market will adjust until it reaches an efficiency level that arbitrage cannot take place. Therefore, the unobserved effect will correlate with the past outcome, i.e., c_i correlates with $y_{i,t-1}$. In this setting, the parameter α is refer to as the state dependence parameter.
2. The variance of the unobserved effect c_i is greater than zero (0), i.e., $var(c_i) > 0$. This indicate that there is unobserved heterogeneity among the price pairs.
3. Following Wooldridge (2005), I assume that

$$\boldsymbol{c_i | y_{i0}, X_i \sim Normal(\alpha_0 + \alpha_1 y_{i0} + X_i \alpha_2, \sigma_a^2)} \quad \textbf{Equation 15}$$

where X_i is the row vector of all (nonredundant) independent variables in all the time periods. The parameters in Equation 14 and the marginal effects can be estimated by specifying a density for the unobserved heterogeneity, c_i given the initial values of the price pairs and the exogenous variables values (y_{i0}, X_i).

One major problem with the dynamic probit model specified above is the presence of endogeneity problem because of the dependent variable y_{it}^* correlates with the unobserved random effect c_i (initial conditions). A solution to the initial condition issue was introduced by Wooldridge (2005). Wooldridge (2005) avoided obtainment of the joint distribution of all outcomes of the endogenous variables by finding the initial distribution conditional on the initial value. From equation Equation 14, I denote the probit function as;

$$f(y_1, y_2, \ldots, y_T | y_0, X, c; \beta) =$$

$$\boldsymbol{\Pi_{t=1}^{T}\{\Phi(\alpha y_{t-1} + X_t\delta + c)^{y_t} \times [1 - \Phi(\alpha y_{t-1} + X_t\delta + c)]^{1-y_t}\}} \quad \textbf{Equation 16}$$

where $\beta = (\gamma', \rho)'$. For easy estimation, the density can be specified in a way it can be fit in a standard random effects probit software. Instead of writing y_{i0} as a function of c_i *and* X_i, Wooldridge (2005) differentiate the model from Heckman (1987) by writing c_i as a function of y_{i0} and X_i.

$$\boldsymbol{c_i = \alpha_0 + \alpha_1 y_{i0} + X_i\alpha_2 + a_i} \quad \textbf{Equation 17}$$

where $a_i|(y_{i0}, X_i) \sim Normal(0, \sigma_a^2)$ and independent of y_{i0} and X_i. y_{it} given $(y_{i,t-1}, \ldots, y_{i0}, X_i, a_i)$ follows a probit model with response probability

$$\boldsymbol{\Phi(\alpha y_{i,t-1} + X_{it}\delta + \alpha_0 + \alpha_1 y_{i0} + X_i\alpha_2 + a_i)} \quad \textbf{Equation 18}$$

This is easily achieved by combining Equation 12 and Equation 17 to get

$$\boldsymbol{y_{it}^* = \alpha y_{i,t-1} + X_{it}\delta + \alpha_0 + \alpha_1 y_{i0} + X_i\alpha_2 + a_i + u_{it}} \quad \textbf{Equation 19}$$

given $y_{i0} = y_0$, $X_i = X, a_i = a$ in the probit function defined above and integrating the function against the $Normal\ (0, \sigma_a^2)$ density gives the density of $(y_{i1}, \ldots, y_{iT})|(y_{i0} = y_0, X_i = X)$:

$$\int \Pi_{t=1}^{T} \left\{\Phi\left(\alpha y_{i,t-1} + X_{it}\delta + \alpha_0 + \alpha_1 y_{i0} + X_i\alpha_2 + a\right)\right\}^{y_{it}}$$

$$\times \left\{1 - \Phi\left(\alpha y_{i,t-1} + X_{it}\delta + \alpha_0 + \alpha_1 y_{i0} + X_i\alpha_2 + a\right)\right\}^{(1-y_{it})} \left(\frac{1}{\sigma_a}\right) \phi \left(\frac{a}{\sigma_a}\right) da$$

Equation 20

Fixed effect panel model

A regression model is fit to the arbitrage panel data to elicit the impact of selected variables on arbitrage. Following Greene (2018), the linear panel model is fixed as;

$$\boldsymbol{y_{it} = \alpha + x_{it}\beta + \eta_i + \varepsilon_{it}}$$

Equation 21

where y_{it} represents the price difference between two markets after transaction cost has been accounted for. x_{it} is a panel of covariates that determines the value of y_{it}. The error term η_i is a market pair specific error term (unique within a pair of markets) and is also referred to as the omitted effect, while ε_{it} is the regular error term. The fixed effects model assumes that the omitted effects, η_i, are correlated with the included variables, x_{it}, in the linear model.

Identification strategy

The inadequacy of earlier studies on factors affecting arbitrage opportunities in the livestock markets makes it difficult to identify critical variables affecting arbitrage opportunities. In place of previous studies, I use studies that discussed the livestock price differential. Mintert et. al. (1990) addressed factors affecting cow auction differentials using the Kansas auction markets. Mintert et. al. (1990) analysis was focused on the price dispersion within an auction market. This study differs from Mintert et. al. (1990) because it examines the price difference between markets. The factors analyzed by Mintert et. al. (1990) are weight, lot size, health, pregnancy, grade, dressing percent, breed, time of sale, and market location. One thing to note here is that some of these factors can translate across markets and can be captured by using the relative values between markets. In this study, one of the variable includes is the relative lot size. A change in the available feeder cattle head in the market will have an impact on the equilibrium price. The differences in lot sizes between two markets may have an influence on the price differential. The lot sizes will serve as a proxy for the demand and supply equilibrium in the market. Nearby corn futures prices are included to examine if corn price has an influence on the price differential between markets. Other variables that can lead to cost differential in prices between two market locations are included.

Seasonal dummies: Seasonal fixed effect for the four seasons are included in the model. This will control for the seasonality in the livestock market and the transportation cost.

Distance between markets: Since the distance between markets is constant over the study period, the impact of distance between markets will be captured by market pair fixed effect.

Transportation cost and Diesel prices: Diesel prices can have a significant impact on arbitrage opportunity. A price differential must overcome the transfer cost (transportation cost as a proxy) for arbitrage to occur. Apart from the base transportation cost, the truck servicing company mostly have a surcharge for diesel.

Data

This study examines the LOP in selected feeder cattle markets in the United States using the weekly weighted average prices. The feeder cattle auction markets are selected based on the fed cattle 1994 and 2014 concentration map (Figures 2.1 & 2.2). The selection of these markets is inspired by the significant changes in the geographical concentration of the cattle slaughter density between the year 1994 (Figure 2.1) and 2014 (Figure 2.2). Due to many factors, such as drought, the cattle feeding industry map has changed within 2 decades. The industry is now concentrated in the corn belt region of the Midwest (Figure 2.2). The original data is a transaction level data. We derived the weekly weighted average prices using the number of heads involved in transactions. I apply 16 years of datasets, from 2000 to 2016. The dataset is collected from a website with a rich dataset on the feeder cattle transactions in the United States called beefbasis.com. The selected markets and their street address are as follow;

Pratt Livestock: 30274 US-54, Pratt, KS 67124 (Thursdays).[6]

Amarillo Livestock Auction: 100 S Manhattan St, Amarillo, TX 79104 (Mondays 11:00 a.m.).

Joplin Regional Stockyards: 10131 Cimarron Rd, Carthage, MO 64836 (Mondays 6:00 a.m.).

Farmers and Ranchers Livestock Commission: 1500 Old U.S. 40, Salina, KS 67401 (Thursdays at 10:00 a.m.).

Oklahoma National Stockyards Company: 2501 Exchange Ave, Oklahoma City, OK 73108 (Mondays at 8:00 a.m.).

Figure 2.3 shows the markets locations on the United States map. Distances between the markets are acquired from the google map (Table 2.1). To accurately capture transaction cost between markets, information on the average travel time between these locations are collected. The combination of time of travel, distance, truck hauling prices are used in calculating the transaction cost between two markets. The number of head involved in transaction captures the demand and supply situation between two markets. The analyses are divided by weight and sex into 10 feeder cattle classes. The weight groups in pounds are: “450-500”, “500-550”, “600-650”, “650-700”, and “700-750” pounds. The sex groups are both the heifers and the steers. Table 2.3 - 2.8 show the summary statistics of the datasets by weight categories and sex. Figure 2.4 – 2.10 shows the time series plots of the markets by sex group (heifers and steers).

[6] Feeder cattle auction days and starting time in parentheses.

Results and discussion

Spatial arbitrage opportunities

Following Negassa & Myers (2007), I present mean arbitrage opportunities over the study period in Tables 2.9 and 2.10. The arbitrage opportunities are subdivided into weight categories in Tables 2.11 - 2.16. In each table, the arbitrage opportunities between markets are reported in the number of times they occurred throughout the sample period, and in probabilities.

The probabilities of arbitrage opportunities for the whole sample are presented in Tables 2.9 and 2.10, for heifer and steer categories, respectively. Considering the whole heifer market (Table 2.9), I combine all the times in each weight groups per week that price differentials between markets exceeded the transaction cost. I also examined the number of times it exceeded two and three folds of transaction cost. Apart from the weight groups, the number of cattle head also influence the transaction cost between markets. The analyses are conducted for 20 and 50[7] head. I will focus my discussion on the 20 cattle head analysis.

The market pairs are sorted according to the distance between the markets, from shortest (Pratt-Salina) to the longest (Amarillo-Salina). The highest frequency of arbitrage opportunity is between Pratt-Salina (50%), followed by Amarillo-Pratt (44%). The least amount of arbitrage opportunities (11%) is in between Amarillo and Joplin markets. Amarillo-Oklahoma, Amarillo-Salina, Joplin-Pratt, Oklahoma-Pratt, Joplin-Salina, Oklahoma-Salina, and Joplin-Oklahoma market pairs experience 41%, 24%, 23%, 22%, 22%, 19%, and 18%, respectively. In summary, all market pairs except Pratt-Salina have more weeks that the price differentials are below transaction cost than weeks with opportunities for arbitrage. As expected, increasing the

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[7] Because there is fixed cost attached to cattle hauling, the higher the number of cattle head the lower the fixed cost per head. The fixed cost is shared across the cattle head.

transaction cost threshold leads to a significant reduction in the arbitrage opportunities between markets. With five folds of transaction cost thresholds, three market pairs; Amarillo-Oklahoma, Amarillo-Pratt, Pratt-Salina, do have over 20% of weeks with arbitrage opportunities. At three folds of transaction cost (3TC), all the markets pairs are efficient[8] except the Pratt-Salina (10%). It shows that after factoring many unforeseen risks, there is still a high probability of profitable price differential between Pratt and Salina livestock markets. The arbitrage opportunities between these markets increase with the number of heads involved. At 50 cattle heads, all the market pairs have above 10% of arbitrage opportunity except Amarillo-Joplin (7%).

Similarly, in the steers category, on average, the arbitrage opportunities are higher than heifer category. Three market pairs have over 50% arbitrage probability across the sample period; Pratt-Salina, Amarillo-Oklahoma, and Amarillo-Pratt. The rest of the markets have arbitrage probabilities below 30% except Amarillo-Salina (37%). In an effort to minimize risks involved with livestock arbitrage, it will be saver to use multiple folds of transaction cost as a threshold for arbitrage to take place. At three transaction cost threshold, Pratt-Salina has about 17% probability of arbitrage existence. Both the Amarillo-Oklahoma and Amarillo-Pratt markets have the next arbitrable price differences standing at 9%. The rest of the markets are efficient at 3TC because they are all below 5%. The steers price difference also shows that the higher the heads, the higher the arbitrage opportunities between the market pairs.

Breaking down the analyses into weight categories gives us differences in arbitrage opportunities by weight categories. Starting with the heifer estimates, Hf450-550 panel (Table 2.11) shows the average price differential over time. Each market pairs number of trading weeks are recorded in the first column and the average spatial price differences across the sample

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[8] The threshold for market efficiency or LOP is when the arbitrage opportunity is below 5%.

period are recorded in the second column. The Joplin-Oklahoma market pairs have the highest number of weeks that the transaction took place. The Hf450-500 has two market pairs above 50% arbitrage opportunities. The Amarillo-Joplin market shows the lowest weeks of arbitrage opportunities. Between Amarillo-Joplin, it is only 11% of the time that we experience price differential is higher than the transaction cost. One thing to note here is that there are many barriers to arbitrage. One major barrier is the risk involved in carrying out the arbitrage. Hidden cost also plays a massive role in limitation to arbitrage in the livestock market. With all these barriers, it is advisable to consider different thresholds when examining arbitrage opportunities. In examining the number of times arbitrage opportunities exist between pair of the market, I use several thresholds of transaction costs. The rest of the heifer weight categories (Tables 2.12 - 2.16) follows the same pattern as Hf450-550 category. What we found is that the higher the weight group, the lesser the price differential between market prices (Tables 2.11 - 2.16). This because the higher weight group mostly purchases directly to the feedlots because heavier weight cattle have less variation in health risk status.

Although the steers group have a similar pattern, there are more arbitrage opportunities in the steer category than the heifer category (Tables 2.17 – 2.22). For instance, the St450-500 weight category has about 3 markets pairs with about 50% of the weeks having price differential exceeding transaction cost (like the St500). The probability of arbitrage opportunity between Pratt and Salina exceeds 60% in the 450 lb. to 600 lb. categories (Tables 2.17 - 2.19). Like what we saw in the heifer, the higher the weight, the lesser the arbitrage opportunities that exist between market pairs. The 700-750 lb category (Table 2.22) has the lowest chances of arbitrage with the highest of 35% chance in the Pratt-Salina market pairs.

One important information that can be deduced from all the markets pairs studied is that the number of cattle head and weight play a critical role in the degree of arbitrage opportunity between market pairs. For instance, there is a higher number of arbitrages opportunities in the 450-500 lb category than the 700-750 lb category. There are higher probabilities of arbitrage opportunities in dealing with 50 head than 20 head of cattle, even at the higher transaction cost thresholds.

The determinant of arbitrage opportunities

I affirmed earlier, based on a weighted average of prices, that there are disparities in prices between spatial markets, which creates arbitrage opportunities between spatial markets. Next is to examine the determinant factors affecting these price disparities between pairs of markets. This is a spatial analysis because I use a panel of prices difference between spatial markets to examine the impact of transportation cost and other factors like diesel prices, past arbitrage occurrence on the arbitrage opportunities between markets. To account for the spatial effect (distance) on the arbitrage opportunities, I include the market pairs fixed effect. I also considered the seasonality effect on spatial arbitrage opportunities by including the seasons fixed effect.

The main finding from both the dynamic probit and the fixed effect panel models is that the arbitrage opportunities in the feeder cattle markets decrease with an increase in the transportation cost. Interpreting the marginal effect in the dynamic panel probit model in Table 2.23 means that one dollar increase in the transportation cost of a hundredweight (Cwt) per mile of the feeder cattle will lead to about 3% decrease in the conditional probability of arbitrage opportunity between market pairs. Table 2.23 also shows that if an arbitrage opportunity occurred in a week earlier, it leads to an increase in the arbitrage opportunity in the present week by $0.10 in the heifer 450-500 lb weight category. The lag effect justifies the use of a dynamic probit model. There is a seasonality effect on the arbitrage opportunity between markets, while both the diesel prices and relative lot size are not statistically significant.

In the panel fixed effect model, the price difference from previous weeks also has an influence on the present week price. For instance, in the 450-500 lb category, a one unit increase in the lag price differences significantly leads to $0.24 increase in the market pairs price difference above the transaction cost. Nearby corn futures price has a higher impact on the arbitrage opportunity in the fixed effect panel model than the previous week price. One dollar increase in the price of corn will lead to $0.49 decrease in arbitrage price differential between markets. The panel fixed effect model shows that there is no seasonality effect on the arbitrage price difference in the 450-500 lb heifer category.

The determinant of arbitrage opportunities is analyzed across all weight categories in this study (Tables 2.23 - 2.28). The aim is to reveal any differences across the weight groups. The transportation cost impact is similar across weight groups. Similarly, the lag arbitrage opportunities (panel probit model) and lag price differences (panel linear fixed effect model) have similar impacts on arbitrage opportunities and arbitrage price differences across all the weight groups. One noticeable difference across weight group is seen in the effect of diesel prices on arbitrage and the seasonality impact.

In the heifer category, the impact of diesel prices is minimal on the probability of arbitrage opportunity. The panel probit model shows that diesel impact on arbitrage opportunity is only significant (at 5 percent level) in the 550-600 lb and 650-700 lb weight groups. The panel fixed effect model shows a similar trend to the panel probit model in terms of diesel significance. Diesel prices are only significant at 5 percent level in 550-600 lb and 600-650 lb weight group.

The panel fixed effect model section of Tables 2.25 and 2.26 show that one dollar increase in the diesel prices will lead to an increase in the above-transaction-cost price differential by $0.23 and $0.39, respectively.

The result also reveals potential differences in seasonality effect on arbitrage opportunity across weight groups. For the seasonal impact assessment, the fall season is set as the base season. There is no significant seasonal effect on the arbitrage opportunity in the lower weight categories (between 450 lb and 600 lb) except for a small difference between summer and fall in the 450 lb category (Tables 2.23 - 2.25). In the highest weight categories (600-650 lb and 700-750 lb), there are similarities between spring season and winter season. This means that between the two seasons (spring and winter), there will be a reduction in arbitrage opportunity compare to summer and fall seasons. In a nutshell, arbitrage opportunities are at the lowest during the fall season, especially in the higher weight categories.

Steers: On average, the highest effect of the transaction cost on spatial arbitrage opportunity occur in steer category in comparison to the heifer category. In steers, the seasonality effect is less comparing to heifers. The major impact of the seasons is only seen in the higher weight categories; 650 lb and above (Table 2.29 - 2.34). In both the probit and the linear effect models, winter season sees a major reduction in the arbitrage opportunity compare to the rest of the seasons (Table 2.7e & 2.7f). In the higher weight categories, there is no difference between the winter and spring seasons. Both the winter and spring have fewer arbitrage opportunities in comparison to summer and fall seasons. Increase in the nearby corn prices also leads to a decrease in the arbitrage opportunities across all the weight categories.

For robustness check, the check for arbitrage opportunity is performed by using two thresholds of transaction cost. The robustness test is carried out using the linear effect model.

The result is similar, only a little difference in magnitudes. In addition, I test for seasonality effect on transportation cost. I assume that the seasonality in the arbitrage opportunity in the higher weight categories is correlated with the seasonality impact on the transportation cost. The assumption here is that increase in demand for transportation during fall season leads to an increase in prices in one location than another, which will reflect in differences in prices in feeder cattle spatial prices. Table 2.A1 shows that there is no seasonal effect on the transportation cost used in this study. It is also important to note here that I dropped the relative transaction frequency as an explanatory variable in all the models because of the insignificancy in all the models.

Conclusion

This study examines spatial arbitrage opportunities in selected feeder cattle markets in the United States. The study further investigates the determinants of arbitrage opportunities between pairs of markets. We reveal that there are arbitrage opportunities between spatially separated feeder cattle markets after transaction cost has been accounted for. Arbitrage opportunities are at the lowest during the winter in the higher weight categories. The higher the number of cattle head the higher the size of arbitrage opportunities available between spatial markets.

Although there is a presence of arbitrage opportunities within the feeder cattle markets, there has been little empirical evidence on why there is or lack of arbitrage activities within markets (Overby and Clarke 2012). Apart from the transportation cost, there are many other factors that limit arbitrage in the feeder cattle markets. One main reason is the lack of information about spatial differences in markets prices to the market participants ahead of time. The long distance between markets can also pose a significant risk on the animals' health, which can lead to a high loss in profit. The main question here is that: can arbitrage take place in this market? The simple answer is YES. Generally, only a few market participants involved in arbitrage (Shleifer and Vishny 1997). In the case of feeder cattle market, the feedlot is the main arbitrager.

Why is the information revealed in this study important? There are few or none of the recent literature that has looked in-depth into the spatial price relationship in the feeder cattle markets. It is evident that market relationships do change over time; understanding recent market dynamics is of significant advantage to the stakeholders in the feeder cattle business. This study is the first to use a time-varying transaction cost in the feeder cattle market spatial analysis. The study also confirmed that the price differential between markets is at the lowest margin during the winters. The arbitrage information here will serve as a guideline for potential investors in the feeder cattle market. Length of an arbitrage opportunity in a market shows how efficient a market is.

Study limitation

Although this study shows that there are opportunities for spatial arbitrage in the feeder cattle auction markets. There are many limits to arbitrage that study is not able to capture. Transporting live animals between geographically separated locations involve very high risk. In a case of animal fallen sick or death will lead to a massive loss. For instance, shipping fever and diarrhea are a significant component of cattle morbidity and mortality (Swanson and Morrow-Tesch 2001). This risk limits the incentive to arbitrage in the market. Another limitation is the intra-market price deviation. Livestock is not a truly homogenous product, and there are always at least minor differences in animal prices within a market. This minor difference can sometimes lead to a price difference. Apart from spatially price diversion between two markets, there is disparity on the prices received on live animals sold within a market. This dispersion poses a very high price risk to an investor.

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Table 2.1 Estimated distances between markets pairs.

Distance between markets (miles)				
	Joplin	Oklahoma	Salina	Amarillo
Oklahoma	233			
Salina	285	251		
Amarillo	486	254	414	
Pratt	274	234	122	297

Table 2.2 Cattle transportation cost summary by weight category and market pairs. Cost is per hundredweight per mile.

Market Pairs	450-500		500-550		550-600		600-650		650-700		700-750	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Pratt-Salina	1.53	0.64	1.39	0.58	1.27	0.53	1.17	0.49	1.08	0.45	1.00	0.42
Joplin-Oklahoma	3.06	1.29	2.77	1.17	2.53	1.06	2.33	0.98	2.16	0.91	2.01	0.84
Oklahoma-Pratt	3.26	1.37	2.95	1.24	2.69	1.13	2.47	1.04	2.29	0.96	2.13	0.90
Amarillo-Oklahoma	3.32	1.39	3.00	1.26	2.74	1.15	2.52	1.06	2.34	0.98	2.18	0.91
Oklahoma-Salina	3.38	1.42	3.06	1.29	2.80	1.17	2.57	1.08	2.39	1.00	2.22	0.93
Joplin-Pratt	3.83	1.61	3.47	1.46	3.17	1.33	2.91	1.22	2.70	1.13	2.51	1.05
Joplin-Salina	3.83	1.61	3.47	1.46	3.17	1.33	2.91	1.22	2.70	1.13	2.51	1.05
Amarillo-Pratt	3.90	1.64	3.52	1.48	3.22	1.35	2.96	1.24	2.74	1.15	2.55	1.07
Amarillo-Joplin	6.39	2.68	5.78	2.43	5.28	2.22	4.85	2.04	4.49	1.89	4.18	1.76
Amarillo-Salina	5.66	1.24	5.12	1.12	4.67	1.03	4.30	0.94	3.98	0.87	3.71	0.81

Table 2.3 Summary statistics of the 450-500 lb category feeder cattle prices.

Heifers						Steers					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Variable**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Joplin	968	117.15	44.62	38.47	267.65	Joplin	966	132.00	50.60	53.33	303.95
Oklahoma	1,014	117.12	47.03	43.51	286.91	Oklahoma	1,013	132.78	52.28	53.75	330.69
Amarillo	941	108.70	41.38	38.12	268.25	Amarillo	902	118.27	44.68	48.50	322.00
Salina	888	119.76	47.41	36.83	282.41	Salina	880	135.78	53.95	52.06	318.22
Pratt	852	117.13	45.90	36	311.88	Pratt	797	133.21	50.80	56.20	337.02

Table 2.4 Summary statistics of the 500-550 lb category feeder cattle prices.

Heifer						Steers					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Variable**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Joplin	968	113.83	43.01	40.91	257.02	Joplin	968	127.40	48.58	54.31	287.43
Oklahoma	1,018	113.44	44.01	44.22	273.66	Oklahoma	1,016	127.68	49.77	53.56	304.17
Amarillo	954	105.46	39.33	42.00	254.88	Amarillo	889	113.02	41.30	45.94	291.76
Salina	909	117.35	45.66	38.47	275.75	Salina	907	131.46	51.28	52.31	307.09
Pratt	903	113.02	44.45	43.09	302.50	Pratt	859	127.54	49.11	55.07	310.16

Table 2.5 Summary statistics of the 550-600 lb category feeder cattle prices.

Heifer						Steers					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Variable**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Joplin	967	110.79	41.10	42.63	245.25	Joplin	966	122.62	45.93	54.07	273.99
Oklahoma	1,018	110.40	42.03	44.72	255.06	Oklahoma	1,020	121.90	46.54	52.02	283.00
Amarillo	936	101.71	36.13	39.62	247.46	Amarillo	880	108.89	38.50	48.31	274.46
Salina	915	113.63	43.14	38.934	259.57	Salina	910	126.46	48.59	53.37	285.93
Pratt	954	109.89	41.67	42.48	295.00	Pratt	908	122.40	47.34	51.21	293.54

Table 2.6 Summary statistics of the 600-650 lb category feeder cattle prices.

Heifer						Steers					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Variable**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Joplin	967	108.06	39.57	41.27	236.71	Joplin	967	118.54	44.09	51.55	259.60
Oklahoma	1,017	107.89	40.12	44.31	240.63	Oklahoma	1,018	117.45	43.97	51.06	268.17
Amarillo	941	99.85	34.25	41.86	233.00	Amarillo	899	105.94	37.12	47.08	258.61
Salina	914	110.44	41.21	40.60	251.10	Salina	914	121.30	45.80	51.63	276.22
Pratt	991	107.19	39.48	42.82	255.00	Pratt	964	117.41	44.07	47.71	280.25

Table 2.7 Summary statistics of the 650-700 lb category feeder cattle prices.

Heifer						Steers					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Variable**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Joplin	963	106.05	38.14	39.67	228.60	Joplin	967	114.99	41.78	37.86	248.86
Oklahoma	1,018	105.72	38.36	45.13	234.37	Oklahoma	1,019	114.06	41.59	49.57	252.63
Amarillo	922	98.37	33.24	40.87	218.29	Amarillo	863	102.43	35.18	45.66	241.77
Salina	912	107.59	38.88	41.80	246.35	Salina	912	116.97	43.14	50.75	264.86
Pratt	1000	105.70	37.88	40.73	246.19	Pratt	980	113.40	41.72	46.03	260.00

Table 2.8 Summary statistics of the 700-750 lb category feeder cattle prices.

Heifer						Steers					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Variable**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Joplin	951	104.26	36.98	41.34	223.47	Joplin	968	112.37	40.17	48.57	241.53
Oklahoma	1,017	103.75	37.08	46.53	229.53	Oklahoma	1,019	111.92	40.05	49.43	245.00
Amarillo	892	99.32	35.11	43.01	228.87	Amarillo	850	102.37	34.38	46.61	231.58
Salina	913	105.84	37.86	41.91	235.61	Salina	912	113.14	40.30	47.33	247.16
Pratt	1011	105.12	36.95	43.23	233.09	Pratt	1012	111.97	39.92	46.87	244.68

Table 2.9 Arbitrage opportunities in all Heifers weight categories across the sample period (2000-2016).

		20 Head				50 Head			
Difference	**Obs**	**No Arb**	**D > TC**	**D >2TC**	**D > 3TC**	**No Arb**	**D > TC**	**D >2TC**	**D > 3TC**
Pratt-Salina	4065	2036	2029	932	410	1465	3106	2371	1726
Joplin-Oklahoma	4658	3839	819	112	12	2531	2543	1222	520
Oklahoma-Pratt	4238	3289	949	173	39	2172	2508	1319	666
Amarillo-Oklahoma	4252	2523	1729	515	131	1593	3096	2125	1380
Oklahoma-Salina	4173	3380	793	113	14	2168	2362	1147	538
Joplin-Pratt	4120	3159	961	149	23	2006	2592	1418	667
Joplin-Salina	4111	3211	900	100	10	1916	2623	1327	576
Amarillo-Pratt	3845	2135	1710	507	136	1392	2934	2081	1389
Amarillo-Joplin	4094	3655	439	31	5	2514	1848	746	276
Amarillo-Salina	3767	2862	905	161	38	1635	2456	1314	618
		Probabilities							
Pratt-Salina		0.50	0.50	0.23	0.10	0.36	0.76	0.58	0.42
Joplin-Oklahoma		0.82	0.18	0.02	0.00	0.54	0.55	0.26	0.11
Oklahoma-Pratt		0.78	0.22	0.04	0.01	0.51	0.59	0.31	0.16
Amarillo-Oklahoma		0.59	0.41	0.12	0.03	0.37	0.73	0.50	0.32
Oklahoma-Salina		0.81	0.19	0.03	0.00	0.52	0.57	0.27	0.13
Joplin-Pratt		0.77	0.23	0.04	0.01	0.49	0.63	0.34	0.16
Joplin-Salina		0.78	0.22	0.02	0.00	0.47	0.64	0.32	0.14
Amarillo-Pratt		0.56	0.44	0.13	0.04	0.36	0.76	0.54	0.36
Amarillo-Joplin		0.89	0.11	0.01	0.00	0.61	0.45	0.18	0.07
Amarillo-Salina		0.76	0.24	0.04	0.01	0.43	0.65	0.35	0.16

Note D = |P1-P2|; Obs – Observations; Arb – Arbitrage; TC – Transportation Cost

Table 2.10 Arbitrage opportunities in all Steers weight categories across the sample period (2000-2016).

		20 Head				50 Head			
Difference	**Obs**	**No Arb**	**D > TC**	**D >2TC**	**D > 3TC**	**No Arb**	**D > TC**	**D >2TC**	**D > 3TC**
Pratt-Salina	3979	1609	2370	1303	669	670	3309	2655	2105
Joplin-Oklahoma	4661	3688	973	176	31	1933	2728	1410	706
Oklahoma-Pratt	4135	2983	1152	283	77	1473	2662	1544	869
Amarillo-Oklahoma	3962	1868	2094	859	337	771	3191	2439	1785
Oklahoma-Salina	4158	3005	1153	223	57	1450	2708	1593	832
Joplin-Pratt	4033	2968	1065	195	48	1489	2544	1448	786
Joplin-Salina	4103	2934	1169	160	26	1311	2792	1620	835
Amarillo-Pratt	3487	1582	1905	741	298	626	2861	2200	1616
Amarillo-Joplin	3822	3046	776	116	20	1637	2185	1134	523
Amarillo-Salina	3492	2191	1301	274	79	900	2592	1700	943
		Probabilities							
Pratt-Salina		0.40	0.60	0.33	0.17	0.17	0.83	0.67	0.53
Joplin-Oklahoma		0.79	0.21	0.04	0.01	0.41	0.59	0.30	0.15
Oklahoma-Pratt		0.72	0.28	0.07	0.02	0.36	0.64	0.37	0.21
Amarillo-Oklahoma		0.47	0.53	0.22	0.09	0.19	0.81	0.62	0.45
Oklahoma-Salina		0.72	0.28	0.05	0.01	0.35	0.65	0.38	0.20
Joplin-Pratt		0.74	0.26	0.05	0.01	0.37	0.63	0.36	0.19
Joplin-Salina		0.72	0.28	0.04	0.01	0.32	0.68	0.39	0.20
Amarillo-Pratt		0.45	0.55	0.21	0.09	0.18	0.82	0.63	0.46
Amarillo-Joplin		0.80	0.20	0.03	0.01	0.43	0.57	0.30	0.14
Amarillo-Salina		0.63	0.37	0.08	0.02	0.26	0.74	0.49	0.27

Note D = |P1-P2|; Obs – Observations; Arb – Arbitrage; TC – Transportation Cost

Table 2.11 Arbitrage opportunities in Heifer 450-500 lb weight categories across the sample period (2000-2016).

		20 Head						50 Head					
Difference	**Obs**	**Mean**	**Std. Dev**	**No Arb**	**D > TC**	**D >2TC**	**D > 3TC**	**Mean**	**Std. Dev**	**No Arb**	**D > TC**	**D >2TC**	**D > 3TC**
Pratt-Salina	596	1.68	4.95	254	342	185	95	3.87	5.05	125	471	381	302
Joplin-Oklahoma	777	-3.10	4.83	616	161	34	2	1.51	4.54	337	440	217	110
Oklahoma-Pratt	620	-1.76	6.07	417	203	39	14	2.87	5.91	201	419	258	149
Amarillo-Oklahoma	717	-0.69	7.09	445	272	79	21	4.06	7.03	207	510	345	211
Oklahoma-Salina	674	-2.94	5.06	505	169	32	2	2.02	4.61	262	412	239	124
Joplin-Pratt	611	-1.59	6.64	402	209	36	5	3.91	6.82	195	416	271	151
Joplin-Salina	669	-2.85	5.69	506	163	23	2	2.83	5.71	222	447	226	107
Amarillo-Pratt	577	1.08	8.96	272	305	98	30	6.46	8.98	119	458	345	248
Amarillo-Joplin	693	-8.96	8.10	616	77	5	1	0.31	6.36	394	299	124	52
Amarillo-Salina	620	-4.04	8.41	488	132	23	6	4.19	8.57	207	413	207	83
							Probabilities						
Pratt-Salina				0.43	0.57	0.31	0.16			0.21	0.79	0.64	0.51
Joplin-Oklahoma				0.79	0.21	0.04	0.00			0.43	0.57	0.28	0.14
Oklahoma-Pratt				0.67	0.33	0.06	0.02			0.32	0.68	0.42	0.24
Amarillo-Oklahoma				0.62	0.38	0.11	0.03			0.29	0.71	0.48	0.29
Oklahoma-Salina				0.75	0.25	0.05	0.00			0.39	0.61	0.35	0.18
Joplin-Pratt				0.66	0.34	0.06	0.01			0.32	0.68	0.44	0.25
Joplin-Salina				0.76	0.24	0.03	0.00			0.33	0.67	0.34	0.16
Amarillo-Pratt				0.47	0.53	0.17	0.05			0.21	0.79	0.60	0.43
Amarillo-Joplin				0.89	0.11	0.01	0.00			0.57	0.43	0.18	0.08
Amarillo-Salina				0.79	0.21	0.04	0.01			0.33	0.67	0.33	0.13

Note D = |P1-P2|; Obs – Observations; Arb – Arbitrage; TC – Transportation Cost

Table 2.12 Arbitrage opportunities in Heifer 500-550 lb weight categories across the sample period (2000-2016).

		20 Head						50 Head					
Difference	**Obs**	**Mean**	**Std. Dev**	**No Arb**	**D > TC**	**D >2TC**	**D > 3TC**	**Mean**	**Std. Dev**	**No Arb**	**D > TC**	**D >2TC**	**D > 3TC**
Pratt-Salina	656	1.82	4.94	271	385	211	102	3.81	5.03	117	539	434	340
Joplin-Oklahoma	778	-3.24	4.01	647	131	19	3	0.92	3.51	361	417	204	77
Oklahoma-Pratt	673	-1.73	5.48	470	203	51	12	2.47	5.29	224	449	262	156
Amarillo-Oklahoma	732	0.03	6.52	393	339	92	25	4.36	6.55	178	554	402	258
Oklahoma-Salina	698	-2.71	4.38	537	161	28	6	1.82	4.02	256	442	230	108
Joplin-Pratt	653	-1.98	6.20	466	187	42	7	3.02	6.19	206	447	258	141
Joplin-Salina	690	-2.54	4.70	504	186	21	2	2.66	4.56	220	470	253	116
Amarillo-Pratt	625	1.09	8.09	312	313	113	29	6	8.21	118	507	377	272
Amarillo-Joplin	705	-7.94	7.37	639	66	6	1	0.52	5.94	365	340	133	36
Amarillo-Salina	649	-2.60	7.72	465	184	27	7	4.9	7.96	171	478	253	122
				Probabilities									
Pratt-Salina				0.41	0.59	0.32	0.16			0.18	0.82	0.66	0.52
Joplin-Oklahoma				0.83	0.17	0.02	0.00			0.46	0.54	0.26	0.10
Oklahoma-Pratt				0.70	0.30	0.08	0.02			0.33	0.67	0.39	0.23
Amarillo-Oklahoma				0.54	0.46	0.13	0.03			0.24	0.76	0.55	0.35
Oklahoma-Salina				0.77	0.23	0.04	0.01			0.37	0.63	0.33	0.15
Joplin-Pratt				0.71	0.29	0.06	0.01			0.32	0.68	0.40	0.22
Joplin-Salina				0.73	0.27	0.03	0.00			0.32	0.68	0.37	0.17
Amarillo-Pratt				0.50	0.50	0.18	0.05			0.19	0.81	0.60	0.44
Amarillo-Joplin				0.91	0.09	0.01	0.00			0.52	0.48	0.19	0.05
Amarillo-Salina				0.72	0.28	0.04	0.01			0.26	0.74	0.39	0.19

Note D = |P1-P2|; Obs – Observations; Arb – Arbitrage; TC – Transportation Cost

Table 2.13 Arbitrage opportunities in Heifer 550-600 lb weight categories across the sample period (2000-2016).

		20 Head						50 Head					
Difference	Obs	Mean	Std. Dev	No Arb	D > TC	D >2TC	D > 3TC	Mean	Std. Dev	No Arb	D > TC	D >2TC	D > 3TC
Pratt-Salina	681	1.36	4.51	288	393	178	77	3.2	4.61	133	548	442	343
Joplin-Oklahoma	779	-2.64	3.47	643	136	18	0	1.16	3.21	332	447	207	87
Oklahoma-Pratt	704	-2.05	4.74	529	175	37	6	1.82	4.55	258	446	243	125
Amarillo-Oklahoma	709	0.46	6.28	386	323	90	26	4.38	6.55	165	544	386	265
Oklahoma-Salina	700	-2.78	4.07	557	143	22	3	1.36	3.64	287	413	200	102
Joplin-Pratt	685	-2.25	5.61	512	173	27	5	2.36	5.55	258	427	246	116
Joplin-Salina	691	-2.59	4.45	536	155	17	2	2.16	4.28	232	459	236	106
Amarillo-Pratt	641	0.72	7.16	326	315	80	24	5.2	7.44	145	496	368	243
Amarillo-Joplin	687	-6.78	6.71	604	83	4	0	0.88	5.84	368	319	137	50
Amarillo-Salina	634	-2.40	7.41	460	174	30	6	4.42	7.7	193	441	242	122
								Probabilities					
Pratt-Salina				0.42	0.58	0.26	0.11			0.20	0.80	0.65	0.50
Joplin-Oklahoma				0.83	0.17	0.02	0.00			0.43	0.57	0.27	0.11
Oklahoma-Pratt				0.75	0.25	0.05	0.01			0.37	0.63	0.35	0.18
Amarillo-Oklahoma				0.54	0.46	0.13	0.04			0.23	0.77	0.54	0.37
Oklahoma-Salina				0.80	0.20	0.03	0.00			0.41	0.59	0.29	0.15
Joplin-Pratt				0.75	0.25	0.04	0.01			0.38	0.62	0.36	0.17
Joplin-Salina				0.78	0.22	0.02	0.00			0.34	0.66	0.34	0.15
Amarillo-Pratt				0.51	0.49	0.12	0.04			0.23	0.77	0.57	0.38
Amarillo-Joplin				0.88	0.12	0.01	0.00			0.54	0.46	0.20	0.07
Amarillo-Salina				0.73	0.27	0.05	0.01			0.30	0.70	0.38	0.19

Note D = |P1-P2|; Obs – Observations; Arb – Arbitrage; TC – Transportation Cost

Table 2.14 Arbitrage opportunities in Heifer 600-650 lb weight categories across the sample period (2000-2016).

		20 Head						50 Head					
Difference	**Obs**	**Mean**	**Std. Dev**	**No Arb**	**D > TC**	**D >2TC**	**D > 3TC**	**Mean**	**Std. Dev**	**No Arb**	**D > TC**	**D >2TC**	**D > 3TC**
Pratt-Salina	705	0.54	3.46	369	336	148	61	2.24	3.53	177	528	396	287
Joplin-Oklahoma	779	-2.83	2.88	671	108	7	0	0.67	2.51	370	409	188	70
Oklahoma-Pratt	738	-2.73	3.58	613	125	20	2	0.85	3.21	352	386	180	83
Amarillo-Oklahoma	722	0.2	5.75	431	291	82	17	3.83	6.07	180	542	373	235
Oklahoma-Salina	701	-2.98	3.35	588	113	10	1	0.83	2.91	314	387	170	72
Joplin-Pratt	720	-3.06	3.93	617	103	13	1	1.2	3.69	322	398	190	71
Joplin-Salina	692	-2.66	3.95	560	132	13	0	1.71	3.83	261	431	216	84
Amarillo-Pratt	683	-0.07	6.36	419	264	69	17	4.09	6.74	186	497	339	207
Amarillo-Joplin	696	-6.32	6	627	69	4	1	0.74	5.55	394	302	115	46
Amarillo-Salina	642	-2.43	7.27	491	151	29	9	3.87	7.65	221	421	223	108
							Probabilities						
Pratt-Salina				0.52	0.48	0.21	0.09			0.25	0.75	0.56	0.41
Joplin-Oklahoma				0.86	0.14	0.01	0.00			0.47	0.53	0.24	0.09
Oklahoma-Pratt				0.83	0.17	0.03	0.00			0.48	0.52	0.24	0.11
Amarillo-Oklahoma				0.60	0.40	0.11	0.02			0.25	0.75	0.52	0.33
Oklahoma-Salina				0.84	0.16	0.01	0.00			0.45	0.55	0.24	0.10
Joplin-Pratt				0.86	0.14	0.02	0.00			0.45	0.55	0.26	0.10
Joplin-Salina				0.81	0.19	0.02	0.00			0.38	0.62	0.31	0.12
Amarillo-Pratt				0.61	0.39	0.10	0.02			0.27	0.73	0.50	0.30
Amarillo-Joplin				0.90	0.10	0.01	0.00			0.57	0.43	0.17	0.07
Amarillo-Salina				0.76	0.24	0.05	0.01			0.34	0.66	0.35	0.17

Note D = |P1-P2|; Obs – Observations; Arb – Arbitrage; TC – Transportation Cost

Table 2.15 Arbitrage opportunities in Heifer 650-700 lb weight categories across the sample period (2000-2016).

		20 Head						50 Head					
Difference	**Obs**	**Mean**	**Std. Dev**	**No Arb**	**D > TC**	**D >2TC**	**D > 3TC**	**Mean**	**Std. Dev**	**No Arb**	**D > TC**	**D >2TC**	**D > 3TC**
Pratt-Salina	710	0.07	2.66	408	302	120	39	1.65	2.66	196	514	369	233
Joplin-Oklahoma	776	-2.55	2.79	647	129	11	1	0.7	2.47	362	414	191	71
Oklahoma-Pratt	745	-2.72	3.02	636	109	10	1	0.61	2.69	379	366	167	70
Amarillo-Oklahoma	701	0.35	5.4	413	288	105	24	3.69	5.7	192	509	349	232
Oklahoma-Salina	700	-3.03	3.1	600	100	10	1	0.51	2.61	349	351	147	66
Joplin-Pratt	722	-2.84	3.42	609	113	8	1	1.13	3.12	296	426	190	73
Joplin-Salina	687	-2.87	3.53	573	114	9	1	1.18	3.34	299	388	177	65
Amarillo-Pratt	669	0.11	5.74	402	267	74	17	3.96	6.08	174	495	330	222
Amarillo-Joplin	675	-5.39	5.61	587	88	7	0	1.12	5.23	355	320	140	56
Amarillo-Salina	628	-2.59	6.32	476	152	30	6	3.22	6.63	249	379	220	108
								Probabilities					
Pratt-Salina				0.57	0.43	0.17	0.05			0.28	0.72	0.52	0.33
Joplin-Oklahoma				0.83	0.17	0.01	0.00			0.47	0.53	0.25	0.09
Oklahoma-Pratt				0.85	0.15	0.01	0.00			0.51	0.49	0.22	0.09
Amarillo-Oklahoma				0.59	0.41	0.15	0.03			0.27	0.73	0.50	0.33
Oklahoma-Salina				0.86	0.14	0.01	0.00			0.50	0.50	0.21	0.09
Joplin-Pratt				0.84	0.16	0.01	0.00			0.41	0.59	0.26	0.10
Joplin-Salina				0.83	0.17	0.01	0.00			0.44	0.56	0.26	0.09
Amarillo-Pratt				0.60	0.40	0.11	0.03			0.26	0.74	0.49	0.33
Amarillo-Joplin				0.87	0.13	0.01	0.00			0.53	0.47	0.21	0.08
Amarillo-Salina				0.76	0.24	0.05	0.01			0.40	0.60	0.35	0.17

Note D = |P1-P2|; Obs – Observations; Arb – Arbitrage; TC – Transportation Cost

Table 2.16 Arbitrage opportunities in Heifer 700-750 lb weight categories across the sample period (2000-2016).

		20 Head						50 Head					
Difference	**Obs**	**Mean**	**Std. Dev**	**No Arb**	**D > TC**	**D >2TC**	**D > 3TC**	**Mean**	**Std. Dev**	**No Arb**	**D > TC**	**D >2TC**	**D > 3TC**
Pratt-Salina	717	-0.2	2.22	446	271	90	36	1.29	2.14	717	506	349	221
Joplin-Oklahoma	769	-2.23	2.99	615	154	23	6	0.81	2.63	769	416	215	105
Oklahoma-Pratt	758	-2.31	2.91	624	134	16	4	0.81	2.49	758	442	209	83
Amarillo-Oklahoma	671	-0.61	4.89	455	216	67	18	2.53	5.06	671	437	270	179
Oklahoma-Salina	700	-2.72	2.93	593	107	11	1	0.56	2.45	700	357	161	66
Joplin-Pratt	729	-2.14	3.59	553	176	23	4	1.6	3.24	729	478	263	115
Joplin-Salina	682	-2.32	3.47	532	150	17	3	1.46	3.21	682	428	219	98
Amarillo-Pratt	650	-0.13	5.33	404	246	73	19	3.53	5.58	650	481	322	197
Amarillo-Joplin	638	-5.8	5.19	582	56	5	2	0.35	4.51	638	268	97	36
Amarillo-Salina	594	-3.26	5.6	482	112	22	4	2.18	5.85	594	324	169	75
				Probabilities									
Pratt-Salina				0.62	0.38	0.13	0.05			1.00	0.71	0.49	0.31
Joplin-Oklahoma				0.80	0.20	0.03	0.01			1.00	0.54	0.28	0.14
Oklahoma-Pratt				0.82	0.18	0.02	0.01			1.00	0.58	0.28	0.11
Amarillo-Oklahoma				0.68	0.32	0.10	0.03			1.00	0.65	0.40	0.27
Oklahoma-Salina				0.85	0.15	0.02	0.00			1.00	0.51	0.23	0.09
Joplin-Pratt				0.76	0.24	0.03	0.01			1.00	0.66	0.36	0.16
Joplin-Salina				0.78	0.22	0.02	0.00			1.00	0.63	0.32	0.14
Amarillo-Pratt				0.62	0.38	0.11	0.03			1.00	0.74	0.50	0.30
Amarillo-Joplin				0.91	0.09	0.01	0.00			1.00	0.42	0.15	0.06
Amarillo-Salina				0.81	0.19	0.04	0.01			1.00	0.55	0.28	0.13

Note D = |P1-P2|; Obs – Observations; Arb – Arbitrage; TC – Transportation Cost

Table 2.17 Arbitrage opportunities in Steers 450-500 lb weight categories across the sample period (2000-2016).

		20 Head						50 Head					
Difference	**Obs**	**Mean**	**Std. Dev**	**No Arb**	**D > TC**	**D >2TC**	**D > 3TC**	**Mean**	**Std. Dev**	**No Arb**	**D > TC**	**D >2TC**	**D > 3TC**
Pratt-Salina	585	2.93	5.8	208	377	223	125	5.15	5.94	86	499	408	343
Joplin-Oklahoma	773	-1.99	5.2	553	220	46	7	2.61	4.97	255	518	297	160
Oklahoma-Pratt	607	-0.82	6.14	366	241	68	15	3.88	5.87	152	455	309	196
Amarillo-Oklahoma	679	2.35	10.22	321	358	161	68	7.02	10.27	123	556	420	317
Oklahoma-Salina	672	-1.77	6.03	457	215	41	13	3.22	5.95	216	456	281	161
Joplin-Pratt	590	-1.14	7.02	364	226	47	12	4.45	6.89	161	429	289	180
Joplin-Salina	666	-1.93	6.1	446	220	30	1	3.79	6.18	191	475	283	146
Amarillo-Pratt	535	3.26	9.86	222	313	147	63	8.62	9.81	79	456	362	281
Amarillo-Joplin	658	-6.52	10.54	522	136	25	6	2.59	9.41	295	363	187	91
Amarillo-Salina	592	-1.56	10.92	381	211	46	12	6.63	10.99	170	422	272	153
							Probabilities						
Pratt-Salina				0.36	0.64	0.38	0.21			0.15	0.85	0.70	0.59
Joplin-Oklahoma				0.72	0.28	0.06	0.01			0.33	0.67	0.38	0.21
Oklahoma-Pratt				0.60	0.40	0.11	0.02			0.25	0.75	0.51	0.32
Amarillo-Oklahoma				0.47	0.53	0.24	0.10			0.18	0.82	0.62	0.47
Oklahoma-Salina				0.68	0.32	0.06	0.02			0.32	0.68	0.42	0.24
Joplin-Pratt				0.62	0.38	0.08	0.02			0.27	0.73	0.49	0.31
Joplin-Salina				0.67	0.33	0.05	0.00			0.29	0.71	0.42	0.22
Amarillo-Pratt				0.41	0.59	0.27	0.12			0.15	0.85	0.68	0.53
Amarillo-Joplin				0.79	0.21	0.04	0.01			0.45	0.55	0.28	0.14
Amarillo-Salina				0.64	0.36	0.08	0.02			0.29	0.71	0.46	0.26

Note D = |P1-P2|; Obs – Observations; Arb – Arbitrage; TC – Transportation Cost

Table 2.18 Arbitrage opportunities in Steers 500-550 lb weight categories across the sample period (2000-2016).

		20 Head						50 Head					
Difference	Obs	Mean	Std. Dev	No Arb	D > TC	D >2TC	D > 3TC	Mean	Std. Dev	No Arb	D > TC	D >2TC	D > 3TC
Pratt-Salina	625	3.04	5.4	206	419	268	154	5.04	5.52	83	542	461	392
Joplin-Oklahoma	778	-2.17	4.45	564	214	39	6	2.00	4.1	268	510	290	159
Oklahoma-Pratt	642	-1.28	5.54	419	223	70	23	2.99	5.27	216	426	274	177
Amarillo-Oklahoma	669	1.98	7.4	278	391	160	57	6.14	7.38	111	558	445	335
Oklahoma-Salina	692	-1.36	5.19	453	239	56	14	3.15	5.02	186	506	313	183
Joplin-Pratt	635	-1.43	6.19	416	219	61	15	3.64	5.91	202	433	280	181
Joplin-Salina	684	-1.42	5.28	437	247	40	5	3.74	5.12	173	511	329	192
Amarillo-Pratt	551	3.23	8.16	207	344	150	71	8.01	8.2	84	467	375	298
Amarillo-Joplin	645	-5.78	8.08	516	129	20	3	2.35	6.94	271	374	193	90
Amarillo-Salina	592	-0.14	8.8	328	264	47	15	7.23	8.88	124	468	333	188
								Probabilities					
Pratt-Salina				0.33	0.67	0.43	0.25			0.13	0.87	0.74	0.63
Joplin-Oklahoma				0.72	0.28	0.05	0.01			0.34	0.66	0.37	0.20
Oklahoma-Pratt				0.65	0.35	0.11	0.04			0.34	0.66	0.43	0.28
Amarillo-Oklahoma				0.42	0.58	0.24	0.09			0.17	0.83	0.67	0.50
Oklahoma-Salina				0.65	0.35	0.08	0.02			0.27	0.73	0.45	0.26
Joplin-Pratt				0.66	0.34	0.10	0.02			0.32	0.68	0.44	0.29
Joplin-Salina				0.64	0.36	0.06	0.01			0.25	0.75	0.48	0.28
Amarillo-Pratt				0.38	0.62	0.27	0.13			0.15	0.85	0.68	0.54
Amarillo-Joplin				0.80	0.20	0.03	0.00			0.42	0.58	0.30	0.14
Amarillo-Salina				0.55	0.45	0.08	0.03			0.21	0.79	0.56	0.32

Note D = |P1-P2|; Obs – Observations; Arb – Arbitrage; TC – Transportation Cost

Table 2.19 Arbitrage opportunities in Steers 550-600 lb weight categories across the sample period (2000-2016).

		20 Head						50 Head					
Difference	**Obs**	**Mean**	**Std. Dev**	**No Arb**	**D > TC**	**D >2TC**	**D > 3TC**	**Mean**	**Std. Dev**	**No Arb**	**D > TC**	**D >2TC**	**D > 3TC**
Pratt-Salina	655	2.42	4.88	240	415	249	134	4.27	4.94	91	564	455	379
Joplin-Oklahoma	776	-2.6	3.76	616	160	30	4	1.2	3.28	321	455	235	124
Oklahoma-Pratt	677	-1.27	4.66	448	229	61	22	2.61	4.35	205	472	302	178
Amarillo-Oklahoma	660	1.58	6.77	303	357	143	52	5.39	6.9	121	539	412	300
Oklahoma-Salina	698	-1.19	4.63	449	249	55	14	2.95	4.46	201	497	321	178
Joplin-Pratt	658	-2.05	4.9	459	199	29	5	2.58	4.64	204	454	267	139
Joplin-Salina	687	-1.63	4.81	461	226	28	6	3.11	4.67	196	491	307	160
Amarillo-Pratt	567	2.78	7.73	212	355	138	61	7.18	7.89	83	484	398	306
Amarillo-Joplin	633	-4.99	7.44	486	147	19	1	2.47	6.5	252	381	209	91
Amarillo-Salina	584	0.1	8.55	336	248	50	16	6.83	8.83	116	468	313	184
								Probabilities					
Pratt-Salina				0.37	0.63	0.38	0.20			0.14	0.86	0.69	0.58
Joplin-Oklahoma				0.79	0.21	0.04	0.01			0.41	0.59	0.30	0.16
Oklahoma-Pratt				0.66	0.34	0.09	0.03			0.30	0.70	0.45	0.26
Amarillo-Oklahoma				0.46	0.54	0.22	0.08			0.18	0.82	0.62	0.45
Oklahoma-Salina				0.64	0.36	0.08	0.02			0.29	0.71	0.46	0.26
Joplin-Pratt				0.70	0.30	0.04	0.01			0.31	0.69	0.41	0.21
Joplin-Salina				0.67	0.33	0.04	0.01			0.29	0.71	0.45	0.23
Amarillo-Pratt				0.37	0.63	0.24	0.11			0.15	0.85	0.70	0.54
Amarillo-Joplin				0.77	0.23	0.03	0.00			0.40	0.60	0.33	0.14
Amarillo-Salina				0.58	0.42	0.09	0.03			0.20	0.80	0.54	0.32

Note D = |P1-P2|; Obs – Observations; Arb – Arbitrage; TC – Transportation Cost

Table 2.20 Arbitrage opportunities in Heifer Steers 600-650 lb weight categories across the sample period (2000-2016).

		20 Head						50 Head					
Difference	Obs	Mean	Std. Dev	No Arb	D > TC	D >2TC	D > 3TC	Mean	Std. Dev	No Arb	D > TC	D >2TC	D > 3TC
Pratt-Salina	691	1.69	3.93	267	424	231	116	3.41	3.92	111	580	476	370
Joplin-Oklahoma	778	-2.75	3.22	646	132	21	4	0.75	2.7	372	406	207	93
Oklahoma-Pratt	721	-1.95	3.96	532	189	40	7	1.66	3.64	252	469	262	130
Amarillo-Oklahoma	678	1.54	6.28	307	371	141	56	5.09	6.48	126	552	436	313
Oklahoma-Salina	697	-1.43	4.18	482	215	38	10	2.37	4.05	224	473	294	155
Joplin-Pratt	701	-2.7	4.54	541	160	21	3	1.61	4.14	276	425	219	113
Joplin-Salina	688	-1.88	4.44	482	206	31	6	2.49	4.18	214	474	287	155
Amarillo-Pratt	623	1.6	6.94	275	348	108	35	5.7	7.2	105	518	401	285
Amarillo-Joplin	655	-4.39	6.68	516	139	13	0	2.54	6.39	250	405	201	87
Amarillo-Salina	594	0.15	7.58	339	255	47	13	6.34	7.92	109	485	332	178
								Probabilities					
Pratt-Salina				0.30	0.48	0.26	0.13				0.65	0.54	0.42
Joplin-Oklahoma				0.73	0.15	0.02	0.00				0.46	0.23	0.10
Oklahoma-Pratt				0.60	0.21	0.05	0.01				0.53	0.30	0.15
Amarillo-Oklahoma				0.35	0.42	0.16	0.06				0.62	0.49	0.35
Oklahoma-Salina				0.54	0.24	0.04	0.01				0.53	0.33	0.17
Joplin-Pratt				0.61	0.18	0.02	0.00				0.48	0.25	0.13
Joplin-Salina				0.54	0.23	0.03	0.01				0.53	0.32	0.17
Amarillo-Pratt				0.31	0.39	0.12	0.04				0.58	0.45	0.32
Amarillo-Joplin				0.58	0.16	0.01	0.00				0.46	0.23	0.10
Amarillo-Salina				0.38	0.29	0.05	0.01				0.55	0.37	0.20

Note D = |P1-P2|; Obs – Observations; Arb – Arbitrage; TC – Transportation Cost

Table 2.21 Arbitrage opportunities in Steers 650-700 lb weight categories across the sample period (2000-2016).

		20 Head						50 Head					
Difference	Obs	Mean	Std. Dev	No Arb	D > TC	D >2TC	D > 3TC	Mean	Std. Dev	No Arb	D > TC	D >2TC	D > 3TC
Pratt-Salina	702	1.48	3.78	280	422	216	96	3.07	3.88	118	584	474	371
Joplin-Oklahoma	778	-2.76	2.89	668	110	14	3	0.48	2.33	372	406	169	73
Oklahoma-Pratt	732	-2.02	3.66	575	157	27	6	1.32	3.42	293	439	225	110
Amarillo-Oklahoma	641	1.51	5.93	297	344	145	56	4.72	6.11	126	515	395	293
Oklahoma-Salina	700	-2.17	3.5	563	137	20	4	1.37	3.32	286	414	223	94
Joplin-Pratt	713	-2.7	4.1	579	134	19	4	1.28	3.77	311	402	201	91
Joplin-Salina	691	-2.38	3.82	545	146	13	2	1.66	3.6	244	447	224	97
Amarillo-Pratt	598	1.08	6.34	302	296	110	33	4.78	6.55	117	481	349	248
Amarillo-Joplin	616	-3.86	6.61	479	137	19	3	2.4	6.3	263	353	197	99
Amarillo-Salina	575	-0.83	7.13	376	199	45	11	4.88	7.42	147	428	266	146
				Probabilities									
Pratt-Salina				0.32	0.48	0.24	0.11				0.66	0.53	0.42
Joplin-Oklahoma				0.75	0.12	0.02	0.00				0.46	0.19	0.08
Oklahoma-Pratt				0.65	0.18	0.03	0.01				0.49	0.25	0.12
Amarillo-Oklahoma				0.33	0.39	0.16	0.06				0.58	0.45	0.33
Oklahoma-Salina				0.63	0.15	0.02	0.00				0.47	0.25	0.11
Joplin-Pratt				0.65	0.15	0.02	0.00				0.45	0.23	0.10
Joplin-Salina				0.61	0.16	0.01	0.00				0.50	0.25	0.11
Amarillo-Pratt				0.34	0.33	0.12	0.04				0.54	0.39	0.28
Amarillo-Joplin				0.54	0.15	0.02	0.00				0.40	0.22	0.11
Amarillo-Salina				0.42	0.22	0.05	0.01				0.48	0.30	0.16

Note D = |P1-P2|; Obs – Observations; Arb – Arbitrage; TC – Transportation Cost

Table 2.22 Arbitrage opportunities in Steers 700-750 lb weight categories across the sample period (2000-2016).

		20 Head						50 Head					
Difference	**Obs**	**Mean**	**Std. Dev**	**No Arb**	**D > TC**	**D >2TC**	**D > 3TC**	**Mean**	**Std. Dev**	**No Arb**	**D > TC**	**D >2TC**	**D > 3TC**
Pratt-Salina	721	0.33	2.96	408	313	116	44	1.82	3.01	181	540	381	250
Joplin-Oklahoma	778	-2.33	3.01	641	137	26	7	0.69	2.52	345	433	212	97
Oklahoma-Pratt	756	-2.51	3.05	643	113	17	4	0.62	2.63	355	401	172	78
Amarillo-Oklahoma	635	0.96	6.76	362	273	109	48	4.03	6.98	164	471	331	227
Oklahoma-Salina	699	-2.64	3.19	601	98	13	2	0.64	2.77	337	362	161	61
Joplin-Pratt	736	-2.82	3.72	609	127	18	9	0.9	3.23	335	401	192	82
Joplin-Salina	687	-2.68	3.68	563	124	18	6	1.07	3.28	293	394	190	85
Amarillo-Pratt	613	0.48	6.81	364	249	88	35	4.07	7.01	158	455	315	198
Amarillo-Joplin	615	-4.2	6.97	527	88	20	7	1.77	6.78	306	309	147	65
Amarillo-Salina	555	-2.06	7.44	431	124	39	12	3.32	7.72	234	321	184	94
							Probabilities						
Pratt-Salina				0.46	0.35	0.13	0.05				0.61	0.43	0.28
Joplin-Oklahoma				0.72	0.15	0.03	0.01				0.49	0.24	0.11
Oklahoma-Pratt				0.72	0.13	0.02	0.00				0.45	0.19	0.09
Amarillo-Oklahoma				0.41	0.31	0.12	0.05				0.53	0.37	0.26
Oklahoma-Salina				0.68	0.11	0.01	0.00				0.41	0.18	0.07
Joplin-Pratt				0.69	0.14	0.02	0.01				0.45	0.22	0.09
Joplin-Salina				0.63	0.14	0.02	0.01				0.44	0.21	0.10
Amarillo-Pratt				0.41	0.28	0.10	0.04				0.51	0.36	0.22
Amarillo-Joplin				0.59	0.10	0.02	0.01				0.35	0.17	0.07
Amarillo-Salina				0.49	0.14	0.04	0.01				0.36	0.21	0.11

Note D = |P1-P2|; Obs – Observations; Arb – Arbitrage; TC – Transportation Cost

Table 2.23 Dependent Variable: Arbitrage (Heifer 450-500 lb Category).

	Panel Probit		
	Estimates	Marginal Effect	Panel Fixed Effect Model
Lag Arbitrage	0.320***	0.101***	
	(0.053)	(0.016)	
Diesel Prices	-0.0276	-0.00871	0.105
	(0.037)	(0.012)	(0.119)
Transport	-0.0870***	-0.0274***	-0.645***
	(0.013)	(0.005)	(0.101)
Nearby Corn	-0.109***	-0.0342***	-0.486***
	(0.027)	(0.008)	(0.045)
Relative Lot Size	-7.31E-08	-2.30E-08	-1.57E-05
	(0.000)	(0.000)	(0.000)
Spring	-0.262**	-0.0826**	-0.901
	(0.088)	(0.029)	(0.405)
Summer	-0.212*	-0.0678*	0.0895
	(0.106)	(0.034)	(0.543)
Winter	-0.0448	-0.0148	0.0148
	(0.084)	(0.028)	(0.243)
Trend	0.00116***	0.000364***	0.00726***
	(0.000)	(0.000)	(0.001)
Lag Price Difference			0.242***
			(0.027)
Constant	0.207		2.757***
	(0.133)		(0.331)
lnsig2u	-2.772***		
	(0.440)		
Observations	6554	6554	5246
Chi2	12551.6		
Log Likelihood	-3586.7		-16345.5
Sigma_u	0.25		1.296
Rho	0.0589		0.0532

Standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001

Table 2.24 Dependent Variable: Arbitrage - Heifer 500-550 lb Category.

	Panel Probit		
	Estimates	Marginal Effect	Panel Fixed Effect Model
Lag Arbitrage	0.410***	0.128***	
	(0.041)	(0.015)	
Diesel Prices	0.0437	0.0136	0.284
	(0.036)	(0.011)	(0.132)
Transport	-0.0915***	-0.0285***	-0.596***
	(0.019)	(0.006)	(0.083)
Nearby Corn	-0.138***	-0.043***	-0.445***
	(0.012)	(0.005)	(0.062)
Relative Lot Size	7.47E-07	2.33E-07	5.47E-07
	(0.000)	(0.000)	(0.000)
Spring	-0.023	-0.007	-0.468
	(0.102)	(0.032)	(0.304)
Summer	-0.160	-0.048	-0.272
	(0.120)	(0.036)	(0.461)
Winter	0.075	0.024	0.103
	(0.091)	(0.029)	(0.342)
Trend	0.001***	0.001***	0.006***
	(0.000)	(0.000)	(0.001)
Lag Price Difference			0.315***
			(0.024)
Constant	-0.039		2.005***
	(0.174)		(0.401)
lnsig2u	-2.372***		
	(0.327)		
Observations	6859	6859	5740
Chi2	1610		
Log Likelihood	-3718.7		-17502.1
Sigma_u	0.305		1.237
Rho	0.0853		0.0553

Standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001

Table 2.25 Dependent Variable: Arbitrage - Heifer 550-600 lb Category.

	Panel Probit		
	Estimates	Marginal Effect	Panel Fixed Effect Model
Lag Arbitrage	0.310***	0.0963***	
	(0.054)	(0.018)	
Diesel Prices	0.0441*	0.0137*	0.227*
	(0.019)	(0.006)	(0.088)
Transport	-0.0858***	-0.0266***	-0.565***
	(0.020)	(0.006)	(0.040)
Nearby Corn	-0.170***	-0.0529***	-0.532***
	(0.023)	(0.008)	(0.085)
Relative Lot Size	-3.74E-06	-1.16E-06	-8.70E-06
	(0.000)	(0.000)	(0.000)
Spring	-0.0723	-0.0227	-0.393
	(0.058)	(0.019)	(0.243)
Summer	-0.117	-0.0364	0.209
	(0.094)	(0.028)	(0.470)
Winter	-0.0467	-0.0147	-0.281
	(0.070)	(0.022)	(0.131)
Trend	0.00142***	0.000440***	0.00645***
	(0.000)	(0.000)	(0.001)
Lag Price Difference			0.302***
			(0.026)
Constant	-0.0821		1.654***
	(0.134)		(0.317)
lnsig2u	-2.326***		
	(0.273)		
Observations	6911	6911	5737
Chi2	544.9		
Log Likelihood	-3723.6	-16943.6	
Sigma_u	0.312	0.989	
Rho	0.089	0.0433	

Standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001

Table 2.26 Dependent Variable: Arbitrage - Heifer 600-650 lb Category.

	Panel Probit		
	Estimates	Marginal Effect	Panel Fixed Effect Model
Lag Arbitrage	0.362***	0.102***	
	(0.052)	(0.018)	
Diesel Prices	0.0351	0.00986	0.392*
	(0.046)	(0.013)	(0.122)
Transport	-0.0595*	-0.0167*	-0.593***
	(0.026)	(0.007)	(0.041)
Nearby Corn	-0.138***	-0.0388***	-0.467***
	(0.022)	(0.007)	(0.069)
Relative Lot Size	-4.11E-06	-1.15E-06	-1.95E-06
	(0.000)	(0.000)	(0.000)
Spring	-0.142	-0.0414	-0.647*
	(0.076)	(0.023)	(0.209)
Summer	-0.139*	-0.0404*	-0.416
	(0.068)	(0.020)	(0.228)
Winter	-0.233**	-0.0659**	-0.758**
	(0.079)	(0.025)	(0.162)
Trend	0.00117***	0.000330***	0.00523***
	(0.000)	(0.000)	(0.001)
Lag Price Difference			0.274***
			(0.026)
Constant	-0.428**		1.333**
	(0.142)		(0.298)
lnsig2u	-2.326***		
	(0.237)		
Observations	7078	7078	6035
Chi2	26462.1		
Log Likelihood	-3471.7		-16994.6
Sigma_u	0.313		1.034
Rho	0.089		0.0612

Standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001

Table 2.27 Dependent Variable: Arbitrage - Heifer 650-700 lb Category.

	Panel Probit		
	Estimates	Marginal Effect	Panel Fixed Effect Model
Lag Arbitrage	0.326***	0.0922***	
	(0.047)	(0.017)	
Diesel Prices	-0.0747*	-0.0211*	-0.043
	(0.037)	(0.010)	(0.083)
Transport	-0.0682**	-0.0193**	-0.586***
	(0.025)	(0.007)	(0.053)
Nearby Corn	-0.0666*	-0.0188*	-0.252***
	(0.027)	(0.008)	(0.042)
Relative Lot Size	-1.62E-06	-4.58E-07	5.02E-06
	(0.000)	(0.000)	(0.000)
Spring	-0.292**	-0.0856**	-1.084*
	(0.101)	(0.032)	(0.355)
Summer	-0.165	-0.0501	-0.294
	(0.089)	(0.029)	(0.286)
Winter	-0.332***	-0.0960***	-0.878*
	(0.071)	(0.025)	(0.278)
Trend	0.00112***	0.000317***	0.00499**
	(0.000)	(0.000)	(0.001)
Lag Price Difference			0.264***
			(0.018)
Constant	-0.281**		1.549***
	(0.098)		(0.155)
lnsig2u	-2.379***		
	(0.238)		
Observations	7013	7013	5943
Chi2	204682.2		
Log Likelihood	-3475.5		-16077.4
Sigma_u	0.304		0.957
Rho	0.0848		0.0651

Standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001

Table 2.28 Dependent Variable: Arbitrage - Heifer 700-750 lb Category.

	Panel Probit		
	Estimates	Marginal Effect	Panel Fixed Effect Model
Lag Arbitrage	0.280***	0.0796***	
	(0.051)	(0.017)	
Diesel Prices	-0.0282	-0.00801	-0.058
	(0.033)	(0.009)	(0.077)
Transport	-0.0945***	-0.0268***	-0.557***
	(0.023)	(0.006)	(0.075)
Nearby Corn	-0.0765***	-0.0217***	-0.287***
	(0.020)	(0.006)	(0.037)
Relative Lot Size	7.34E-07	2.08E-07	5.08E-06
	(0.000)	(0.000)	(0.000)
Spring	-0.409***	-0.119***	-1.258***
	(0.058)	(0.016)	(0.201)
Summer	-0.159**	-0.0499***	-0.672**
	(0.052)	(0.015)	(0.143)
Winter	-0.353***	-0.105***	-1.258**
	(0.054)	(0.017)	(0.298)
Trend	0.000804***	0.000228***	0.00404**
	(0.000)	(0.000)	(0.001)
Lag Price Difference			0.185***
			(0.020)
Constant	-0.0792		1.836***
	(0.086)		(0.273)
lnsig2u	-3.027***		
	(0.384)		
Observations	6908	6908	5753
Chi2	1939.3		
Log Likelihood	-3481.3		-15547.6
Sigma_u	0.22		0.834
Rho	0.0462		0.0505

Standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001

Table 2.29 Dependent Variable: Arbitrage - Steer 450-500 lb Category.

	Panel Probit		
	Estimates	Marginal Effect	Panel Fixed Effect Model
Lag Arbitrage	0.258***	0.0889***	
	(0.040)	(0.014)	
Diesel Prices	-0.0568	-0.0196	-0.274
	(0.048)	(0.017)	(0.388)
Transport	-0.100***	-0.0346***	-0.710***
	(0.012)	(0.004)	(0.035)
Nearby Corn	-0.0447*	-0.0154*	-0.378**
	(0.018)	(0.006)	(0.108)
Relative Lot Size	2.51E-06	8.67E-07	4.03E-05
	(0.000)	(0.000)	(0.000)
Spring	-0.0947	-0.0329	-0.577
	(0.072)	(0.025)	(0.415)
Summer	-0.137	-0.0472	-0.38
	(0.094)	(0.032)	(0.467)
Winter	-0.0611	-0.0213	-0.546
	(0.083)	(0.029)	(0.383)
Trend	0.00121***	0.000418***	0.00995***
	(0.000)	(0.000)	(0.002)
Lag Price Difference			0.174***
			(0.029)
Constant	0.371**		3.953***
	(0.124)		(0.250)
lnsig2u	-2.692***		
	(0.425)		
Observations	6357	6357	5054
Chi2	995.8		
Log Likelihood	-3880.9		-17019.7
Sigma_u	0.26		1.941
Rho	0.0634		0.0708

Standard errors in parentheses; * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 2.30 Dependent Variable: Arbitrage - Steer 500-550 lb Category.

	Panel Probit		
	Estimates	Marginal Effect	Panel Fixed Effect Model
Lag Arbitrage	0.351***	0.120***	
	(0.048)	(0.016)	
Diesel Prices	-0.00408	-0.0014	0.0185
	(0.037)	(0.013)	(0.214)
Transport	-0.101***	-0.0346***	-0.697***
	(0.011)	(0.004)	(0.051)
Nearby Corn	-0.0728***	-0.0250***	-0.240*
	(0.016)	(0.006)	(0.092)
Relative Lot Size	-3.91E-06	-1.34E-06	-1.58E-05
	(0.000)	(0.000)	(0.000)
Spring	-0.0799	-0.0276	-0.292
	(0.111)	(0.038)	(0.525)
Summer	-0.16	-0.0548	-0.0731
	(0.096)	(0.032)	(0.448)
Winter	0.0209	0.00726	0.028
	(0.099)	(0.035)	(0.437)
Trend	0.000847***	0.000291***	0.00633***
	(0.000)	(0.000)	(0.001)
Lag Price Difference			0.204***
			(0.017)
Constant	0.394**		3.377***
	(0.127)		(0.455)
lnsig2u	-2.375***		
	(0.344)		
Observations	6513	6513	5295
Chi2	12740.9		
Log Likelihood	-3923.7		-16679.6
Sigma_u	0.305		1.723
Rho	0.0851		0.0848

Standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001

Table 2.31 Dependent Variable: Arbitrage - Steer 550-600 lb Category.

	Panel Probit		
	Estimates	Marginal Effect	Panel Fixed Effect Model
Lag Arbitrage	0.268***	0.0920***	
	(0.046)	(0.014)	
Diesel Prices	0.0446	0.0153	0.383*
	(0.034)	(0.012)	(0.146)
Transport	-0.111***	-0.0381***	-0.806***
	(0.013)	(0.004)	(0.068)
Nearby Corn	-0.0519*	-0.0178*	-0.171*
	(0.021)	(0.007)	(0.075)
Relative Lot Size	1.69E-07	5.82E-08	9.77E-07
	(0.000)	(0.000)	(0.000)
Spring	0.0979	0.0338	0.394
	(0.073)	(0.026)	(0.300)
Summer	-0.0398	-0.0135	0.361
	(0.088)	(0.030)	(0.411)
Winter	0.0634	0.0218	0.407
	(0.071)	(0.025)	(0.257)
Trend	0.000915***	0.000314***	0.00648***
	(0.000)	(0.000)	(0.001)
Lag Price Difference			0.186***
			(0.022)
Constant	0.066		1.952*
	(0.095)		(0.627)
lnsig2u	-2.126***		
	(0.401)		
Observations	6595	6595	5346
Chi2	1656.5		
Log Likelihood	-4002.5		-16405.2
Sigma_u	0.345		1.989
Rho	0.107		0.127

Standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001

Table 2.32 Dependent Variable: Arbitrage - Steer 600-650 lb Category.

	Panel Probit		
	Estimates	Marginal Effect	Panel Fixed Effect Model
Lag Arbitrage	0.294***	0.0992***	
	(0.044)	(0.016)	
Diesel Prices	-0.0215	-0.00727	-0.0804
	(0.035)	(0.012)	(0.143)
Transport	-0.0805**	-0.0272**	-0.571***
	(0.030)	(0.010)	(0.066)
Nearby Corn	-0.0766***	-0.0259***	-0.313***
	(0.014)	(0.005)	(0.063)
Relative Lot Size	-1.19E-06	-4.01E-07	6.90E-06
	(0.000)	(0.000)	(0.000)
Spring	0.031	0.0106	0.015
	(0.068)	(0.023)	(0.229)
Summer	-0.0229	-0.00775	0.253
	(0.092)	(0.031)	(0.393)
Winter	-0.0983	-0.0329	-0.599**
	(0.063)	(0.021)	(0.143)
Trend	0.000815***	0.000276***	0.00550***
	(0.000)	(0.000)	(0.001)
Lag Price Difference			0.204***
			(0.024)
Constant	0.0533		2.045***
	(0.138)		(0.381)
lnsig2u	-2.034***		
	(0.311)		
Observations	6826	6826	5654
Chi2	2589.7		
Log Likelihood	-3999.4		-16451.3
Sigma_u	0.362		1.469
Rho	0.116		0.0984

Standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001

Table 2.33 Dependent Variable: Arbitrage - Steer 650-700 lb Category.

	Panel Probit		
	Estimates	Marginal Effect	Panel Fixed Effect Model
Lag Arbitrage	0.233***	0.0742***	
	(0.035)	(0.011)	
Diesel Prices	-0.024	-0.00763	0.208
	(0.037)	(0.012)	(0.141)
Transport	-0.0903***	-0.0287***	-0.698***
	(0.014)	(0.004)	(0.046)
Nearby Corn	-0.0918***	-0.0292***	-0.304***
	(0.020)	(0.005)	(0.048)
Relative Lot Size	-9.24E-07	-2.94E-07	2.82E-06
	(0.000)	(0.000)	(0.000)
Spring	0.0135	0.00437	-0.0814
	(0.052)	(0.017)	(0.199)
Summer	-0.00404	-0.00131	0.236
	(0.052)	(0.017)	(0.272)
Winter	-0.198***	-0.0613***	-0.589**
	(0.051)	(0.018)	(0.124)
Trend	0.000997***	0.000317***	0.00485***
	(0.000)	(0.000)	(0.001)
Lag Price Difference			0.137**
			(0.034)
Constant	-0.029		1.742**
	(0.121)		(0.370)
lnsig2u	-1.818***		
	(0.208)		
Observations	6746	6746	5571
Chi2	206631471.9		
Log Likelihood	-3690.2		-15927.3
Sigma_u	0.403		1.496
Rho	0.14		0.111

Standard errors in parentheses; * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 2.34 Dependent Variable: Arbitrage - Steer 700-750 lb Category.

	Panel Probit		
	Estimates	Marginal Effect	Panel Fixed Effect Model
Lag Arbitrage	0.281***	0.0810***	
	(0.057)	(0.020)	
Diesel Prices	0.00769	0.00221	0.0643
	(0.036)	(0.010)	(0.098)
Transport	-0.0964*	-0.0278**	-0.661***
	(0.038)	(0.011)	(0.077)
Nearby Corn	-0.0896***	-0.0258***	-0.268**
	(0.025)	(0.007)	(0.057)
Relative Lot Size	1.67E-06	4.82E-07	1.14E-05*
	(0.000)	(0.000)	(0.000)
Spring	-0.238**	-0.0723*	-0.755*
	(0.082)	(0.029)	(0.296)
Summer	-0.183	-0.0563	-0.301
	(0.095)	(0.032)	(0.327)
Winter	-0.406***	-0.117***	-1.378**
	(0.087)	(0.032)	(0.362)
Trend	0.000757***	0.000218***	0.00475***
	(0.000)	(0.000)	(0.001)
Lag Price Difference	0.204***		
	(0.028)		
Constant	-0.107	1.696***	
	(0.140)	(0.332)	
lnsig2u	-2.358***		
	(0.277)		
Observations	6795	6795	5639
Chi2	1361.1		
Log Likelihood	-3406.2		-16264
Sigma_u	0.308		1.233
Rho	0.0864		0.0748

Standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001

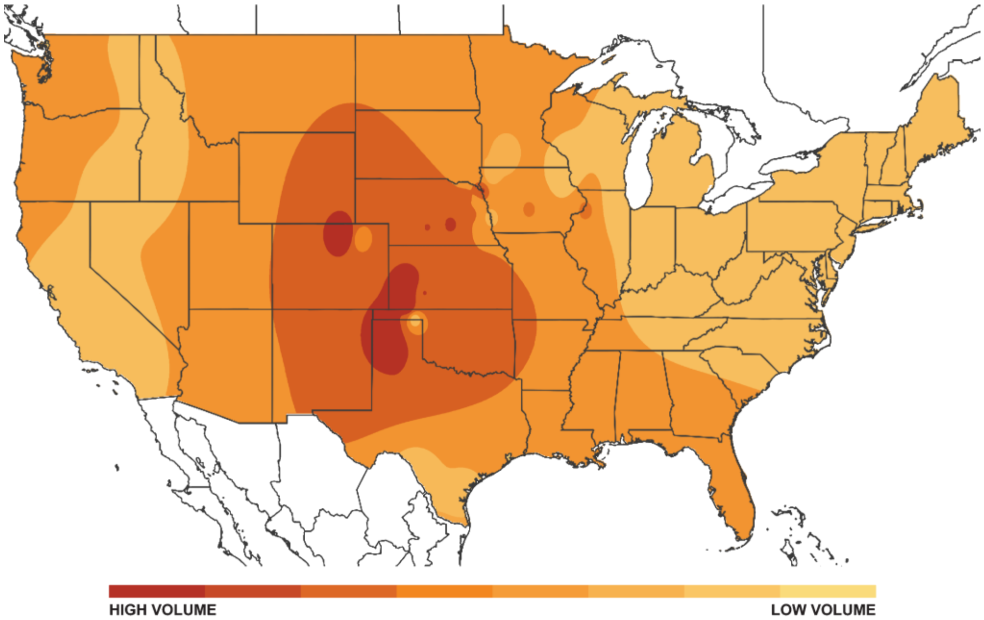

Figure 2.1 Cattle and Cattle Slaughter Industry (1994).
This map shows the concentration of the cattle slaughter in the United States by year 1994.
Source: http://dryagebeef.meatingplace.com/

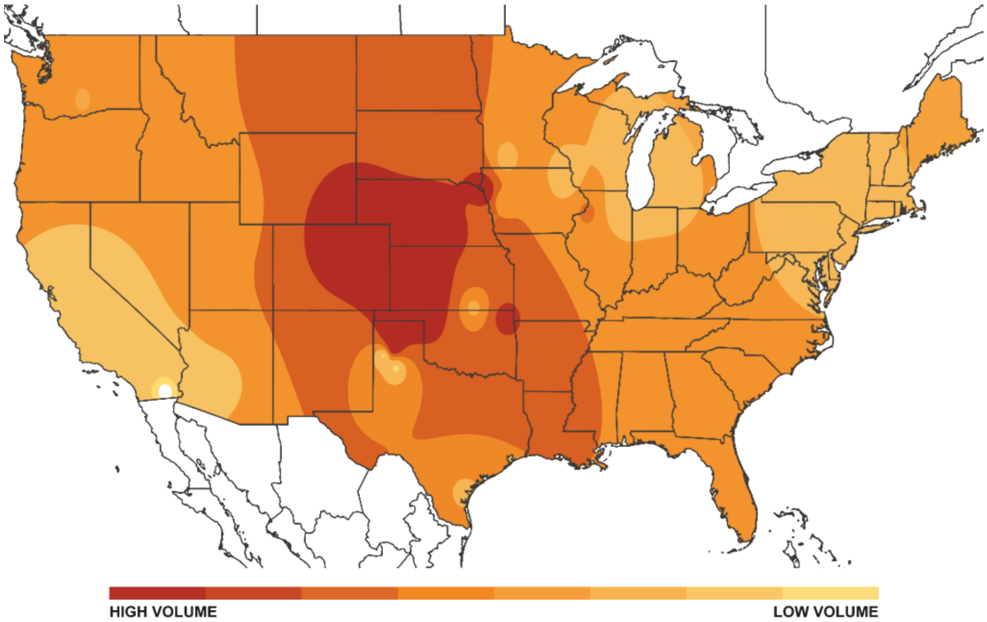

Figure 2.2 Cattle and Cattle Slaughter Industry (2014).
This map shows the concentration of the cattle slaughter in the United States by year 2014.
Source: http://dryagebeef.meatingplace.com/

Figure 2.3 The Selected Five Markets Across Four States.
Map created with mapchart.net

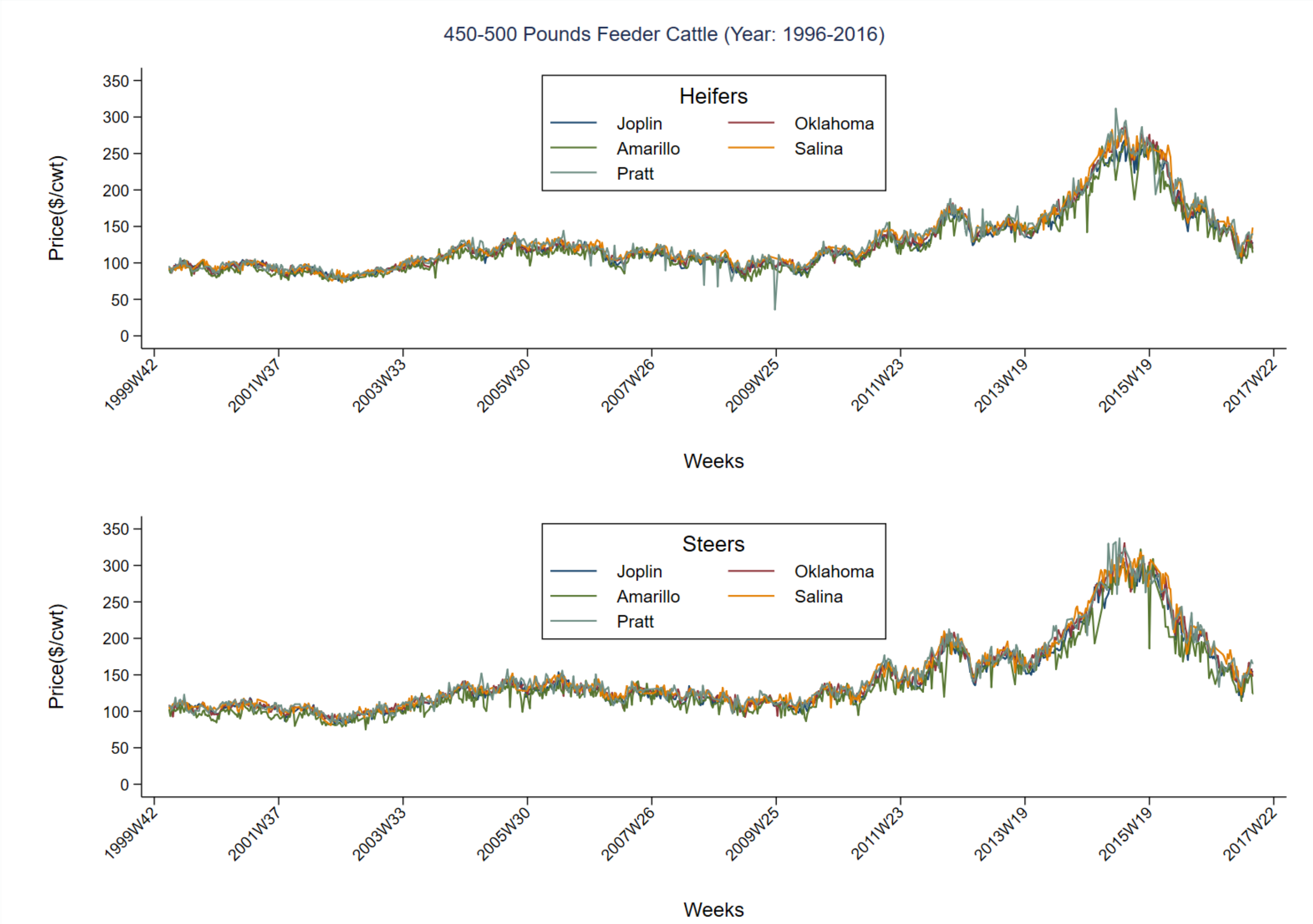

Figure 2.4 Plot of Prices of Selected Markets, 450-500 lb Category (1996-2016).

Note: Oklahoma stands for Oklahoma City.

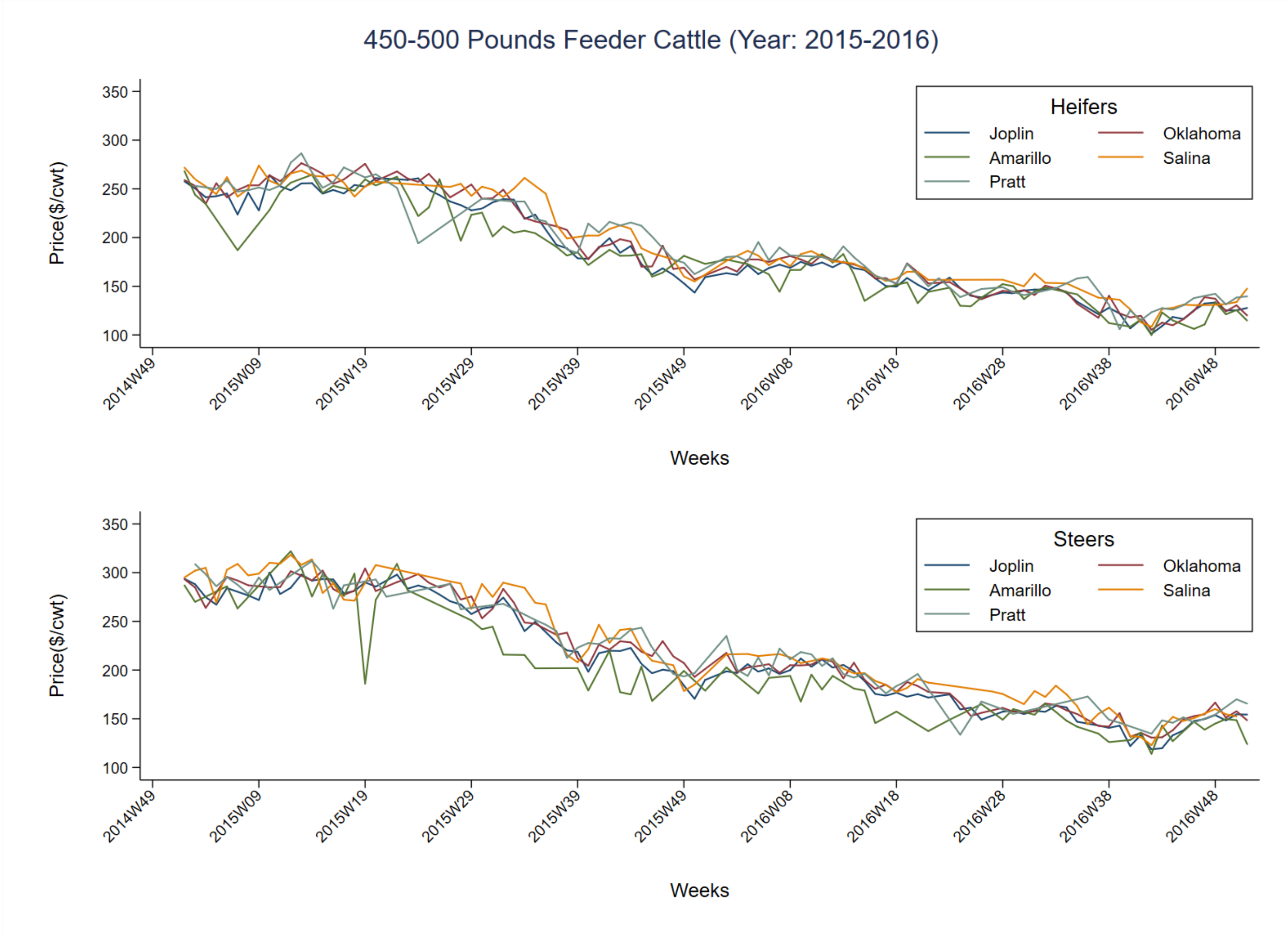

Figure 2.5 Plot of Prices of Selected Markets, 450-500 lb Category (2015-2016).

Note: Oklahoma stands for Oklahoma City.

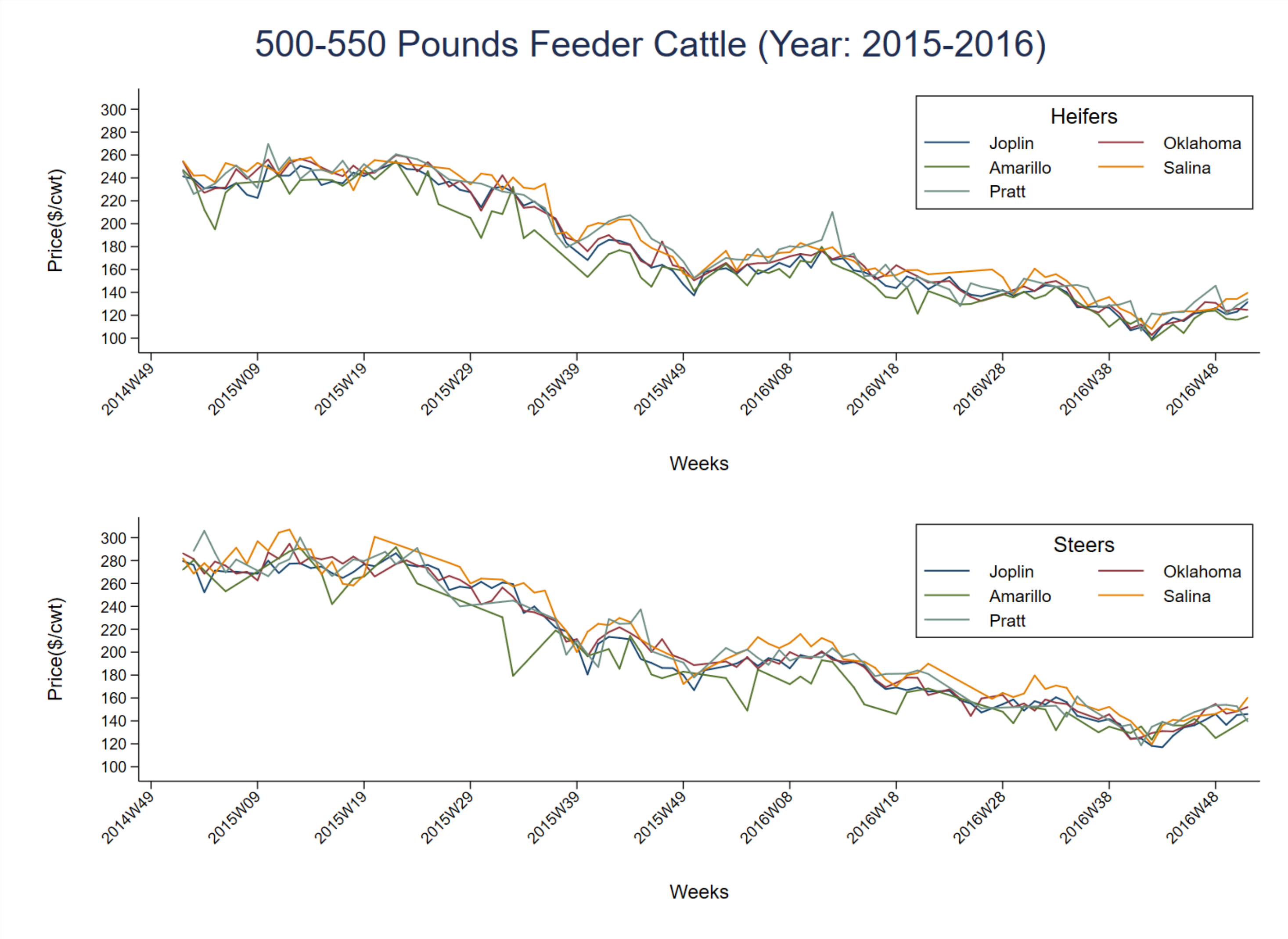

Figure 2.6 Plot of Prices of Selected Markets, 500-550 lb Category (2015-2016).

Note: Oklahoma stands for Oklahoma City.

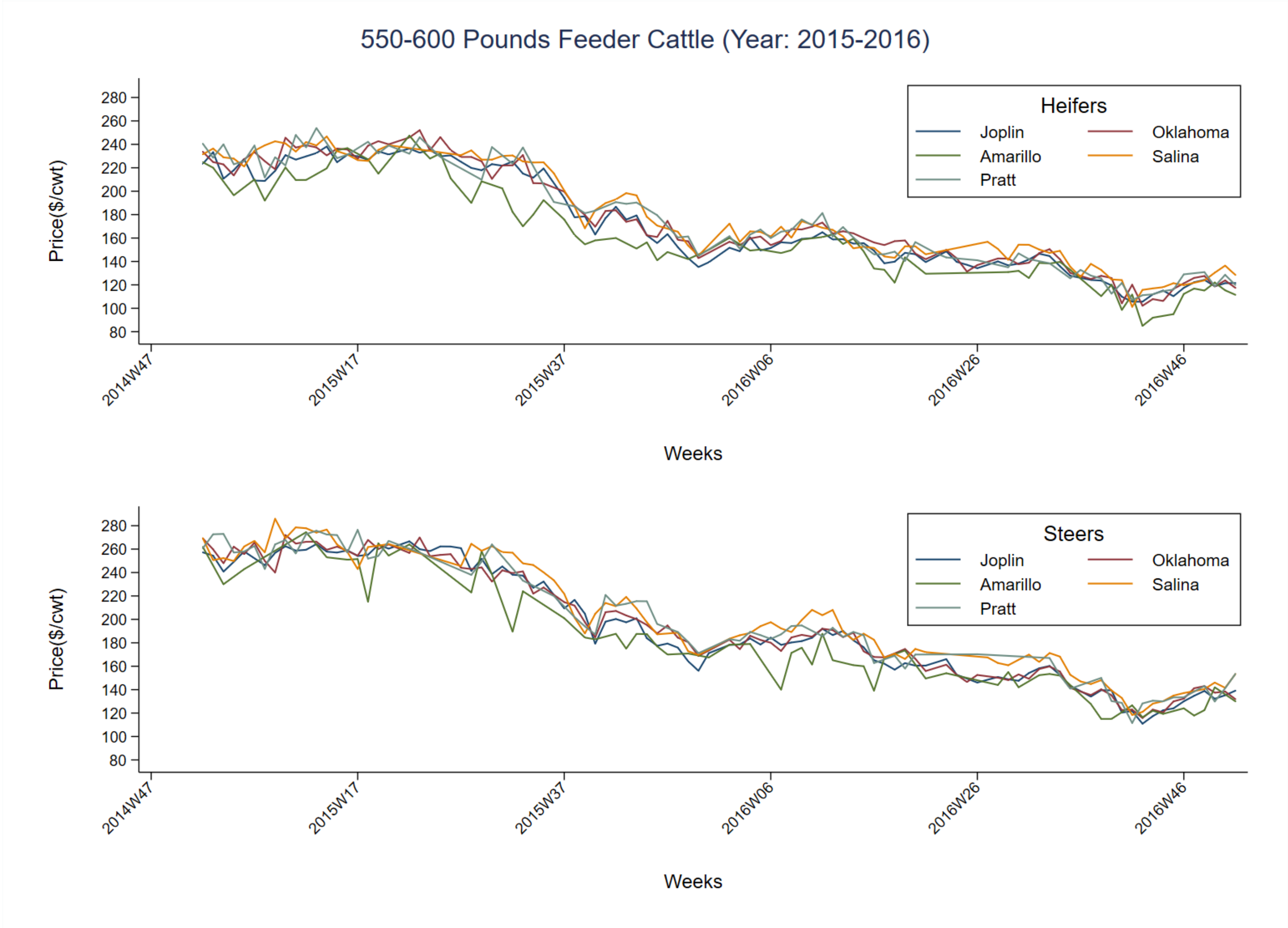

Figure 2.7 Plot of Prices of Selected Markets, 550-600 lb Category (2015-2016).

Note: Oklahoma stands for Oklahoma City.

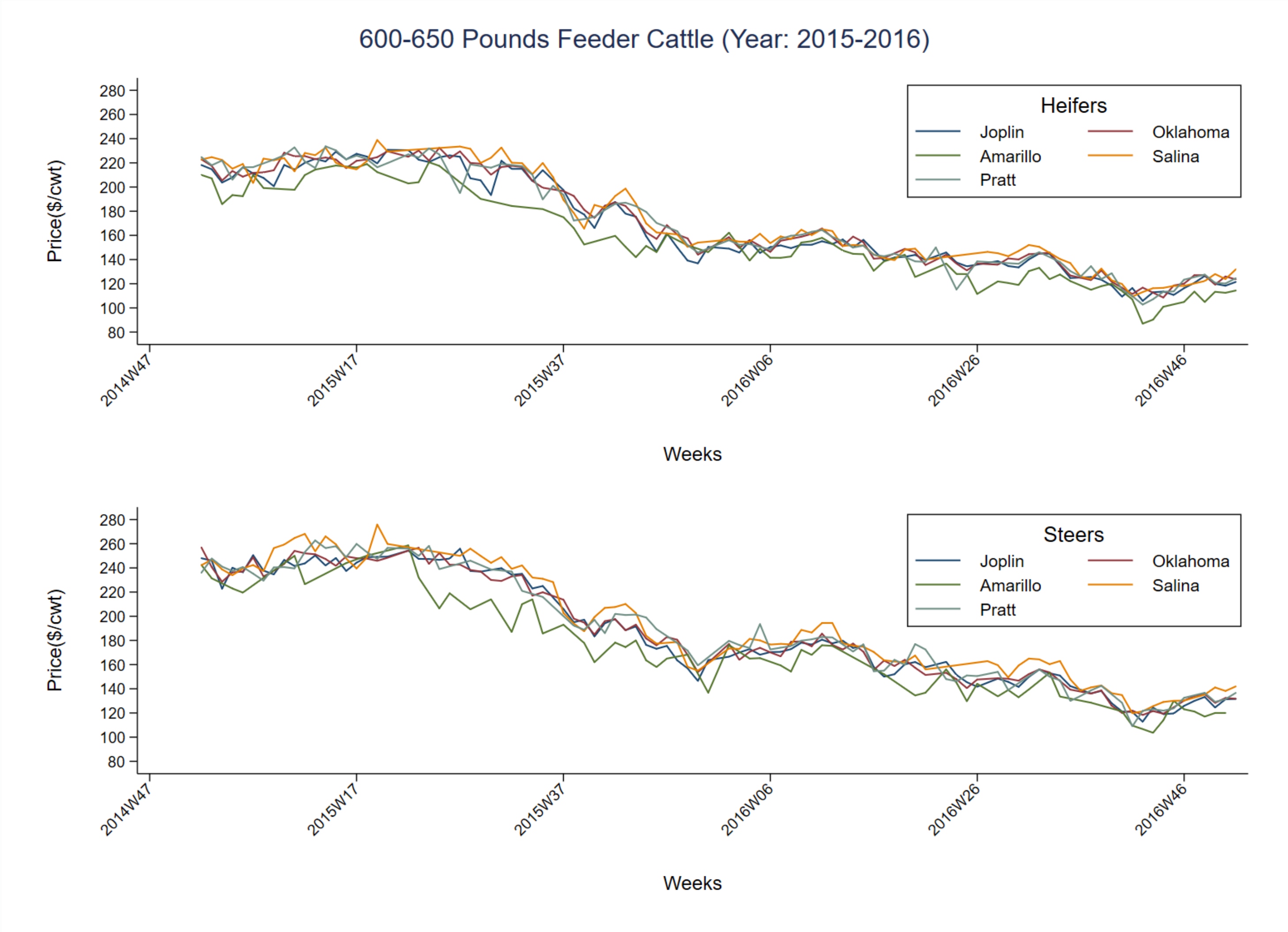

Figure 2.8 Plot of Prices of Selected Markets, 600-650 lb Category (2015-2016).

Note: Oklahoma stands for Oklahoma City.

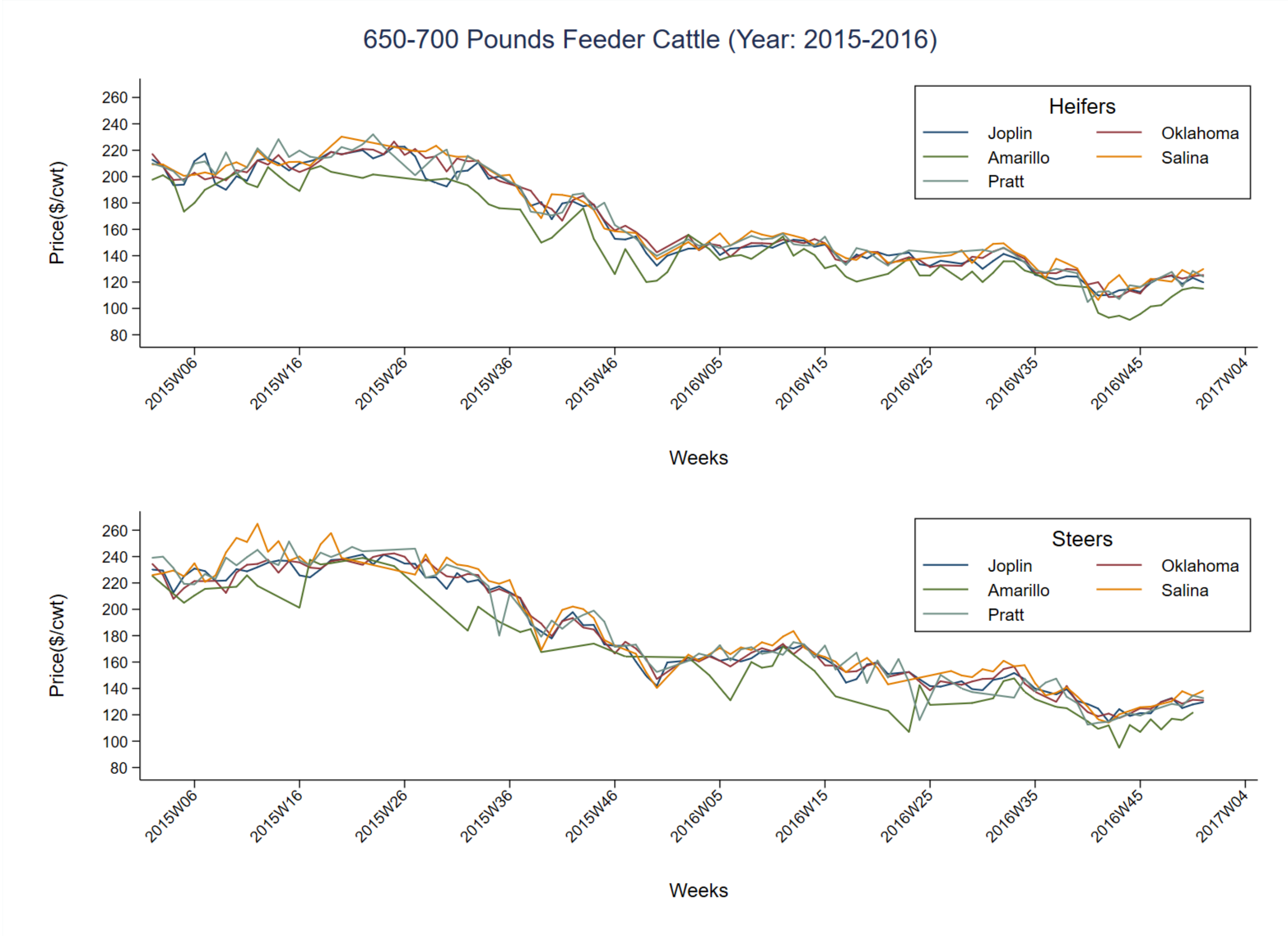

Figure 2.9 Plot of Prices of Selected Markets, 650-700 lb Category (2015-2016).

Note: Oklahoma stands for Oklahoma City.

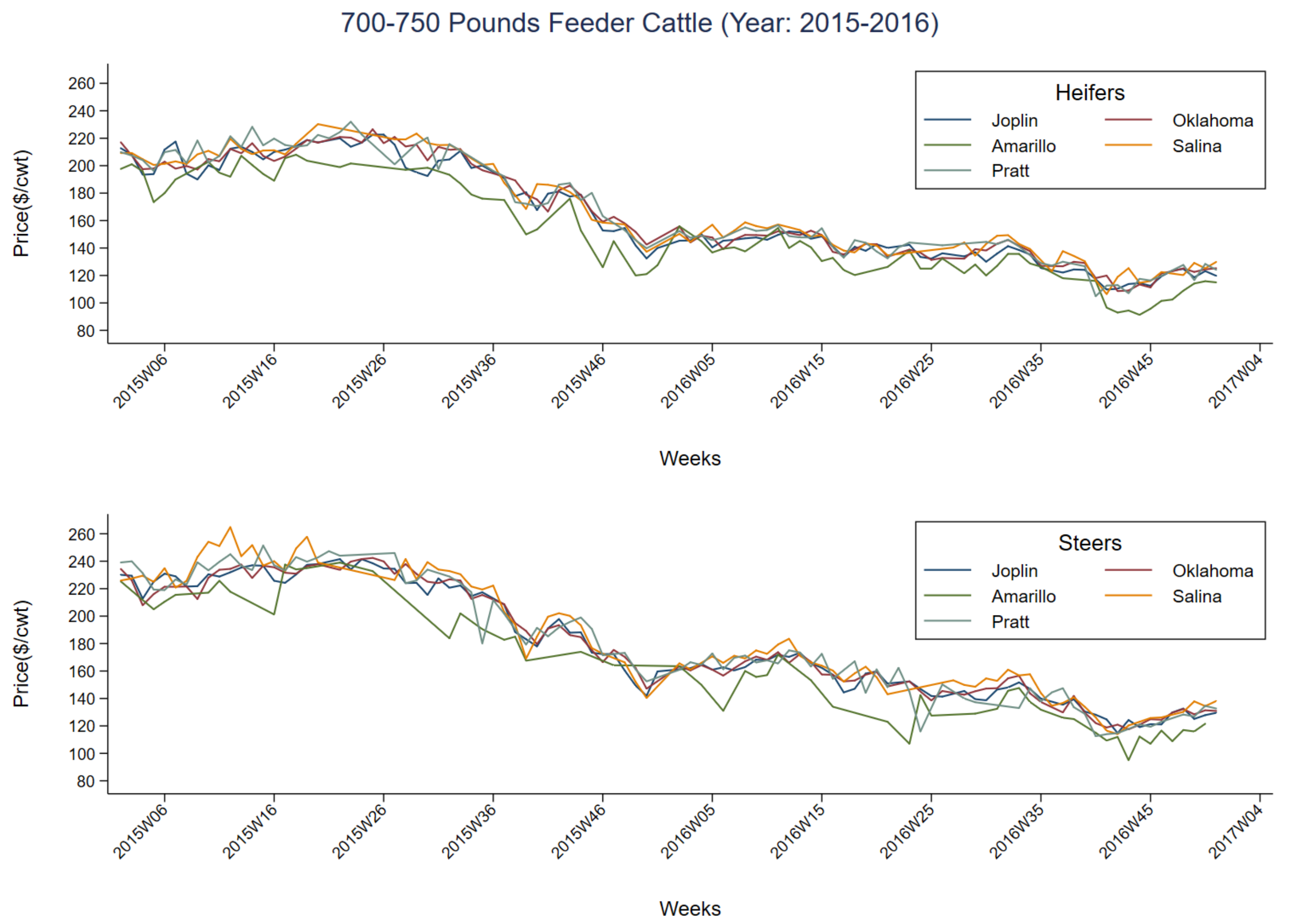

Figure 2.10 Plot of Prices of Selected Markets, 700-750 lb Category (2015-2016).

Note: Oklahoma stands for Oklahoma City.

APPENDIX

Table 2.A1 Seasonality Effect on the Cattle Transportation Cost.

	TC_Index	Ama-Jop	Jop-OKC	OKC-Pratt	Pratt-Sal	Diesel
Diesel	0.0833***	0.324***	0.155***	0.156***	0.0813***	
	(0.002)	(0.006)	(0.003)	(0.003)	(0.002)	
Spring	-0.007	-0.028	-0.013	-0.013	-0.007	-0.035
	(0.004)	(0.017)	(0.008)	(0.008)	(0.004)	(0.091)
Summer	-0.004	-0.016	-0.007	-0.007	-0.004	0.002
	(0.004)	(0.017)	(0.008)	(0.008)	(0.004)	(0.091)
Winter	0.001	0.005	0.002	0.002	0.001	-0.163
	(0.004)	(0.017)	(0.008)	(0.008)	(0.004)	(0.091)
Constant	0.695***	2.704***	1.296***	1.301***	0.679***	2.717***
	(0.005)	(0.021)	(0.010)	(0.010)	(0.005)	(0.064)
Obs	887	887	887	887	887	887
R-Square	0.748	0.748	0.748	0.748	0.748	0.00499

Standard errors in parentheses

* p<0.05, ** p<0.01, *** p<0.001

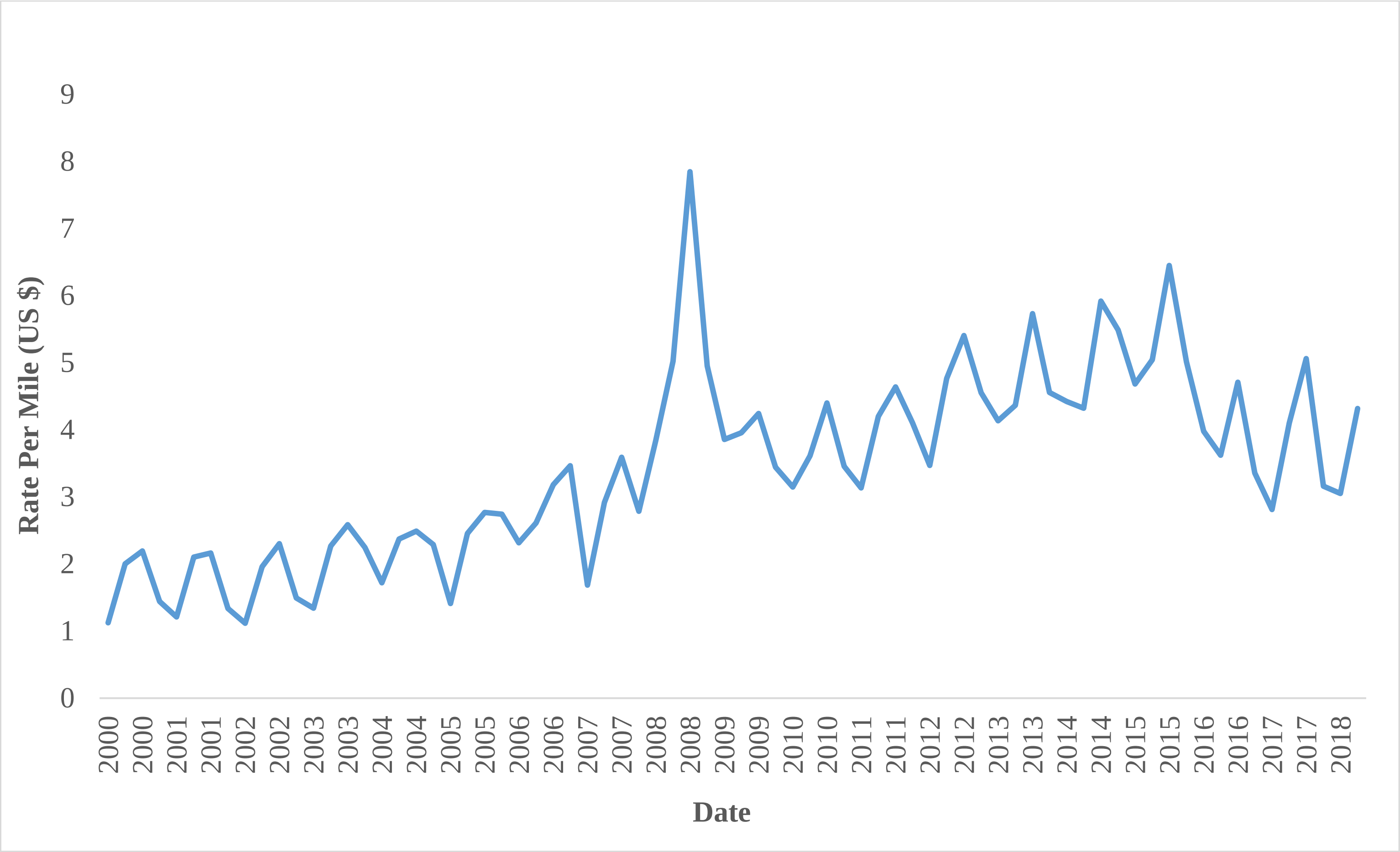

Figure 2.A1 United States Historical Average United States Department of Agriculture Short Distance Quarterly Truck Rates (500 miles and less)[9].

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[9] https://www.ams.usda.gov/services/transportation-analysis/agricultural-refrigerated-truck-quarterly-datasets

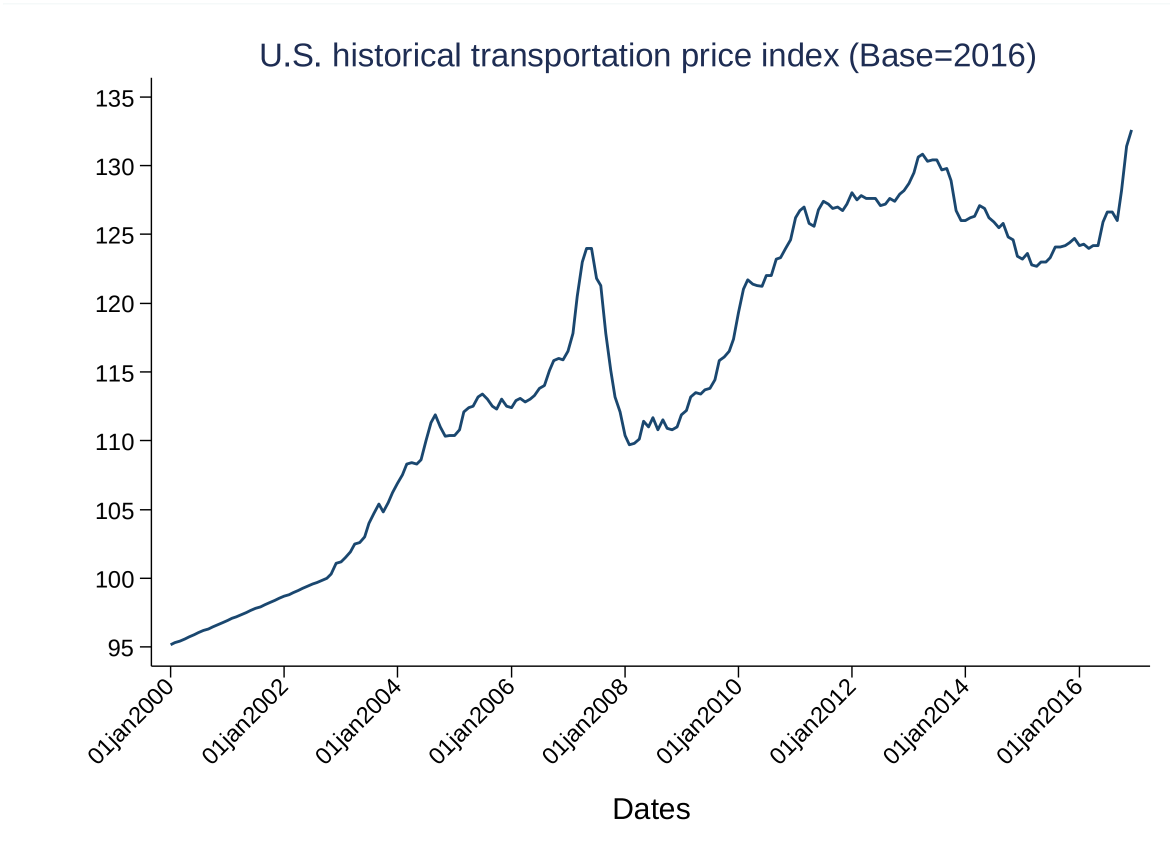

Figure 2.A2 United States Historical Transportation Price Index.

Chapter 3 - Shocks Transmission "TO" and "FROM" Kansas Feeder Cattle Markets: A Rolling Sample Analysis

This study examines the degree of connectedness of the feeder cattle markets in the United States over time. Also, I evaluate the influence of spatiotemporal factors that may impact the degree of market connectedness over the same period. This study is unique because it is the first to apply a time-varying approach to study feeder cattle market linkages at the auction level and factors influencing the variation in market connectedness.

Livestock prices are determined by the supply and demand conditions in local markets (Goodwin and Schroeder 1991). Prices across spatial markets can differ at any point in time depending on many factors including transaction costs, information flows, structure of potential buyers, and other trade barriers between markets. Many factors can influence the level of market connectedness. Extreme weather is one common factor that can create differences in prices across spatial markets. For instance, extreme heat in Texas from 2010 till 2014[10] and current drought conditions facing the southwestern part of the United States can significantly impact regional feeder cattle market price relationships. The question of interest in this study is, whether there is evidence of changes in spatial market connectedness over time. If yes, can we elicit the changes in the market connectedness over time? Do the changes in market forces significantly affect Kansas feeder cattle markets? How connected are Kansas feeder cattle markets within the state and with feeder cattle markets from other states?

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[10] Timeline of Droughts in Texas http://twri.tamu.edu/publications/txh2o/fall-2011/timeline-of-droughts-in-texas/

The first objective of this study is to elicit time variation in selected feeder cattle auction market price relationships. Second, to determine the impact of extreme events, drought specifically, on the degree of market connectedness over time.

Extreme weather events have always impacted the United States cattle industry. The 2011and 2012 drought across the United States impacted more than 70% of the U.S. crop and livestock production (Countryman, Paarlberg and Lee 2016). During the period of the drought in the Texas region, many animals were transported to zones less affected by the drought. According to an article in the Washington Post[11], substantial incidence of wildfires in the state of Texas occurred as a result of the extensive drought. Increases in the occurrence of wildfires have significantly impacted the availability of forages. The lack of adequate food for livestock confounds already increased heat stress of animals. Texas agricultural industry loss to drought ranged between $316 million to about $7.6 billion, annually (Fannin 2012). The severity of droughts varies across the United States. The severity of droughts leads to other research questions; how does drought impact the spatial feeder cattle market connectedness over time? Do periods of severe drought lead to greater or lesser connectedness?

Drought impact on livestock markets

Apart from measuring market connectedness, we also examined factors influencing the degree of market integration. It is important to determine what factors influence feeder cattle market connectedness in order to enhance future market forecasts and price discovery. The most important factor considered is drought. There have been several episodes of severe drought in past decades. The most recent is the extreme drought of 2010-2012 in the United States. The

[11] https://www.washingtonpost.com/blogs/capital-weather-gang/post/drought-fueled-wildfires-burn-out-of-control-in-texas/2011/09/05/gIQACfXx6J_blog.html?utm_term=.0683c12a3432

most severe region affected was the southern plains of the United States (Texas water resource institute 2011).

Although more drought-resistant crops are being developed (Yu and Babcock 2010), long-term persistence of extreme weather can affect feeder cattle prices through forage availability. In a case of extreme dryness for a very long time, there will be shortages of forage for feeder cattle, which will increase costs of production. Many studies has reported that in the short term, extreme drought will reduce livestock productivity, posing welfare loss to both producers and consumers (Anderson et al., 2012; Bauman et al., 2013; Wang, et al., 2013; Watkins, 2012). Extreme dryness also impacts feeder cattle prices through corn prices. Feeder cattle sold at an auction generally go to either a stocker or to a feedlot. High corn prices reduce derived demand for feeder cattle resulting in lower feeder cattle prices due to the increase in the cost of feeding them. Extreme weather also causes stress on animals, which can affect animal health and feeding efficiency. I hypothesize that extreme drought significantly impacts the spatial price transmission and arbitrage opportunities in feeder cattle markets.

There are two major contributions of this study to the literature. First, this study examines less explored dynamics in feeder cattle auction markets linkages. Second, this is the first study to adopt a time-varying model in examining livestock market price relationships at auctions in the United States.

The rest of the chapter is organized as follow: First I provide a background to the market linkage analysis in the livestock market and drought in the United States. After, the methodology section details the Diebold & Yilmaz (2012) market connectedness measure employed in the study. Then, the results section presents the study findings, followed by conclusions.

Background

Many past studies have examined the dynamics of prices in the livestock markets (Ajewole, et. al., 2016; Coffey et. al., 2019; Goodwin & Schroeder, 1991; Herath et. al., 2005; Kesavan et. al , 1992; Pendell & Schroeder, 2006; Rahman & Palash, 2016). Studies that have examined cattle markets focused mostly on the fed cattle markets. The feeder cattle market is an integral part of the cattle markets which motivates this study focused on this market sector.

Spatial market connectedness & LOP:

Spatial market integration (connectedness) can be used to study price relationships between markets separated by geographical space. Fackler & Goodwin, (2001) defined market integration as a measure of the degree to which a demand or supply shock in one market is transmitted to another market. In accessing market integration, trade barrier between markets can play a significant role. In case of a traded homogenous good, such as feeder cattle, within the United States, transportation cost is one of the major factors impacting trade between two markets. The complexity of the agricultural commodities market gives rise to the in-depth study of the markets. Many past studies on agricultural commodity market prices have been conducted to gain insights into market price co-movements and associated market performance (Fackler and Goodwin 2001). Testing price dynamics in these markets is important because the relationship between most agricultural commodities markets is expected to change over time. This study is the first to use a time-varying rolling index model to access market relationships in the feeder cattle markets.

Several methods have been employed in the past to examine spatial market integration: The methods employed include correlations (Mundlak and Larson, 1992; Gardner and Brooks, 1994), co-integration (Goodwin, 1992; Williams and Bewley, 1993), causality (Baulch, 1997), path analysis (Blank and Schmiesing, 1988), error correction models (Ravallion, 1986), parity bound models (Negassa and Myers, 2007), Copula dependency (Qiu and Rude, 2016), and threshold autoregressive models (Goodwin and Piggott, 2001). Several of these spatial market linkage analyses have treated spatial price transmission as constant over time. However, factors affecting spatial prices in livestock markets certainly evolve over time. Such changes in driving market forces affecting prices over time need to be considered when modeling spatial market linkages. To achieve this, we follow the methodology by Diebold & Yilmaz (2012, 2014) of spillover index analysis.

Several recent studies have applied the spillover modeling framework developed by Diebold and Yilmaz (2012, 2014) to examine prices and volatilities relationships, especially in financial markets. Though the method has been used to examine futures market relationships (Balli et. al., 2017; Magkonis & Tsouknidis, 2017; Wang, et. al., 2016a; Wang et. al., 2016b) for instance, the relationship between the energy and the agricultural markets (Xiarchos and Burnett 2018) and commodity futures market connectedness (Diebold et al., 2018) this is the first study to use the method on thinly traded cash localized markets. In this study, I examine the level of market connectedness using weekly weighted average prices in local feeder cattle markets.

Methodology

I follow the DY spillover index measure developed by Diebold and Yilmaz (2012; 2014) to capture the impact of price shocks within selected feeder cattle markets on market connectedness. As noted earlier, I aim to examine feeder cattle market co-movements across spatial markets. One advantage of the Diebold and Yilmaz (2012; 2014) model is that it captures the degree (level) of connectedness within markets and access the time-variation in the connectedness level.

Following Diebold and Yilmaz (2012; 2014), the DY spillover index follows variance decomposition associated with an N-variable vector autoregression (VAR).

Let y_t be the first difference of natural log prices. Consider a basic VAR model of lag order (p)

$$\boldsymbol{y_t = \sum_{i=1}^{p} \beta_i y_{t-i} + \varepsilon_t} \qquad \textbf{Equation 22}$$

Where β_i is a coefficient matrix and $\varepsilon_t \sim (0, \Sigma)$ is a vector of independently and identically distributed disturbances.

Representing y_t in form of moving averages will gives

$$\boldsymbol{y_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}} \qquad \textbf{Equation 23}$$

Where $N \times N$ coefficient matrices A_i follows the recursion

$$\boldsymbol{A_i = \phi_i A_{i-1} + \phi_i A_{i-2} + \ldots + \phi_i A_{i-p}} \qquad \textbf{Equation 24}$$

The orthogonal white noise innovation in the system can be achieved through Cholesky decomposition. One major problem in using the standard VAR framework is that the variance decomposition depends on the ordering of the variables, which means that the Cholesky factorization will be influenced by the ordering of the endogenous variables. I follow Diebold and Yilmaz (2012) to avoid this problem by employing the generalized VAR framework of (Koop et al., 1996; Pesaran & Shin, 1998). The approach is called Generalized Forecast Error Variance Decomposition (GFEVD). One significant advantage of this approach is that it does not orthogonalize the shocks from each variable but allows correlated shocks. This is done by accounting for the shocks using the historically observed distribution of the errors (Diebold and Yilmaz, 2012; 2014).

Representing the own variance shares as the fraction of the H-step-ahead error variances in forecasting y_i due to the shocks to y_i, for $i = 1, 2, \ldots, N$, spillovers as the fractions of the H-step-ahead error variances in forecasting y_i due to shocks to y_j, for $i, j = 1, 2, \ldots, N$, such that *i* not equal to *j* ($i \neq j$).

The H-step-ahead GFEVD is represented by $\theta_{ij}^{g}(H)$.

$$\boldsymbol{\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}(e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1}(e_i' A_h \Sigma A_h' e_i)}} \qquad \textbf{Equation 25}$$

where Σ is the variance matrix for the error vector ε, σ_{jj} is the standard deviation of the error term for the *jth* feeder cattle market and e_i is the selection vector, with one as the *ith* element and zeros otherwise. The sum of elements in each row of the variance decomposition is not equal to one. To use the information in the variance decomposition matrix in generating the spillover index, Diebold and Yilmaz (2012; 2014) normalized each entry of the variance decomposition matrix by the row sum, as presented in the equation below;

$$\boldsymbol{\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N}\theta_{ij}^{g}(H)}} \qquad \textbf{Equation 26}$$

By construction, this makes the normalized variance decomposition to be equal to one, i.e.,

$$\boldsymbol{\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}(H) = 1} \qquad \textbf{Equation 27}$$

and

$$\boldsymbol{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H) = N} \qquad \textbf{Equation 28}$$

Total spillovers

The total spillover index measures the spillover contribution across all the feeder cattle markets in the system to the total forecast error variance. The total spillover in the system can be constructed using the volatility contributions from the GFEVD. The total spillover index, $S^g(H)$, is defined as;

$$\boldsymbol{S^g(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100} \qquad \textbf{Equation 29}$$

$$\boldsymbol{= \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100} \qquad \textbf{Equation 30}$$

Directional spillovers

One advantage of using the Diebold and Yilmaz (2012; 2014) spillover index is the ability to measure the direction of the spillover. Here we will be able to determine the amount of shock from one market to another, because the generalized VAR approach gives generalized impulse responses and variance decomposition that are invariant to the ordering of the variables. To calculate the directional spillover received by market *i* from all other markets *j*, Diebold and Yilmaz (2012; 2014) used the normalized elements of the generalized variance decomposition matrix, as defined below;

$$\boldsymbol{S_{i\leftarrow}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100} \qquad \textbf{Equation 31}$$

$$\boldsymbol{= \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100} \qquad \textbf{Equation 32}$$

Similarly, this approach measures the directional spillover transmitted by market i to all other markets j as;

$$\boldsymbol{S^{g}_{\rightarrow i}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}^{g}_{ji}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^{g}_{ji}(H)} \times 100} \qquad \textbf{Equation 33}$$

$$\boldsymbol{= \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}^{g}_{ji}(H)}{N} \times 100} \qquad \textbf{Equation 34}$$

Net spillovers

Apart from the bi-directional spillover in each market, we can also calculate the net spillover. The net spillover effect can be achieved by subtracting the spillover effect “from other markets” from the spillover effect “to other markets.”

$$\boldsymbol{S^{g}_{i}(H) = S^{g}_{\rightarrow i}(H) - S^{g}_{i\leftarrow}(H)} \qquad \textbf{Equation 35}$$

The net spillover summarized the net contribution of one market to the volatility in other markets.

Net pairwise spillovers

Another advantage of this approach is that we can pairwise directional spillover effect within two markets in the system. The net pairwise spillovers is defined as;

$$\boldsymbol{S^{g}_{i}(H) = \left(\frac{\tilde{\theta}^{g}_{ji}(H)}{\sum_{i,k=1}^{N} \tilde{\theta}^{g}_{ik}(H)} - \frac{\tilde{\theta}^{g}_{ij}(H)}{\sum_{i,k=1}^{N} \tilde{\theta}^{g}_{ik}(H)}\right) \times 100} \qquad \textbf{Equation 36}$$

$$\boldsymbol{= \left(\frac{\tilde{\theta}^{g}_{ji}(H) - \tilde{\theta}^{g}_{ij}(H)}{N}\right) \times 100} \qquad \textbf{Equation 37}$$

This is the pairwise spillover effect between two markets *i* and *j*; it is merely the difference between the gross price shocks transmitted from market *i* to market *j* and the shocks transmitted from market *j* to market *i*.

Data

In this study, the objective is to determine how connected Kansas feeder cattle markets are with markets located in other states. Seven major auction markets across five states are selected, three markets within the state of Kansas and four markets outside Kansas. The data are collected from two sources: 1) Beef-Basis (2018), which was used for feeder cattle market prices for Pratt, Amarillo, Joplin, Salina, and Oklahoma City, and 2) Dodge city and Clovis market data were obtained from the Livestock Marketing Information Center (LMIC, 2019).

Apart from the individual markets, I also examined spillover effects across states. The objective here is to determine how price shocks are transmitted to and from the Kansas feeder cattle markets at the state level. Here, average prices for a state are used. Six states' combined feeder cattle auction prices are selected. The markets are involved in the estimations are Kansas, Missouri, Nebraska, Oklahoma, Texas, and New Mexico. The distance between the markets varies. The distance between the markets can reveal the impact of distance between two markets on price spillover between markets. The distance between markets are shown in appendix Table 2.A1.

The selection of these markets is inspired by the significant changes in the geographical concentration of cattle slaughter density in year 1994 (Figure 2.1) and 2014 (Figure 2.2). The objective is to choose markets that are in the high-volume area. The choice of markets in this concentration area of the maps will also allow us to see how changes in the cattle slaughter density has affected the price relationship between markets over time. For instance, the Clovis New Mexico market was part of the high-volume region in 1994 but not in 2014. The original data from Beef-Basis is a transaction level data. Weekly head-weighted average prices were derived using from the individual transactions.

One problem in time series analysis of these data are the presence of gaps (missing values). Missing data is unavoidable in livestock market. This is due to many factors such as weather and other unplanned emergencies that can lead to closure of some markets[12]. Although, it is possible to carry out the analysis with the observations that have compete information and ignore those with missing values, this kind of analysis can lead to a biased estimate (Sterne et al. 2009). Several statistical methods have been employed in handling missing data. The most commonly used approach is replacing the missing observation with the average of the entire variable or simply by the value next to the observation. Other approaches of dealing with missing data is weighing the analysis to control for the missing values and maximum likelihood estimation accounting for the missing values, and multiple imputation (Carpenter et. al., 2006; Schafer, 1997; Sterne et al., 2009).

To avoid unnecessary data lost and wrong inferences, missing values were replaced through multiple imputation (MI) for missing data (Abayomi, Gelman and Levy 2008; Royston 2005; Rubin 1972) by using the state level or regional weekly data of each market's location. The regional prices are the weekly average of multiple markets in each state or region where feeder cattle are commonly auctioned.[13] Other variables included in the MI imputation include the corn future prices, weekly dry grain prices, weekly cow slaughter, weekly feeder nearby cattle futures, and the Chicago mercantile exchange weekly feeder cattle index. The combined weekly feeder cattle are collected from the LMIC (2019). The yearly summary of the missing data is provided in Table 3.A2 – 3.A5 in the appendix.

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[12] Also, there are times of the year when trade is limited. For example, there is limited trade of 550lb feeders in July.

[13] In the model estimation, there is consideration for the use of feeder cattle cash settlement for the remaining missing observations that cannot been filled, especially the Amarillo dataset.

Since weight and sex of a feeder cattle can make a significant difference in prices received for the animal, to have an accurate comparison of prices across markets, the study focus on the heifer's 600-700 lb weight category. This study focuses on the heifer market instead of steers because heifers can go into both the dairy cow[14] and beef cow production. Another reason is because of the selected markets. For instance, New Mexico is predominantly into dairy cow production, selecting heifer will gives more information about the time variation between Clovis market and other markets that are predominantly beef producers. This weight group is selected because it falls into the average of the weight groups commonly reported in the feeder cattle auction markets.The heifer 600-700 lb weight group also had less weeks of missing data.The summary statistics of the feeder cattle prices in this study are provided in Tables 2.1 and 2.2. Table 2.1 shows the descriptive statistics of the selected local feeder cattle auction market prices. The descriptive statistics of the state level feeder cattle prices are presented in Table 2.2. There is the presence of unit root in all the auction prices except Amarillo (Table 2.A6) and in all the state level prices except for Missouri, Nebraska, and Oklahoma (Table 2.A7). Because of the unit root presence, the first difference of all the data are used in estimation.

Empirical Results

In this section, I present the results in two subsections, the local market level, and the state level. The total spillover index (Equation 29) for both the auction market prices and the state level prices are presented in Table 2.3 & 2.4, respectively. Overall, the total spillover indexes are above 50 percent, at both the local and state level markets. After conducting several tests,

[14] Dairy prices not included in estimation.

including the lag order selection, cointegration test, the analysis is conducted using a vector autoregressive model and GFEVD of 10-week ahead volatility forecast errors and 100-week rolling window. I conduct a sensitivity test at different GFEVD of 2-week to 12-week ahead horizons, there is no significant difference from the 10-week horizon. Before selection of the 100 weeks rolling window, the analysis was carried out on multiple rolling windows (50, 100, 150, and 200 weeks). There is no significant difference in the result from 100 weeks and above. A 100-week rolling window will give enough time for market adjustment. The 100-week rolling window also corresponds to about 2 years of price relationship. The optimal lag of 2 were selected using the Akaike information criterion for the lag-order selections statistics in STATA 15 statistical software (Akaike 1973; Lütkepohl 2005; StataCorp 2017).

Spatial markets connectedness (auction level)

System-Wide Connectedness

Table 3.3 presents the average spillover analysis across the markets over the entire study period. This table can be referred to as the market spillover index table because it provides the approximate "input-output" decomposition of the total market spillover index. Each entry (ijth entry) of this table can be interpreted as the estimated contribution to the forecast error variance of market i coming from an innovation in another market j. The far-right column (labeled FROM) is the gross spillover received by a market from other markets combined. The row labeled "contribution TO others" stands for the total spillover contribution by each market to all other markets combined and including to itself [15]. The net spillover (Equation 35) for each

[15] The "FROM" sums up to 100 because it is the total contribution of shocks received by a market from all other markets in the system. The "contribution TO others" may not sum up to 100 because it is the contribution of shocks by a market to itself and other markets. All the rows must sum up to 600 (100 multiply by the number of markets in the system) and all the columns sums up 600 too.

market is derived by subtracting “TO” from “FROM”. The “TSI” is the total spillover index, it represents the sum of all the spillover transmission “FROM” AND “TO” to all the markets in this study. The TSI is an average market connectedness index over the entire sample period. The TSI of 52% indicates that, across the entire study period, about 52% of the price forecast error variance in all the studied feeder cattle market comes from spillovers arriving within the markets studied. It can also be interpreted as; during the entire study period, on average, about 52% of the combined spillover in the markets’ prices originated within an innovation in the selected markets.

Starting from the directional spillover, it shows (Table 3.3) that the directional spillover from other markets to each of the markets are similar to each other in value. Only two markets (Amarillo, TX and Clovis, NM) are below 50% (FROM), which means the majority of innovations to these markets are not due to shocks originating within this system. Joplin, MO, Oklahoma City, OK, and Salina, KS are the most significant contributors of shocks to other markets at about 79%, 93%, and 73%, respectively.

Kansas intra-market connectedness

Focusing on Kansas feeder cattle markets, Dodge City is a net receiver of shocks from other markets contributing only 12% of information innovations to price variation in the markets in the system while Salina contributes to innovations in the system at over 70% of the time with a net spillover index of 19.5% (highest of the three Kansas markets included). In Table 3.3, looking across the row is the contribution from other markets while across the columns represents the contribution to other markets. Within the Kansas markets, Salina is a net contributor to the innovations in the market. Salina has a net spillover index of 3% (15.56 - 12.73) with Pratt KS and 9% (10.10 - 1.17) with Dodge city feeder cattle markets. The

Oklahoma City market contributed most to innovations in the Kansas feeder market prices than any other market outside Kansas. Oklahoma City contributed about 15%, 18%, and 12% to the feeder cattle markets in Pratt KS, Salina KS and Dodge City KS, respectively.

One important outcome derived from Table 3 is that proximity impacts the level of connectedness between markets. Using the top three net market innovation contributors (Oklahoma City, Joplin, and Salina), the closer a market spatially to another market, the higher the shock transmitted to the market. For instance, Joplin MO is closer to Oklahoma City than Amarillo TX, and it reflects in the connectedness to the markets with spillover index of 11% and 20% to Oklahoma City and Amarillo TX, respectively. The same can be said of Salina KS. Salina transmitted a gross spillover index of 16% to Pratt KS while it only caused 9% of innovation in the Clovis NM market.[16]

Dynamic (rolling-window) connectedness

The static spillover in Table 3.3 only presents the average across the sample period. There is a clear indication that there are many changes that took place during the sample period that may affect the level of connectedness between markets. To elicit the changes in the price shock spillover within the market, I employ the rolling window spillover index approach, as presented by Diebold and Yilmaz (2012). We use the same VAR model here with the optimal lag of 2. Rolling-window of 100 weeks with 10-week-ahead forecast effort for generalized decomposition is applied to model the dynamics in the price connectedness among the markets in our sample.

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[16] The spillover index between the markets are graphically represented in Figure 3.A1 & 3.A2. Although not for all, the figures show that markets that are closer to each other are tends to be more connected. Another important information in the plots is that Dodge City, KS and Clovis, NM are less connected with other markets.

To avoid confusion in result interpretations, I will be presenting the results from the heifer 600-650 pounds category. Figure 3.3 presents the total price spillover index based on the 100-week rolling window. It is evident that the total spillover within the markets is varying across the sample period. The market has been in the range of 50%-60% spillover index in most of the time across the sample period. It is not surprising that the dynamic connectedness stays between 50% and 60% most of the study period because the TSI in the static connectedness presented in Table 3.3 is 51.75%. There are some periods with very low spillover index; those periods look like structural changes to the spillover series. There are several phases to the market connectedness. The first phase of lower spillover index is seen between at the beginning of the data period up to 2003. Although the spillover index is lower during this period, it is experiencing an increase in trend. After the end of 2003, there is a drastic increase in the price transmission within the market, and it stays between 55% and 60% until toward the end of 2005. The markets experienced a sharp drop in the spillover index towards the end of 2005, and it continues to drop until mid-2005 where it was about 40%. From mid-2005, the markets started to experience strong connectedness which stays for up until mid-2010 where it started dropping again. Though the markets shifted back to the usual trend after mid-2011, the markets experienced lower connectedness between mid-2013 until end of 2015.

It is the combination of all the markets price shocks transmissions that produced the total connectedness in Figure 3.3. The dynamic connectedness can be broken down into the individual market. Figures 3.4 - 3.10 show the dynamic price shock transmission to and from each market. Also, the net shocks transmission in individual markets is also presented for easy comparison. Looking across the study periods, we can see that, most of the time, some markets received more shocks than they give out. For instance, Clovis (New Mexico) and Dodge City feeder cattle markets are mostly a net shock receiver. In contrast, Salina (Kansas), Joplin (Missouri), and Oklahoma City (Oklahoma) are net price shock transmitters to other markets. Amarillo market is a mixture of being net price shock transmitter and receiver. Amarillo was a net price shock transmitter in the early period of the study sample (2002 – 2006). After the end of 2006, the Amarillo market received more shocks than transmitted. Pratt (Kansas) shows a similar trend with the Amarillo market.

Focusing on the Kansas markets, although there is variation in the price shock transmission to and from the Dodge City market, the market is a net price shock receiver throughout the sample period. It means that the market is dominated by one or more markets in the study sample. In this situation, there is likely one market or a combination of more markets that serves as price discovery for Dodge City. Unlike Dodge City, Salina feeder cattle market is a net price transmitter in most periods in our sample. The Pratt market shows a mixed reaction to other markets, similar to the Amarillo market. The Pratt market is a net price transmitter between 2007 and 2008, and most of 2010 onward, and net receiver in rest of study time. Looking at the whole picture, Pratt transmitted shocks to other markets in more periods that received.

Pairwise-spillover

After examining the individual market spillover index, it is crucial to show how the markets transmit shocks to one another, which is referred to as pairwise spillover. Here, I present a detailed spillover from one market to another. To avoid overwhelming numbers of comparisons, I focus here on the Kansas intra-markets connectedness and Kansas markets dynamic spillover behavior with other states' markets. The Kansas intra-market connectedness is presented in Figures 3.11- 3.13. In most of the study period, Pratt and Salina are net price shock transmitters to Dodge City, with Salina having the strongest influence. There was not a single period where Dodge City had a net shock transmitted to the Salina market (Figure 3.12). Figure 3.13 also shows that the Salina KS feeder cattle market transmitted price shocks to Pratt more often than otherwise. One has to be careful in the interpretation of these price shock transmission because of the small values of the spillover index. Since the intra-market price shock spillover index does not exceed 2.5%, this suggests there are other major factors or markets influencing individual market prices apart from the nearby markets within Kansas.

Now, looking into details of price shock transmission from the markets outside of Kansas. It is noticeable that Dodge City market is still dominated by most of the other markets. There is no strong connectedness between the Kansas markets and the Amarillo feeder cattle auction market, except for Salina Kansas. It is shown in Figure 3.14 that Salina is a net transmitter to the Amarillo market with the peak period between 2007 and 2008. There was a change between 2014 and 2016 where Amarillo was a net transmitter. Oklahoma City feeder cattle market also follows a mixed pattern relationship with the Kansas feeder cattle markets but has a net price shock spillover over Dodge City KS over the study period. On average, Kansas markets are showing positive net price shocks transmission to Clovis NM and Joplin MO markets.

State level connectedness

In addition to testing the individual Kansas market connectedness to other markets, I also examine the overall statewide connectedness of Kansas feeder cattle market to other state using the average state prices reported in LMIC (2019). This is important because it will show, on average, the state's market behavior in relation with other states. Kansas plays an essential role in beef production, and there has been a lot of changes in the feedlot operations over the years. The main question here how much feedlot operation changes have affected price dynamics in the feeder cattle markets. Kansas is the 3rd largest producer of beef in the United States, after Texas and Nebraska. In this section, we selected the states based on proximity to Kansas, high production level. For instance, I included Nebraska here because of the volume of beef production in Nebraska is the second highest in the country. Nebraska is also a neighboring state to Kansas, which I expect to have a spillover effect on the Kansas market. New Mexico may not be a major beef cattle producer, but it is one of the top dairy cattle producing states. Since feeder cattle can serve as a replacement for both beef cattle production as well as dairy cattle production (heifer), it is advisable to use the New Mexico market as a control for check the effect of distance market on the Kansas feeder cattle market dynamics.

System-wide connectedness

Table 3.4 shows the static full sample market connectedness. The total market connectedness stands at 58.46%, which is higher than the individual auction markets estimated in Table 3.3 above (this may be due to the fact that state prices comprise many markets). This means that the markets are more connected in the state level than looking at individual markets. Kansas market transmitted the second highest price shocks to other markets (71.49%), Oklahoma transmitted the most (78.29%). Although Oklahoma transmitted the highest price shock to other markets, it is also the highest price shock receiver. One important information to note here is that Kansas is a net price transmitter to the rest of the markets. In descending order, Kansas experienced a net price of 4.68%, 2.35%, 2.31%, 1.79%, and 1.15% with New Mexico, Nebraska, Texas, Missouri, and Texas, respectively.

Dynamic (rolling-window) connectedness

To capture the time variation in the price spillover among the selected markets, I apply a dynamic rolling index approach using a 100-week rolling-window and 10-week ahead forecast horizon. Over the years, there has been an increasing trend in the feeder cattle market connectedness within the selected states. In 2001, less than 50% of innovation to prices was due to joint innovation to the markets' prices (Figure 3.18). As of 2016, the level of market connectedness (total price spillover index) has risen to about 70%. The markets total spillover index remained around 60% for a very long time, between 2005 and 2012.

Figure 3.19 – 3.24 shows the net and directional spillover index for the selected markets. Kansas contribution to the innovations in the system has been steady for a very long time but increased in recent years. Before 2015, Kansas had been contributing between 8% and 10% of the innovation to the system. Since 2007, Kansas markets, on average, have been receiving more price shocks from other markets than previously. Over the years, Figure 3.19 shows that Kansas has been a net receiver of price shocks in most of the study periods, with the highest value experienced between 2007 and 2010. Similar to Kansas, Oklahoma has been receiving more shock to its prices than it sends to others. Texas has transmitted more shocks to other markets than received. Surprisingly, New Mexico markets influence markets in the system more time than otherwise.

Pairwise-spillover

Bidirectional time-varying net pairwise spillover effect is also examined for the state level data. The focus here is to investigate which state has the most influence on Kansas feeder cattle market price discovery. Figures 3.25 – 3.29 show bidirectional relationships between the Kansas Markets and other states. The Kansas feeder cattle market has had a positive net price spillover to other state markets in most of the study period. There are some exceptional periods in the bi-directional relationships. For example, though it was in a minimal range, the Kansas market experienced a long period of price spillover from the Nebraska market during between

2002 and 2006, mid-2011 and 20013, and in 2016 (Figure 3.26). Likewise, the Kansas market mostly received price spillover from the Oklahoma market between 2002 and 2007, with the peak period during 2007 (Figure 3.27). The period with apparent spillover from the Texas market was between 2011 and 2013 (Figure 3.28). The price shock transmitted from the Texas market to Kansas during the period may be due to the extreme drought that affected most of the Texas region. The drought affected livestock production in the Texas western region, which lead to a reduction in the production. Another period of price transmission to the Kansas market from Texas was during the period between 2005 and 2007. There was a drought in Texas between 2005 and 2006 (Texas water resources Institute, 2011).

Until around 2005, there was a minimal spillover effect between the Kansas market and the New Mexico market. Like the relationship with other states, Kansas also received significant price spillover from the New Mexico market between the period of 2005 to 2007 (likely due to the drought). After this period, Kansas was a net price transmitter to the New Mexico market throughout the rest of the sample period. After 2007, the net shock from Kansas market to New Mexico market has been fluctuating, reaching the peak (2.5%) during 2009. We know that there has been an extreme drought in New Mexico which has affected the pasture/rangeland (the primary source of ingredients to the livestock industry in New Mexico). The drought may have made New Mexico market less competitive since most of their animals are raised on pasture. Texas is different because of proximity to the corn belt. Texas livestock industry focused on beef production while New Mexico is dairy.

What is driving market connectedness?

After seeing time variation in the connectedness among the studied markets, I go further to examine the impact of drought on variation in price shocks spillover. In addition to drought, I also examine if the markets connectedness is seasonal. To achieve this, I employ the seemingly unrelated regression (SUREG), using the following equations:

$$\boldsymbol{SI_{,t} = \alpha + \beta DSCI_t + s_t + \gamma' X_t + t + t^2 + \varepsilon_t} \qquad \textbf{Equation 38}$$

$$\boldsymbol{SI_{ij,t} = \alpha_{ij} + \beta_{ij} \Delta DSCI_{ij,t} + s_t + \gamma' X_t + t + t^2 + \varepsilon_{ij,t}} \qquad \textbf{Equation 39}$$

where SI_t is the total spillover index at time t, $SI_{ij,t}$ is the spillover index between market i and j at time t, $DSCI_t$ is the aggregated drought severity and coverage index at time t, $\Delta DSCI_{ij,t}$ is the different in the drought index between the locations of market i and j. The variable s_t is the fixed effect variable standing for the four seasons in a year (Spring, Summer, Fall, and Winter). The vector of variables, X_t , are other exogenous variables expected to impact market connectedness. The trend t and the quadratic trend t^2 are included. The exogenous variables include corn future prices, diesel prices, and monthly replacement cattle.

The drought index and the replacement cattle numbers are aggregated over a 100-week rolling window. This represents a moving average of a 100-week periods. These variables are aggregated because the spillover index is calculated using a 100-week rolling window. The aggregation of this variable will capture the severity of the drought and also serves as the demand proxy for feeder cattle over the 100 weeks rolling window. Similarly, a 100-week moving average of nearby corn futures and the diesel prices are included. I hypothesize that an increase in drought severity will lead to a reduction in market connectedness. It is also expected that the market with the highest severe drought will experience a reduction in the supply of feeder cattle compared to the market in the low drought severity. The shock to the supply will have a massive impact on the market with severe drought while the impact will be minimal in the market that is experiencing lesser drought severity. The SUREG was carried out on both the auction markets prices and the state level aggregated market prices. In the local prices' analysis, I focus on the impact of Amarillo Texas and Clovis New Mexico on the Kansas feeder cattle markets (Dodge City, Pratt, and Salina).

Table 3.5 shows the regression result of the individual markets connectedness. For more straightforward interpretation, the continuous independent variables are transformed into logarithm form while the dependent variable remains in level because it is in percentage form[17]. In Table 3.5, it is shown that the drought index reduces the total spillover index in the markets. A one unit increase in the log of drought severity index across the United States leads to a 2.08 percentage point decline in the feeder cattle markets' spillover index[18]. The reader should be cautious in interpreting this result because only seven markets are involved here. Within the market covered, it is safe to say that drought severity has a significant impact on market connectedness.

Examining the impact of drought severity between markets, there are mix reactions. The drought severity in each market is represented by each market's state drought severity index. For instance, the drought severity difference between Amarillo and Salina is represented by the drought severity difference between Kansas and Texas (Kansas-Texas). An increase in the difference in drought severity index between Texas (covers the Amarillo market) and Kansas leads to a decrease in the market connectedness between the Amarillo market and all the Kansas markets (Salina, Pratt, and Dodge City). Between Clovis (using New Mexico drought index as a proxy) and Kansas markets, there is a mixed result. A one unit increase in the log difference in drought severity between New Mexico and Kansas will lead to about 0.38 and 0.27 percentage

[17]The explanatory variables in Table 5 are described in Table A8.

[18] A percentage increase in the drought severity leads to 0.0208 percentage point increase in the spillover index

points increase in the price spillover from Clovis to Pratt and Dodge City feeder cattle markets, respectively. The price spillover from Clovis to the Salina market will be reduced by 0.17 percentage point with a one unit increase in the log difference in drought severity index between New Mexico and Kansas.

Another variable of interest is the season variable. It is shown that there is seasonality in the market connectedness. The most obvious one is the significant difference between Spring and Fall. The markets spillovers tend to increase during the spring than during the fall by 0.83 percentage point. This is the same story when looking into the price spillover from the Amarillo market to the three Kansas markets, except for spillover from Amarillo to Salina that has a significant difference between summer and fall. Amarillo market tends to show higher connectedness with the Salina market, about 0.13 percentage point higher, during the summer than the fall (fall is the base season). The seasonal impact on market connectedness between Kansas markets and both the Amarillo and Clovis is very minimal.

Another very interesting variable is the diesel prices. The diesel prices serve as a proxy for the transportation cost between markets. An increase in diesel prices leads to a reduction in price spillover between the Kansas markets and Amarillo but otherwise for Clovis. It is hard to justify these results, but it can be inferred that the distance between markets does matter in price discovery. I assume this because Clovis is farther away from Kansas market than Amarillo markets, also with high drought issue, the increase in the cost of transportation between the two states will make them be able to charge similar prices. If the transportation cost is low, it will be easier to source feeder cattle from Kansas than paying higher prices in New Mexico. With the increase in the cost of transportation, the feeder cattle buyers in New Mexico will prefer to source for their need at a nearby feeder cattle auction market. On overall, the level of market total connectedness decreases with an increase in diesel prices.

Corn futures also shows a significant impact on the degree of market connectedness. In the whole system, the price shock transmission within the markets increases with increase in the corn futures prices. The total spillover within the markets increases by 13.96 percentage points with one unit increase in the future price of corn. Corn future price increases reduces the transmission of shocks to Kansas markets from Amarillo and Clovis, except price shocks transmission from Amarillo to Dodge City.

Using the combined state-level prices, I also examine the impact of extreme drought on price dynamics. Included are the total spillover index and the pairwise spillover index between the states of Kansas, Nebraska, and Texas. Table 3.6 shows that the total spillover index will decrease by nine percentage points with a one percent increase in the drought severity. Although it is not the case for all bilateral relationship among the states, extreme drought reduces the connectedness between Kansas and Nebraska, Kansas and Texas, but otherwise between Nebraska and Texas. There are no significant differences between the total price spillover among the four seasons. Apart from the pairwise spillover between Nebraska and Texas, seasonality plays a role in the level of Kansas market connectedness with Nebraska and Texas. In both market pairs, spring season seems to experience less market connectedness compare to the rest of the seasons. This is not surprising since most of the calf operation takes place in the spring for them to be able to mature for the market in the fall. Diesel prices also play a significant role in the level of market connectedness. An increase in diesel prices will lead to a reduction in the level of market connectedness.

It is surprising that the drought increases the price spillover between the Texas and Nebraska but not Kansas. This may be because some part of Kansas does go through extreme drought regularly, similar to that of Texas. For instance, the major livestock production in Texas is in the Northwest region of the states, which is close to the southwest region of Kansas. Prices can be easily transmitted between the two regions.

For robustness check of the results against the market size, I carried out another analysis with the inclusion of Alabama and Georgia state prices. It is shown that the total spillover index increased slightly to 63.95 (Table 3.A9). The bi-directional relationships are all similar but with little differences in the magnitude. It is expected for the magnitude to change because more markets are involved, and the spillover index is calculated in percentage. Though they follow the same pattern, the heifer's markets are more connected than steers. In Figure 3.A6, the total spillover index in the heifer is consistently higher than that of steer.

One major limitation to the spillover index measure in this study is the model dependence on the market included. Connectedness measurement is not robust to the choice of markets and the frequency of data (Diebold and Yilmax, 2012). Therefore, the number of markets and the type of markets included in the model has impact on the connectedness within the markets in this study.

Conclusion

Using the framework of Diebold and Yilmaz (2012, 2014), I examine price shock transmission among selected feeder cattle markets. The approach reveals time variation in the level of market connectedness over the study period. Among the feeder cattle auction markets considered, the Oklahoma City market has the strongest influence on other markets (highest net price spillover to other markets). Dodge City receives the most price shocks from the rest of the markets.

Important differences in using a regional or state level aggregated price and individual level prices are found. For instance, Kansas as an aggregate market transmits the most feeder cattle price information to other states in this study while on an individual market level, the Oklahoma City market is the most dominant market.

Furthermore, I examine the impact of drought on periodic price transmission between markets. Drought plays a vital role in the level of market connectedness. Long term drought severity accounts for some of the dynamics in the feeder cattle market dynamics. This is supported by (Dorfman and Lastrapes 1996). A long period of drought severity can predict the level of market connectedness because of its long-term impact on both crop and livestock production (Bastian et al. 2006). During the period of high drought, fewer price shocks are transmitted between markets. The markets in the area that has experience most drought over the last few years have been the most shock receivers over time.

This study also reveals a seasonality in market connectedness. Markets tend to connect more during the Spring season compared to the rest of the seasons. Another major factor affecting shock transmission between markets is the diesel prices. Diesel prices serve as a proxy for transportation cost. An increase in diesel prices will lead to a reduction in the level of price shocks spillover between markets. This likely because of the higher transportation cost will reduce the incentive of moving livestock between markets.

Across all the markets pairs and total connectedness examined, the period between 2004 and 2006 is the most obvious. It shows that there is a disruption in the market during the period.

One major event that can be linked to this is the drought between 2005 and 2006 (Texas water resource institute, 2011). Most of the markets also show lower connectedness before 2003.

This study differs from other studies on drought impact on the livestock industry. For instance, (Leister, Paarlberg and Lee 2015) examined the impact of drought on the U.S. livestock and crop production. Figures 3.A3 – 3.A5 shows that the total market connectedness (Figure 3.3 and 3.18) follows a similar pattern to the U.S. cattle inventory. Markets are more connected when the inventory is high and decline in connectedness during the period of low inventory. This is the first study to examine the drought impact on market connectedness in the livestock industry.

Since diesel shows an impact on the level of market connectedness, in the next chapter of this dissertation, I will look into the impact of energy market on the feeder cattle market using the markets' implied volatilities from the future markets.

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Table 3.1 Summary Statistics of the Seven Physically Traded Weekly Feeder Cattle Auction Prices for 600-700lbs Heifer. The data covers from 2000 to 2016 and Prices are in Dollars ($).

	Amarillo TX	Joplin MO	Oklahoma City OK	Pratt KS	Salina KS	Clovis NM	Dodge City KS
Mean	112.18	116.68	118.45	119.01	120.49	114.14	119.44
Standard Deviation	34.25	37.82	38.33	38.85	39.52	36.88	38.60
Maximum	233.00	237.56	240.63	255.00	248.90	232.50	248.00
Minimum	71.45	71.20	72.47	72.00	73.10	73.98	72.98
Skewness	1.43***	1.49***	1.45***	1.47***	1.44***	1.39***	1.41***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Kurtosis	1.56***	1.73***	1.58***	1.70***	1.55***	1.33***	1.52***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 3.2 Summary Statistics of the Six States' Average Weekly Feeder Cattle Auction Prices for 600-700lbs Heifer.

The data covers from 2000 to 2016 and Prices are in Dollars ($)

	KS	MO	NE	NM	OK	TX
Mean	120.37	119.22	124.22	112.29	118.90	115.37
Standard Deviation	39.17	38.80	40.50	36.07	38.38	37.20
Maximum	246.00	240.00	255.00	231.00	241.00	242.00
Minimum	75.00	73.00	74.00	66.00	74.00	71.00
Skewness	1.43***	1.45***	1.45***	1.49***	1.41***	1.41***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Kurtosis	1.55***	1.62***	1.59***	1.60***	1.47***	1.50***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.000)

Table 3.3 Static Feeder Cattle Auction Market Connectedness (10 weeks horizon; 100 weeks rolling window).

	Amarillo TX	Joplin MO	Oklahoma OK	Pratt KS	Salina KS	Clovis NM	Dodge KS	FROM
Amarillo TX	57.21	11.26	13.79	7.37	8.80	0.47	1.11	42.79
Joplin MO	8.12	44.31	23.15	8.89	14.09	0.61	0.83	55.69
Oklahoma OK	9.23	19.88	43.15	10.08	15.84	0.82	1.01	56.85
Pratt KS	6.86	12.66	14.53	48.59	15.56	0.38	1.44	51.41
Salina KS	5.75	15.69	18.01	12.73	46.11	0.55	1.17	53.89
Clovis NM	5.66	8.80	11.76	7.04	9.02	51.28	6.46	48.72
Dodge KS	5.92	10.75	12.09	7.45	10.10	6.58	47.11	52.89
Contribution TO others	41.53	79.04	93.32	53.55	73.39	9.40	12.01	**TSI**
Net Directional	-1.26	23.35	36.47	2.14	19.50	-39.33	-40.87	**51.75**

Table 3.4 Static Feeder Cattle Market Connectedness for State Level Prices.

The analysis was carried out with 10 weeks horizon and 100 weeks rolling window

Note: KS – Kansas; MO – Missouri; NE – Nebraska; NM – New Mexico; OK – Oklahoma; TX – Texas.

	KS	MO	NE	NM	OK	TX	FROM
KS	40.80	13.27	12.70	5.20	17.09	10.95	59.20
MO	15.06	37.75	14.95	5.15	18.20	8.88	62.25
NE	15.05	13.19	43.52	5.79	14.28	8.17	56.48
NM	9.88	7.83	9.20	51.47	12.46	9.15	48.53
OK	18.24	16.21	13.85	6.11	33.10	12.51	66.91
TX	13.26	11.48	9.82	6.55	16.26	42.63	57.37
Contribution TO others	71.49	61.98	60.53	28.79	78.29	49.66	**TSI**
Net Directional	12.29	-0.27	4.05	-19.74	11.38	-7.72	**58.46**

Table 3.5 Factors Driving Spillover (Auction Level Prices).

The variables are defined in Table A8.

	Total Spillover	Amarillo - Pratt	Amarillo - Salina	Amarillo - Dodge City	Clovis - Pratt	Clovis - Salina	Clovis - Dodge City
Corn	13.96***	-1.092***	-1.955***	0.189***	-0.755***	-1.790***	-2.238***
	(10.52)	(-10.65)	(-14.13)	(3.30)	(-6.54)	(-21.60)	(-17.62)
Drought Index	-2.080*						
	(-2.40)						
Diesel	-27.20***	-0.923***	-1.739***	-2.272***	0.0281	0.433***	3.181***
	(-18.66)	(-5.98)	(-8.35)	(-26.34)	(0.16)	(3.47)	(16.63)
Replacement Cattle	-49.48***	9.026***	7.879***	4.097***	-3.925***	8.426***	8.533***
	(-5.35)	(12.48)	(8.07)	(10.12)	(-4.82)	(14.45)	(9.53)
Seasonal Dummies							
Spring	0.834*	0.0766*	0.0667	0.0846***	-0.0456	-0.0761*	-0.105*
	(2.28)	(2.04)	(1.32)	(4.03)	(-1.08)	(-2.50)	(-2.26)
Summer	-0.0568	0.0271	0.132**	0.0461*	-0.102*	-0.0760*	-0.0682
	(-0.16)	(0.72)	(2.60)	(2.20)	(-2.42)	(-2.50)	(-1.47)
Winter	0.652	0.0596	0.0357	0.0147	-0.0258	-0.0419	-0.00376
	(1.79)	(1.60)	(0.71)	(0.70)	(-0.61)	(-1.39)	(-0.08)
Drought Differences							
Kansas - Texas		-0.408***	-0.150***	-0.231***			
		(-15.11)	(-4.10)	(-15.27)			
Kansas - New Mexico					0.382***	-0.172***	0.269***
					(12.63)	(-7.95)	(8.08)
Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trend^2	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	526.6***	-84.58***	-72.71***	-37.16***	36.94***	-78.38***	-78.12***
	(5.69)	(-12.54)	(-7.98)	(-9.84)	(4.87)	(-14.41)	(-9.36)
R-Square	0.416	0.514	0.615	0.789	0.414	0.708	0.543
Chi-Square	561.3	829.6	1255.7	2939.8	563.3	1904.9	936.6
Observations	786	786	786	786	786	786	786

Table 3.6 Factors Driving Spillover (State Level).

The variables are defined in Table A8.

	Total Spillover	Kansas-Nebraska	Kansas-Texas	Nebraska-Texas
Corn	12.74***	-0.550**	0.077	-0.0868
	(8.64)	(-2.83)	(0.34)	(-0.34)
Drought Index	-9.165***	-1.644***	-0.357*	1.023***
	(-9.37)	(-12.93)	(-2.10)	-5.48
Diesel	-13.93***	5.048***	2.227***	-2.936***
	(-8.74)	(22.88)	(9.63)	(-10.14)
Replacement Cattle	-102.3***	1.524	-4.051**	9.872***
	(-9.92)	(1.07)	(-2.66)	(5.63)
Seasonal Dummies				
Spring	0.0702	-0.212***	-0.138*	0.002
	(0.18)	(-4.10)	(-2.40)	(0.02)
Summer	0.303	-0.052	-0.054	0.049
	(0.76)	(-1.01)	(-0.95)	(0.73)
Winter	0.01	-0.118*	-0.091	0.058
	(0.03)	(-2.30)	(-1.59)	(0.87)
Drought Differences				
Kansas - Nebraska		-0.242***		
		(-3.92)		
Kansas - Texas			0.148***	
			(9.15)	
Nebraska - Texas				-0.0883***
				(-5.83)
Trend	Yes	Yes	Yes	Yes
Trend^2	Yes	Yes	Yes	Yes
Constant	1084.6***	2.242	42.22**	-101.3***
	(10.49)	(0.16)	(2.74)	(-5.82)
R-Square	0.658	0.549	0.291	0.302
Chi-Square	1513.7	961.2	366	317.9
Observations	786	786	786	786

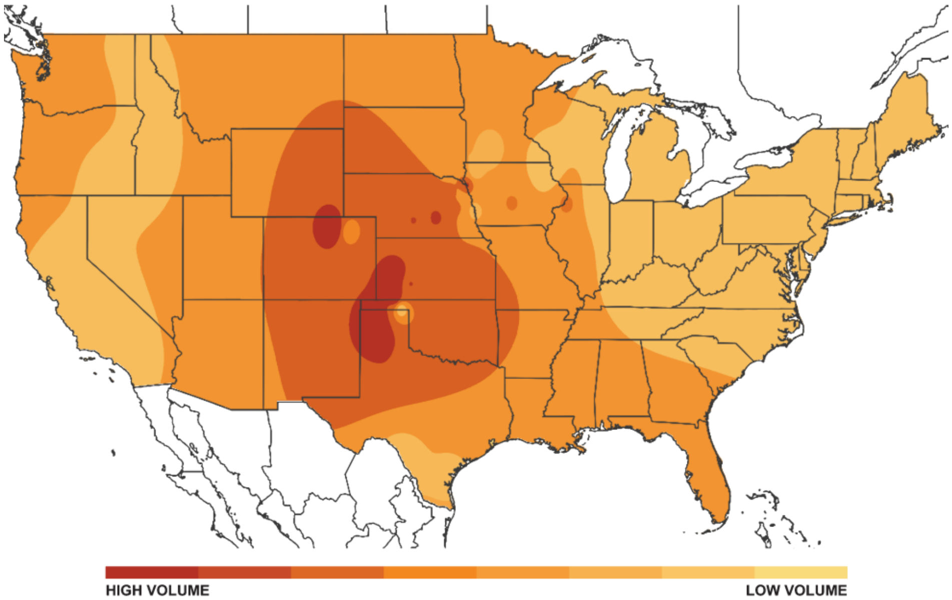

Figure 3.1 Cattle Slaughter Industry (1994).

Source (Figures 3.1 and 3.2): “On the move” http://dryagebeef.meatingplace.com/

Data provided by John Nalivka (Sterling Marketing) and Glynn Tonsor (Kansas State University).

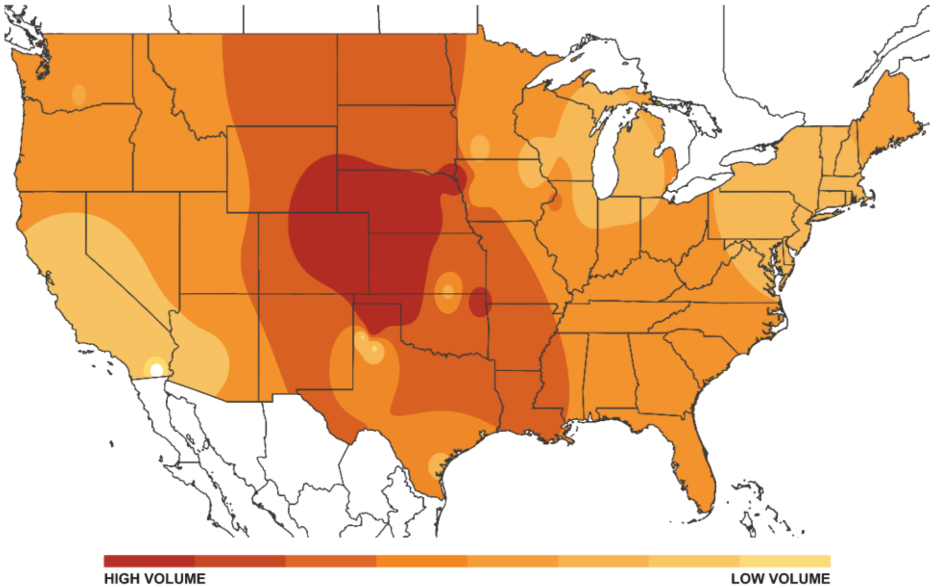

Figure 3.2 Cattle Slaughter Industry (2014).

Source (Figures 3.1 and 3.2): "On the move" http://dryagebeef.meatingplace.com/
Data provided by John Nalivka (Sterling Marketing) and Glynn Tonsor (Kansas State University).

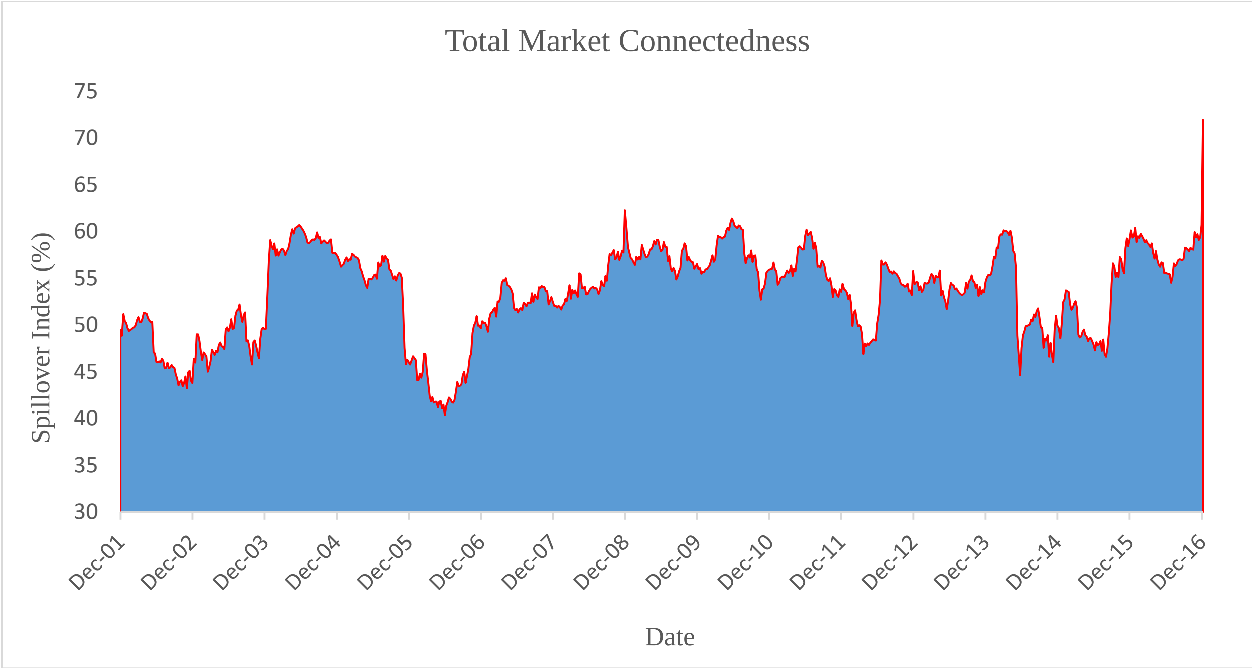

Figure 3.3 Dynamic Total Connectedness with 100-week rolling Window, the 10-week-ahead Predictive Horizon for Variance Decomposition (Auction Level).

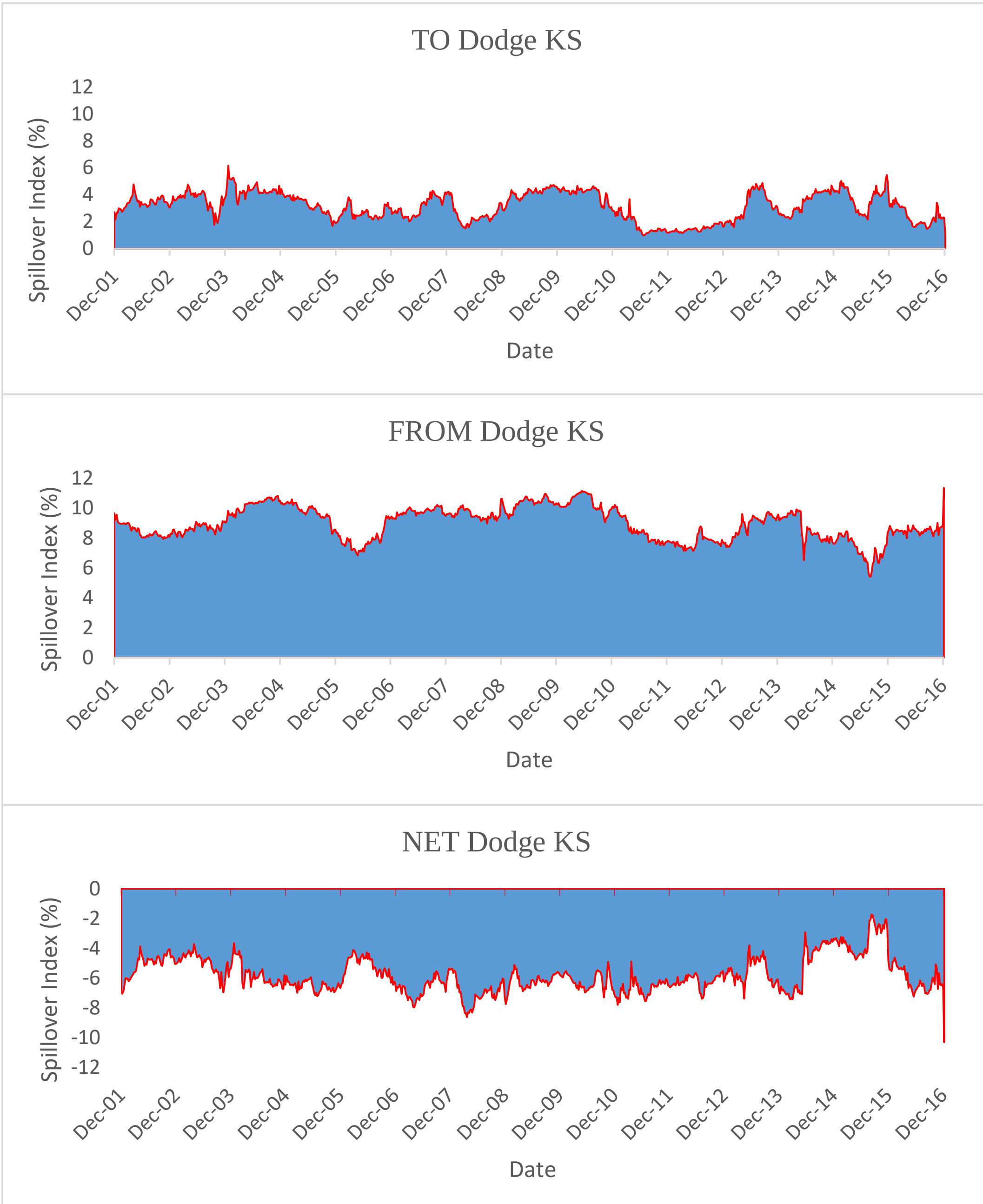

Figure 3.4 Directional and Net Spillover Index – Dodge City, Kansas.

(a) Price Shock from Other Markets to Dodge City (Kansas)

(b) Price Shocks from Dodge City (Kansas) To Other Market

(c) Net Price Shocks to Dodge City (To-From).

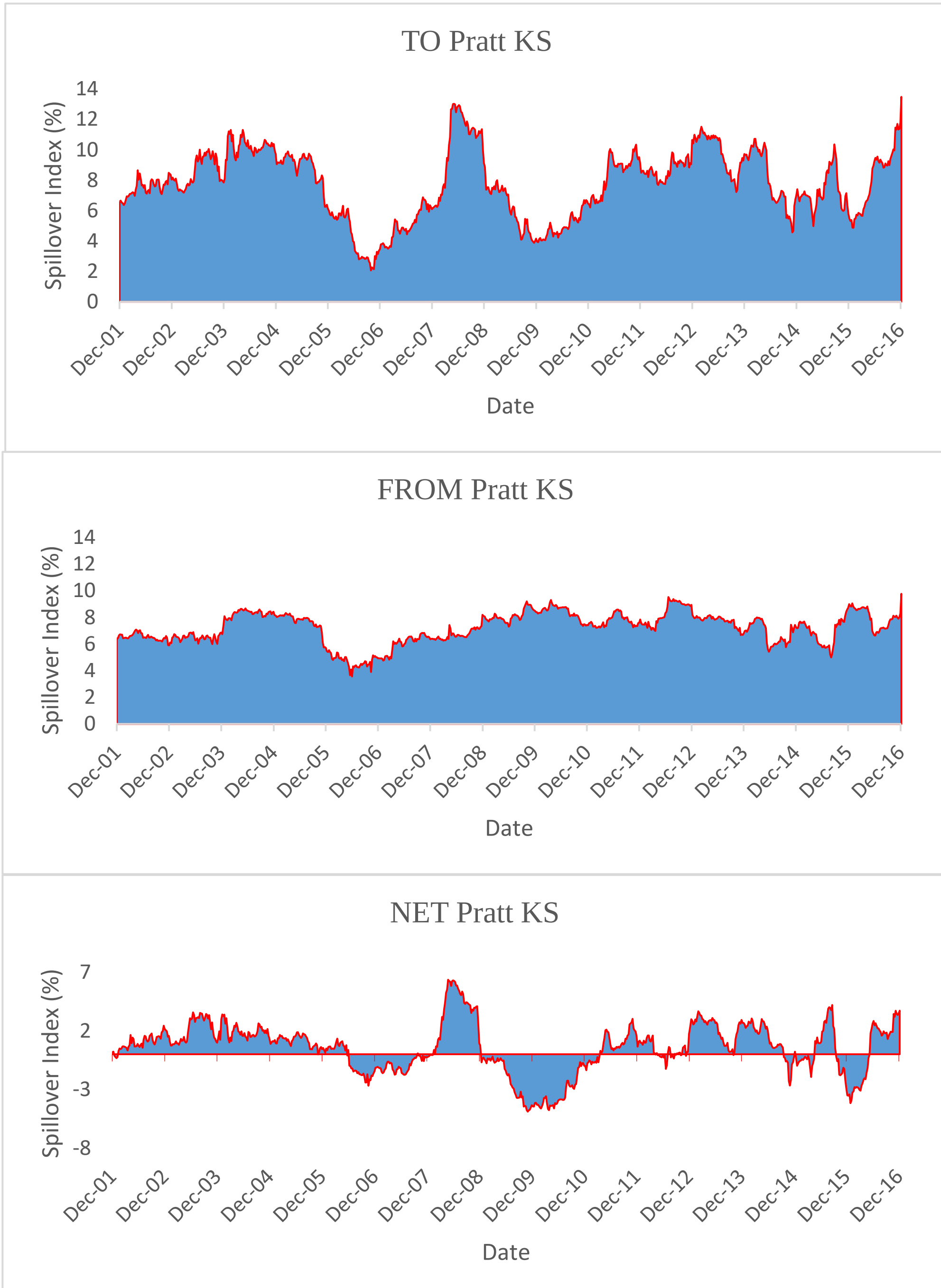

Figure 3.5 Directional and Net Spillover Index – Pratt, Kansas.

(a) Price Shock from Other Markets to Pratt (Kansas)

(b) Price Shocks from Pratt (Kansas) to Other Markets

(c) Net Price Shocks to Pratt (To-From).

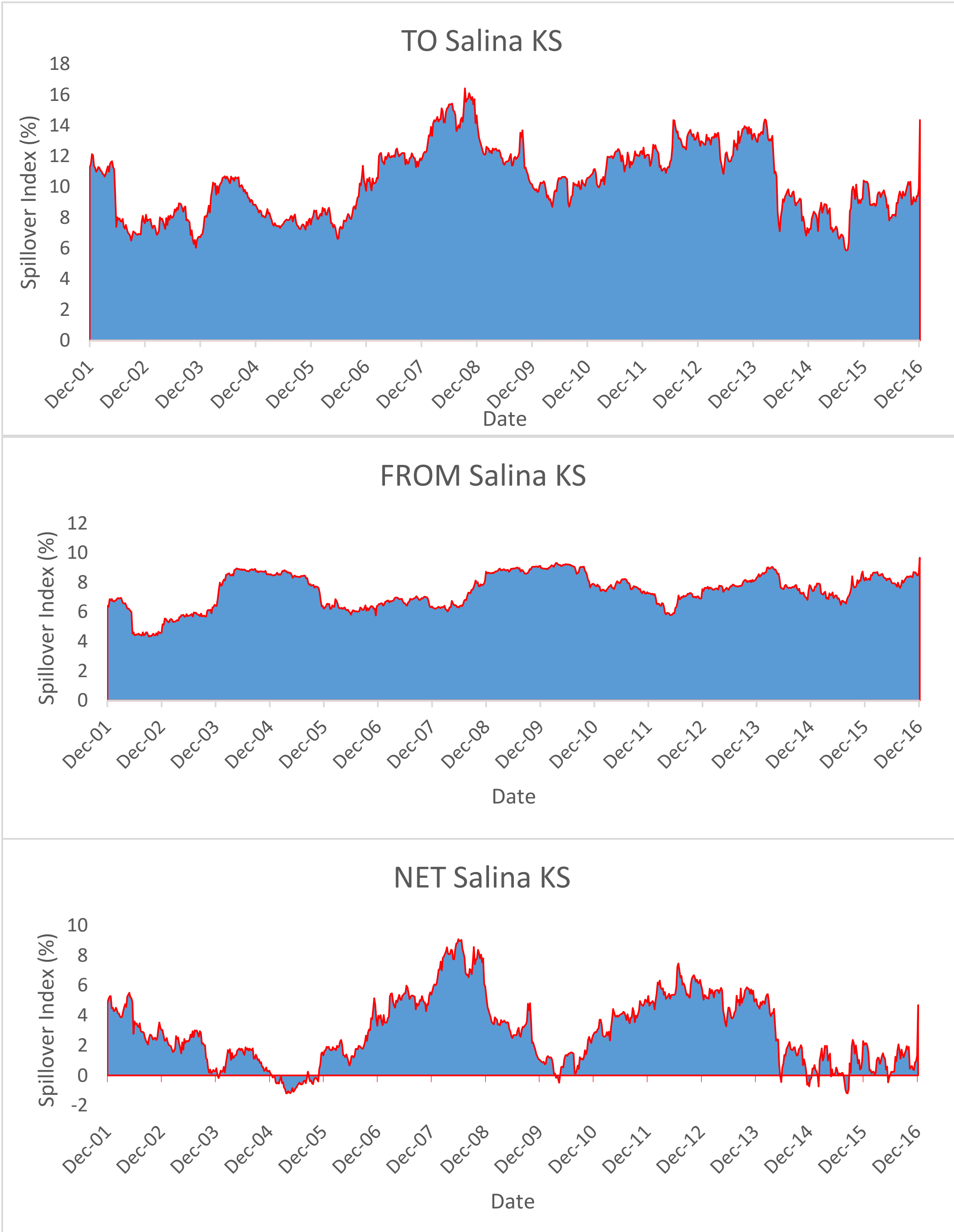

Figure 3.6 Directional and Net Spillover Index – Salina, Kansas.

(a) Price Shock from Other Markets to Salina (Kansas)

(b) Price Shocks from Salina (Kansas) to Other Markets

(c) Net Price Shocks to Salina, Kansas (To-From).

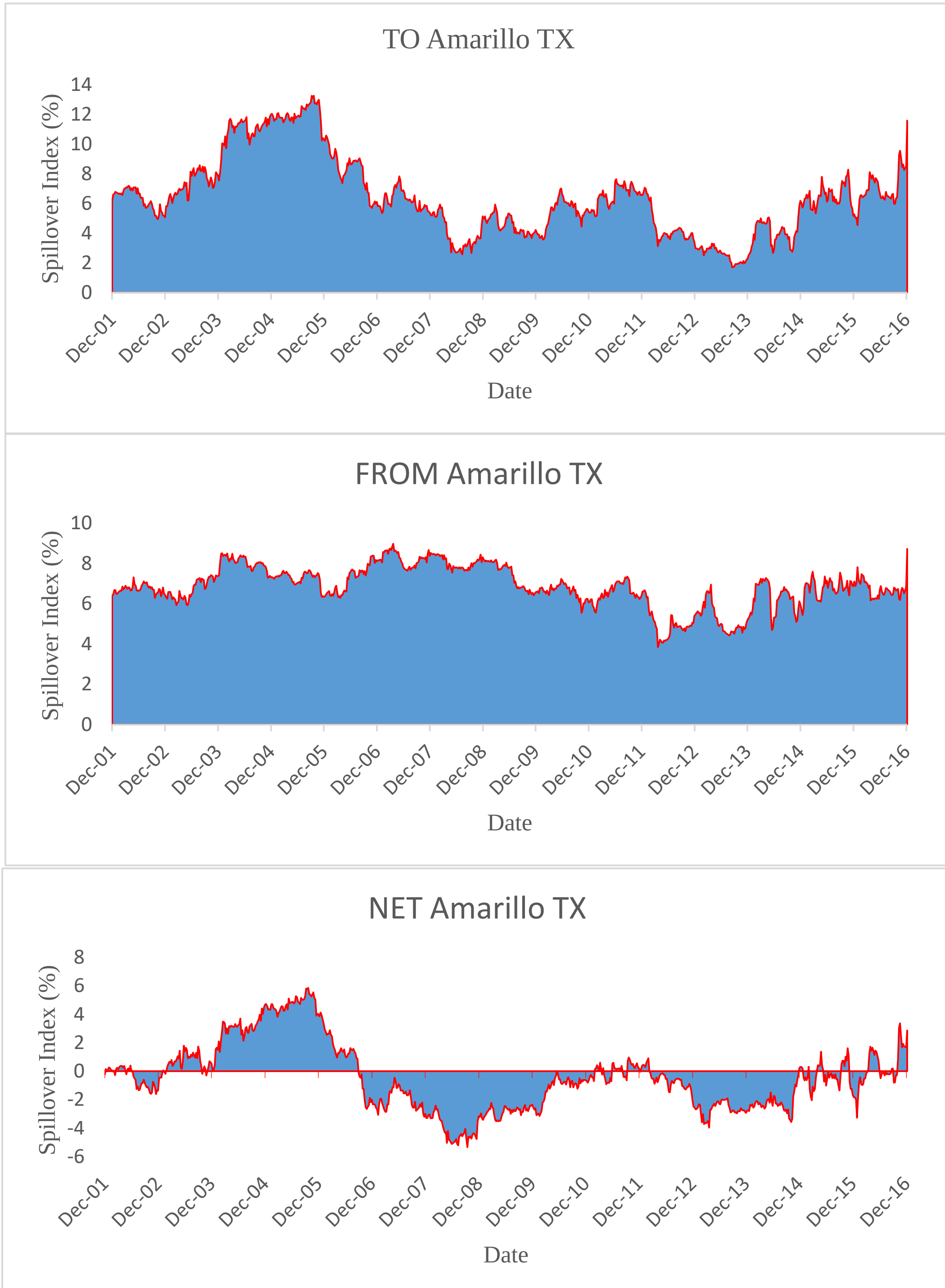

Figure 3.7 Directional and Net Spillover Index – Amarillo, Texas.

(a) Price Shock from Other Markets to Amarillo (Texas)

(b) Price Shocks from Amarillo (Texas) to Other Markets

(c) Net Price Shocks to Amarillo, Texas (To-From).

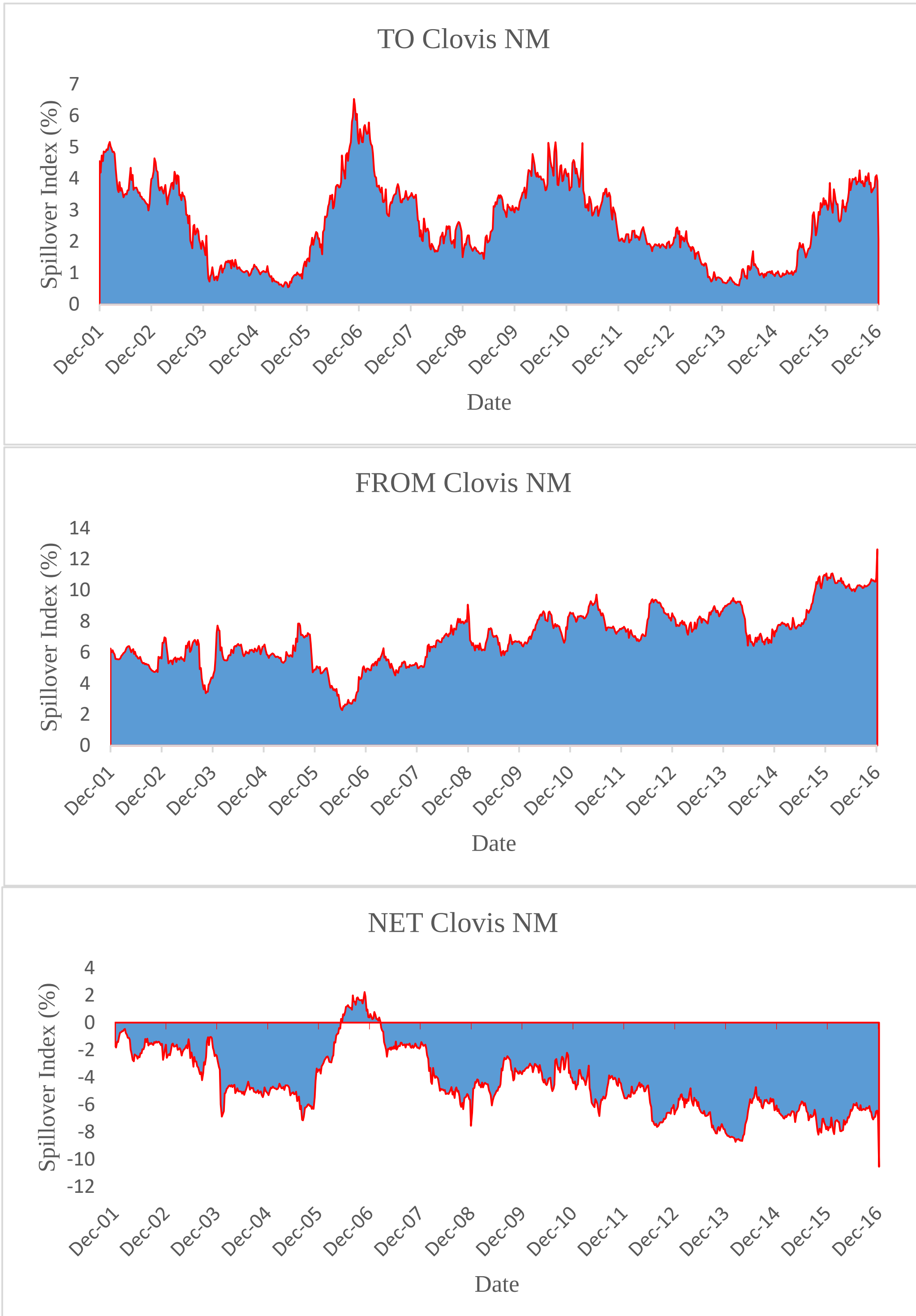

Figure 3.8 Directional and Net Spillover Index – Clovis, New Mexico.

(a) Price Shock from Other Markets to Clovis (New Mexico)

(b) Price Shocks from Clovis (New Mexico) to Other Markets

(c) Net Price Shocks to Clovis, New Mexico (To-From).

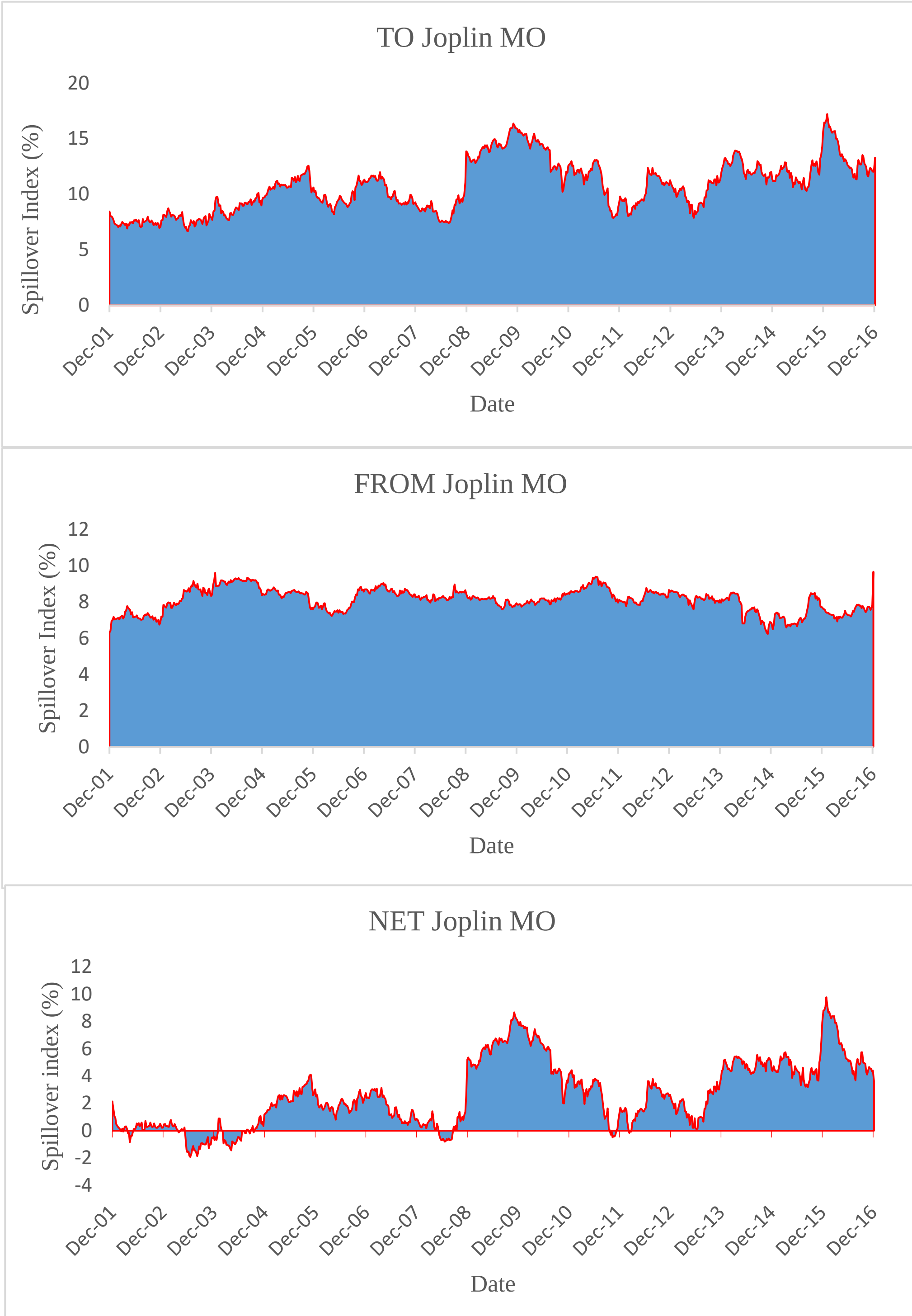

Figure 3.9 Directional and Net Spillover Index – Joplin, Missouri.

(a) Price shock from other markets to Joplin (Missouri)

(b) Price shocks from Joplin (Missouri) to other markets

(c) Net price shocks to Joplin, Missouri (To-From).

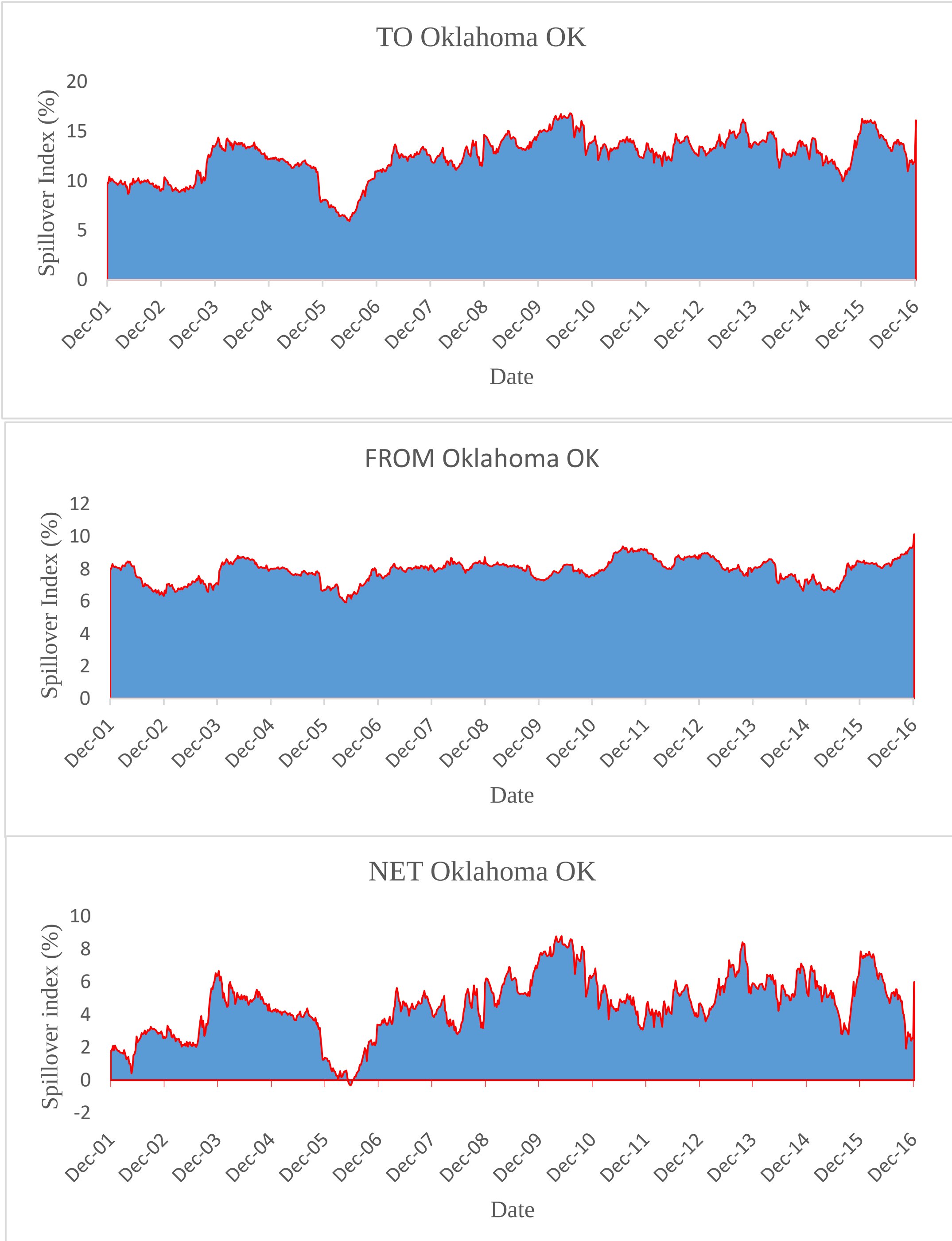

Figure 3.10 Directional and Net Spillover Index – Oklahoma City, Oklahoma.

(a) Price shock from other markets to Oklahoma City (Oklahoma)

(b) Price shocks from Oklahoma City (Oklahoma) to other markets

(c) Net price shocks to Oklahoma City, Oklahoma (To-From).

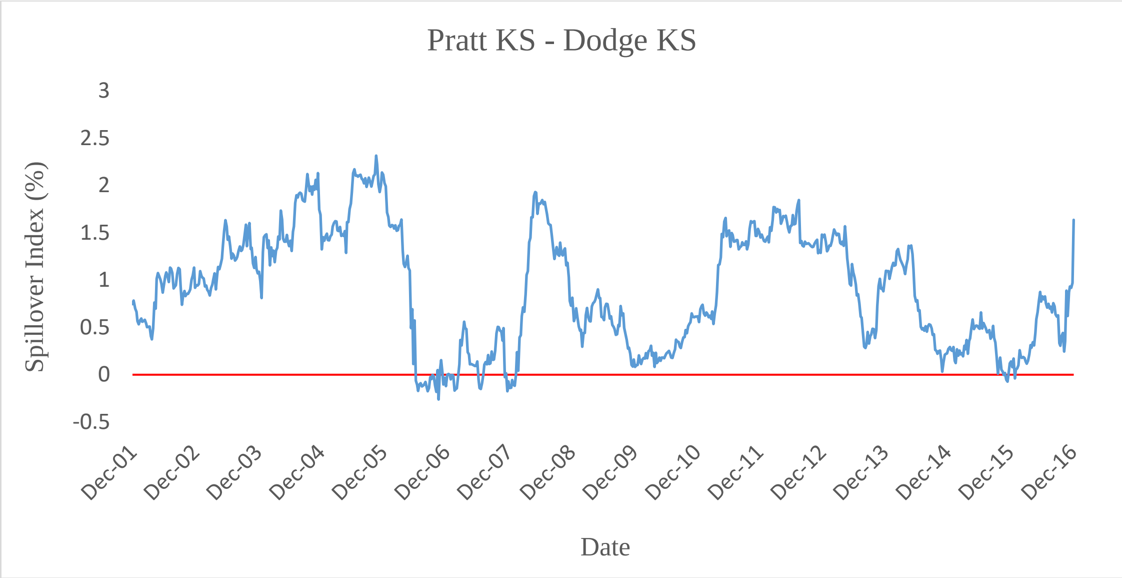

Figure 3.11 Net Spillover from Pratt KS to Dodge KS.

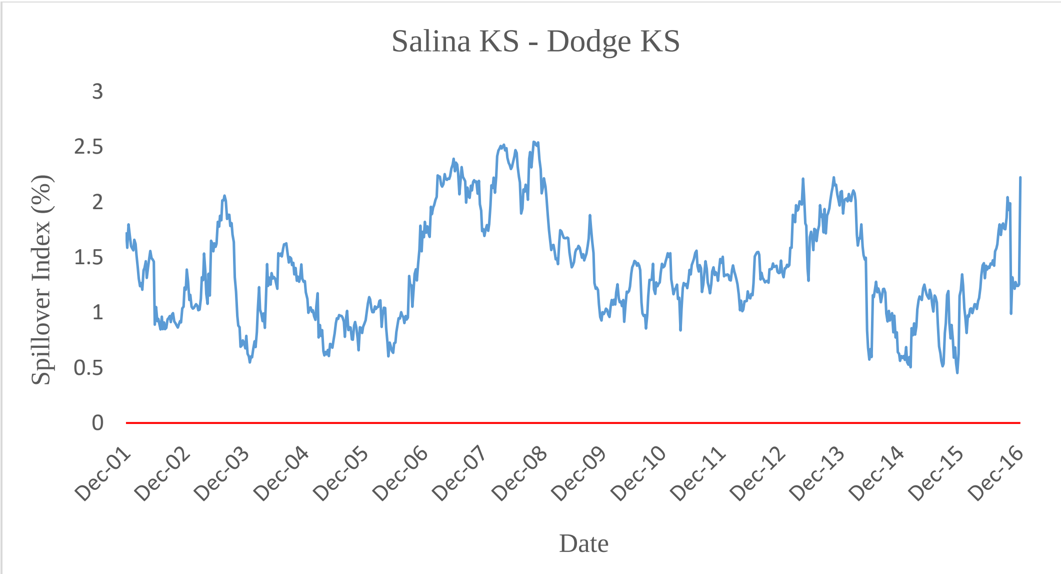

Figure 3.12 Net Spillover from Salina KS to Dodge KS.

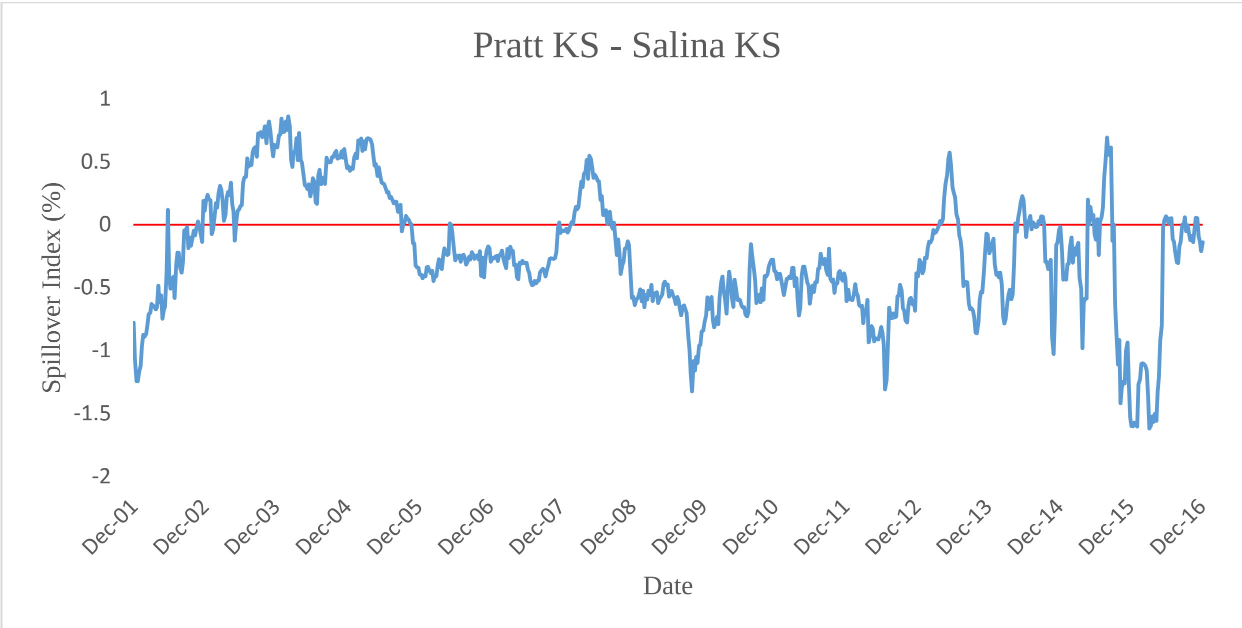

Figure 3.13 Net Spillover from Pratt KS to Salina KS.

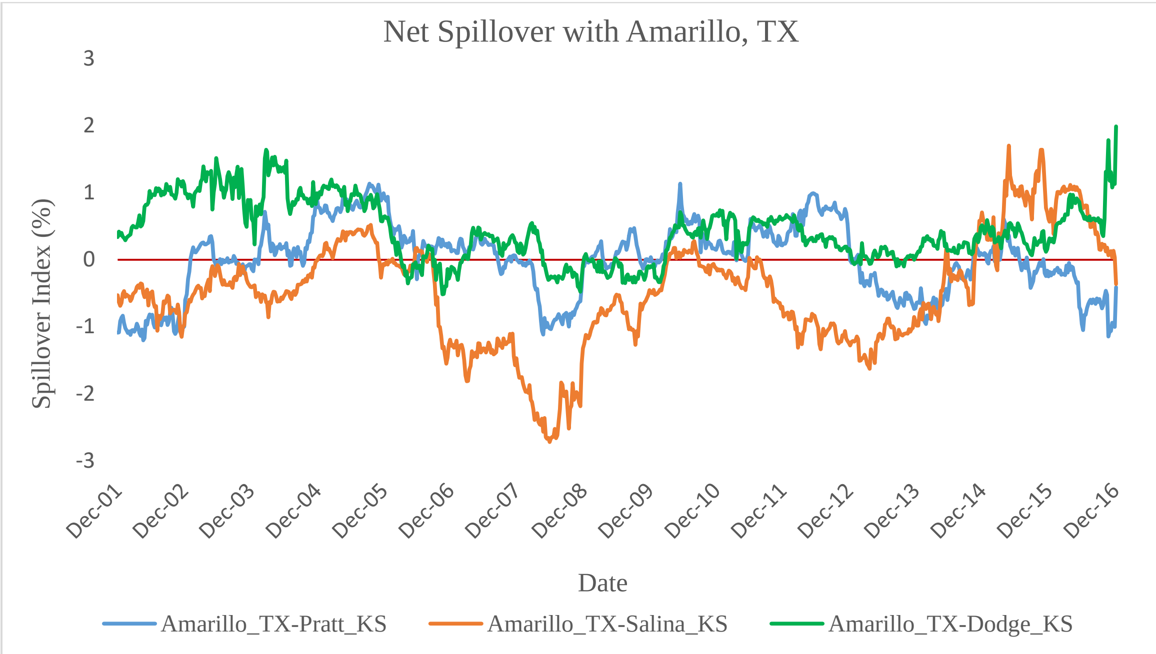

Figure 3.14 Net Spillover from Amarillo TX to Pratt KS, Salina KS, and Dodge City KS.

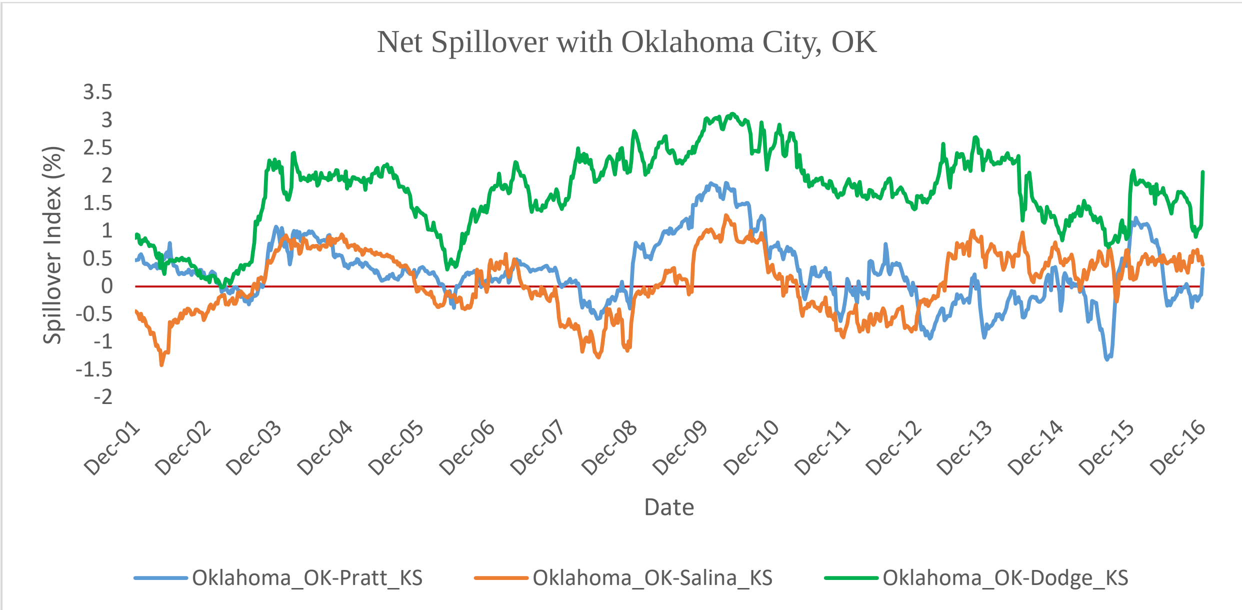

Figure 3.15 Net Spillover from Oklahoma OK to Pratt KS, Salina KS, and Dodge City KS.

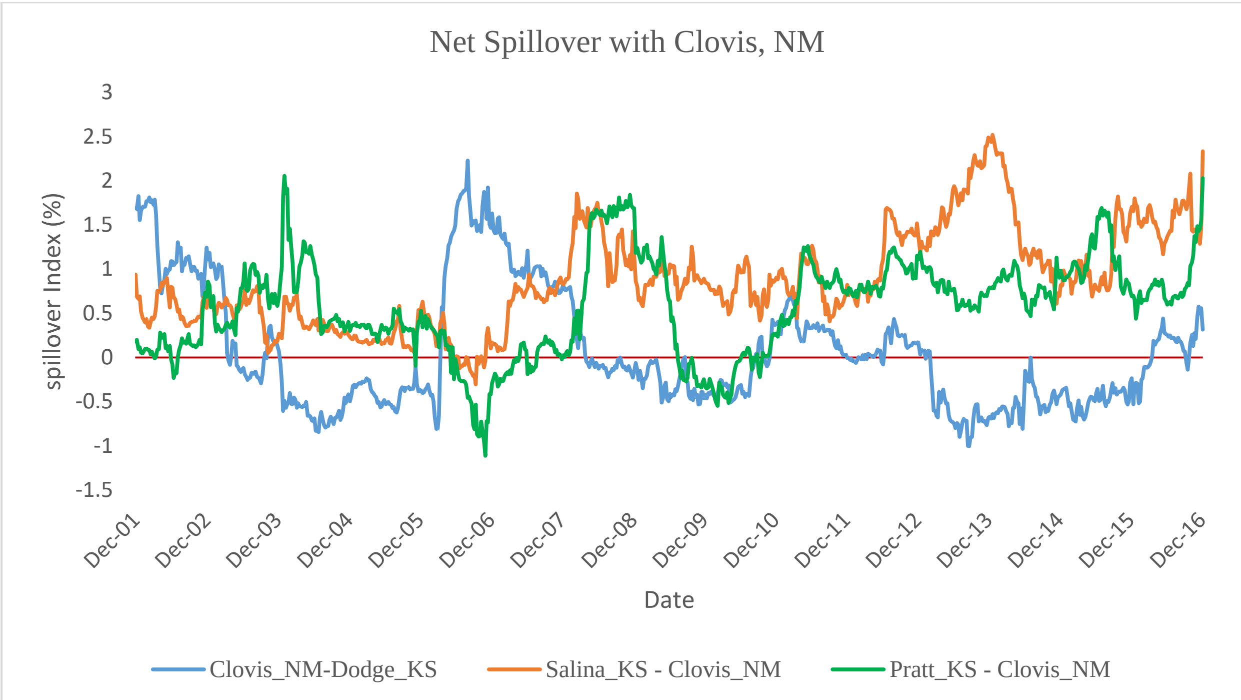

Figure 3.16 Net Spillover from Clovis NM to Pratt KS, Salina KS, and Dodge City KS.

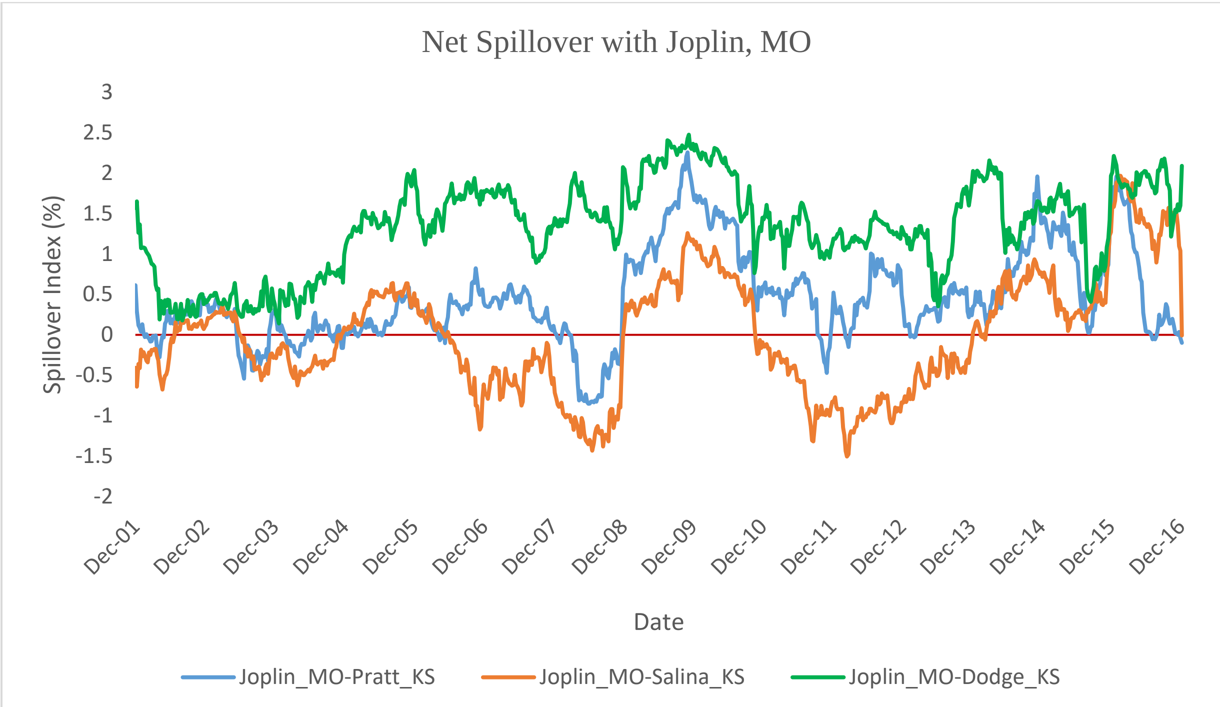

Figure 3.17 Net Spillover from Joplin MO to Pratt KS, Salina KS, and Dodge City KS.

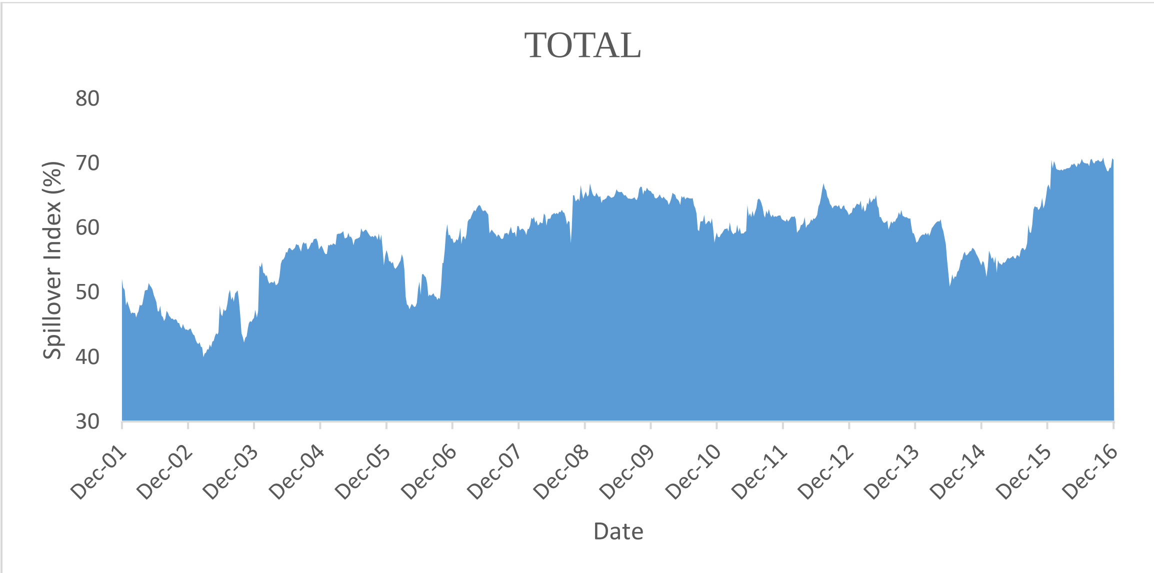

Figure 3.18 Dynamic total connectedness with 100-week rolling window, the 10-week-ahead predictive horizon for variance decomposition (state level prices).

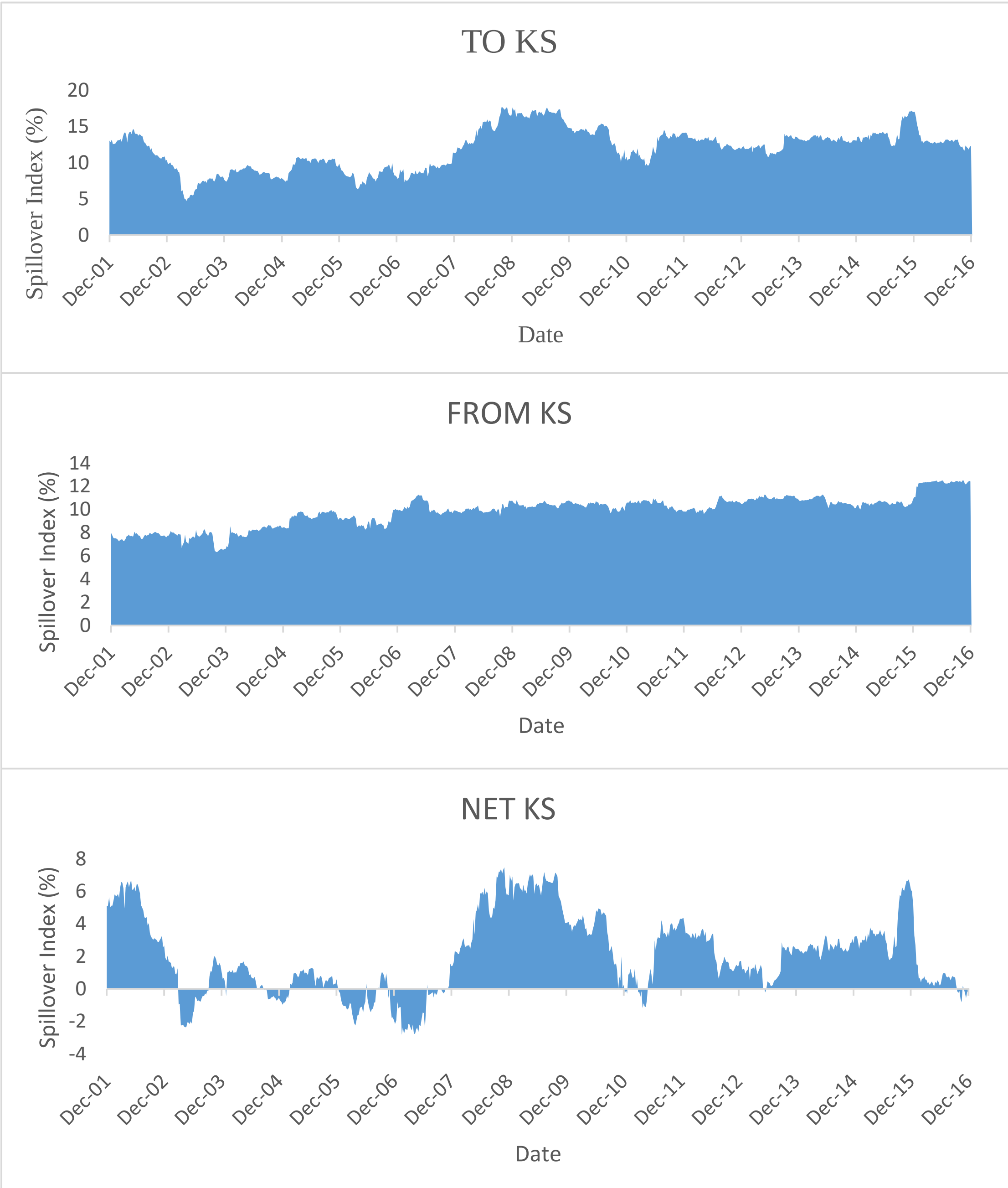

Figure 3.19 Directional and Net Spillover Index – Kansas.

(a) Price shock from other state markets to Kansas markets

(b) Price shocks from Kansas to other state markets

(c) Net price shocks to Kansas, Kansas (To-From).

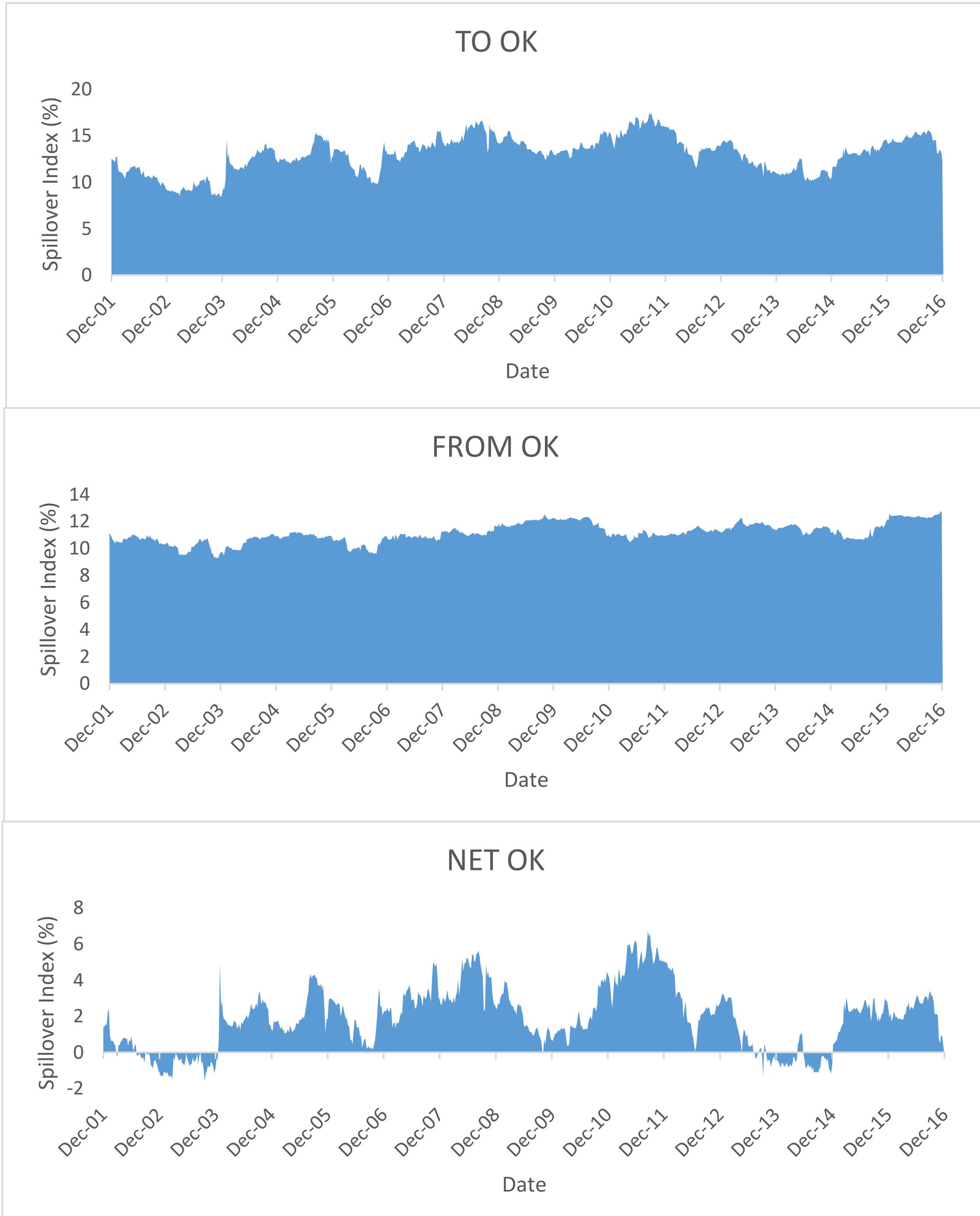

Figure 3.20 Directional and Net Spillover Index – Oklahoma.

(a) Price shock from other state markets to Oklahoma markets

(b) Price shocks from Oklahoma to other state markets

(c) Net price shocks to Oklahoma, Oklahoma (To-From).

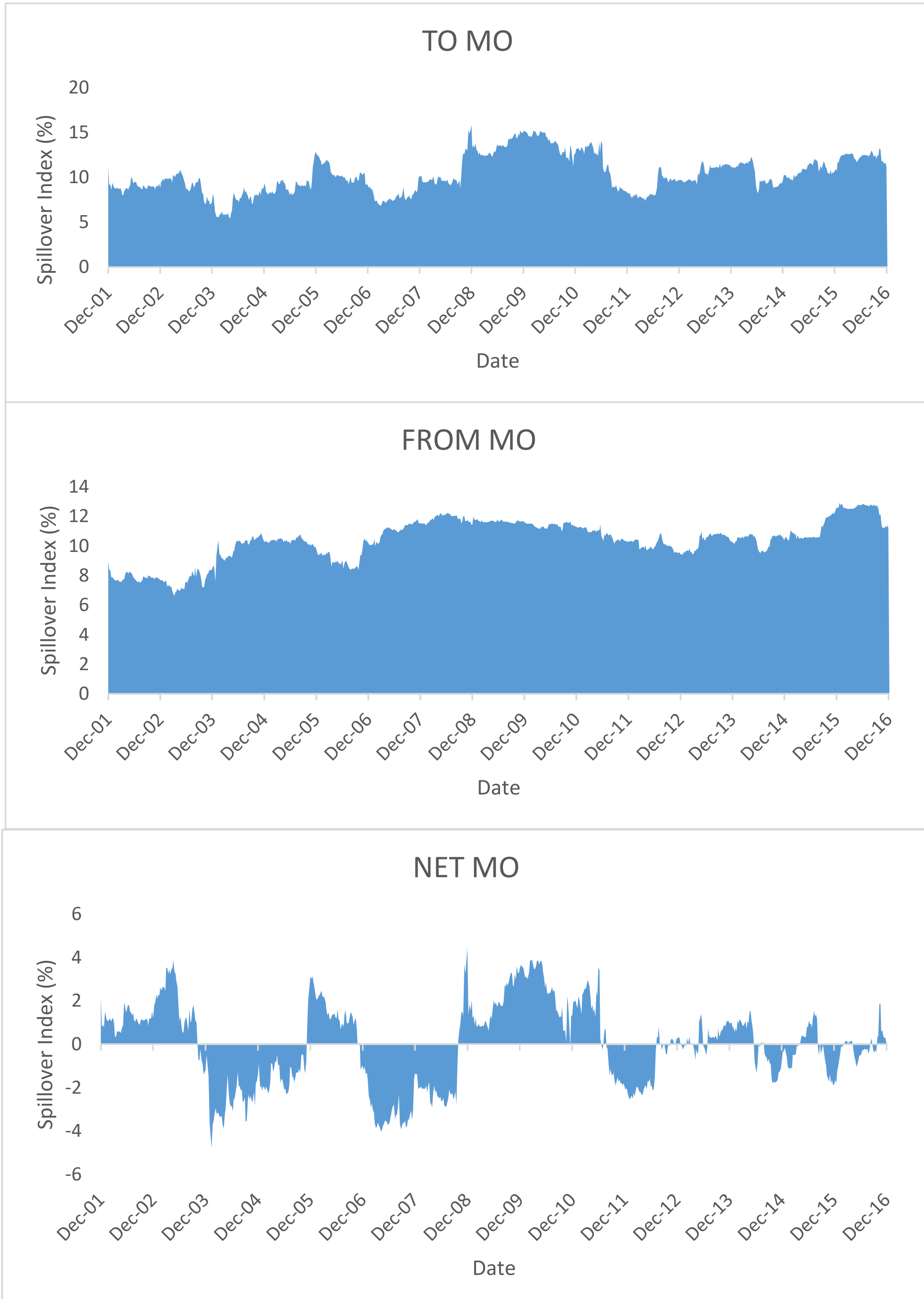

Figure 3.21 Directional and Net Spillover Index – Missouri.

(a) Price shock from other state markets to Missouri markets

(b) Price shocks from Missouri to other state markets

(c) Net price shocks to Missouri, Missouri (To-From).

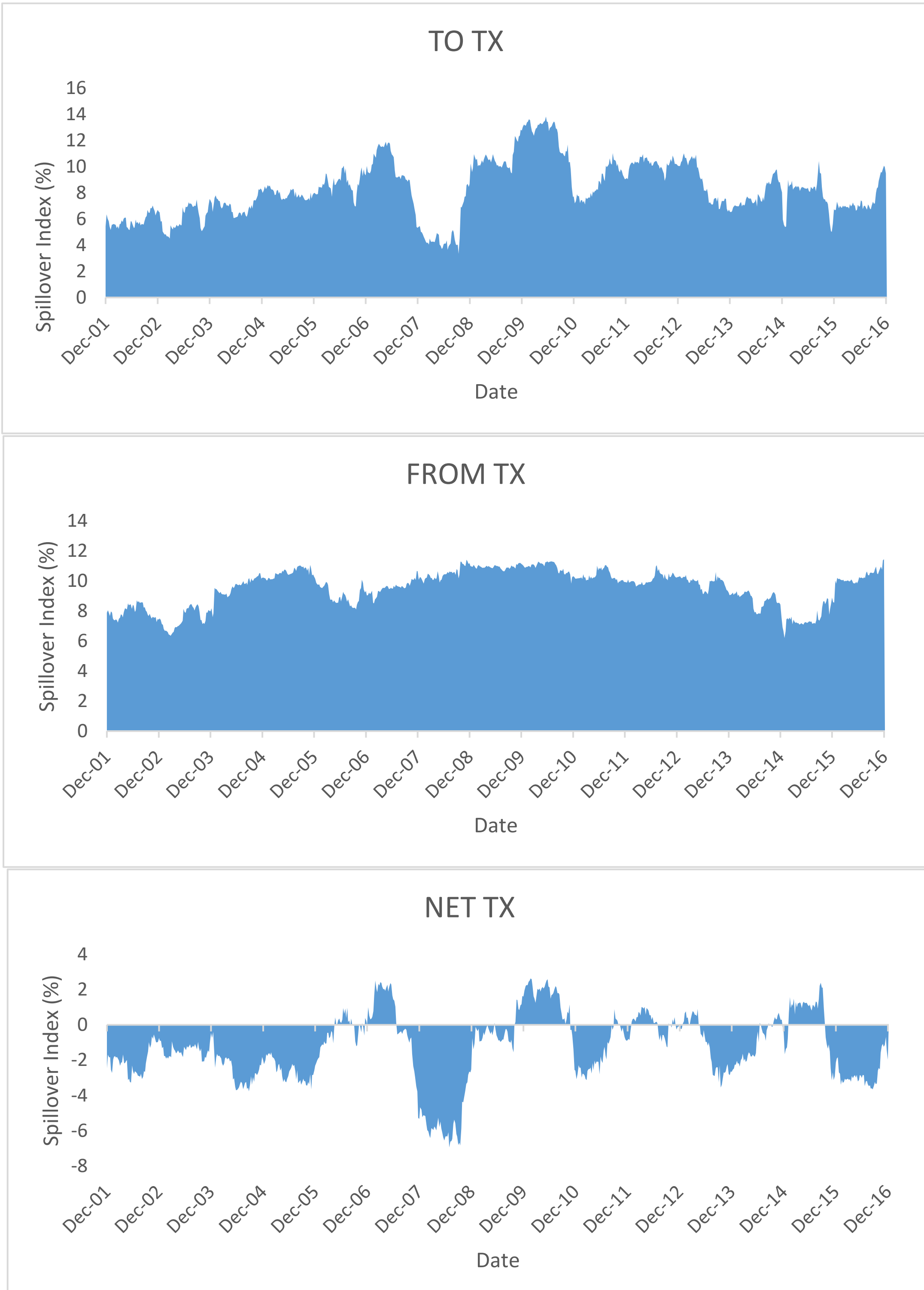

Figure 3.22 Directional and Net Spillover Index – Texas.

(a) Price shock from other state markets to Texas markets

(b) Price shocks from Texas to other state markets

(c) Net price shocks to Texas, Texas (To-From).

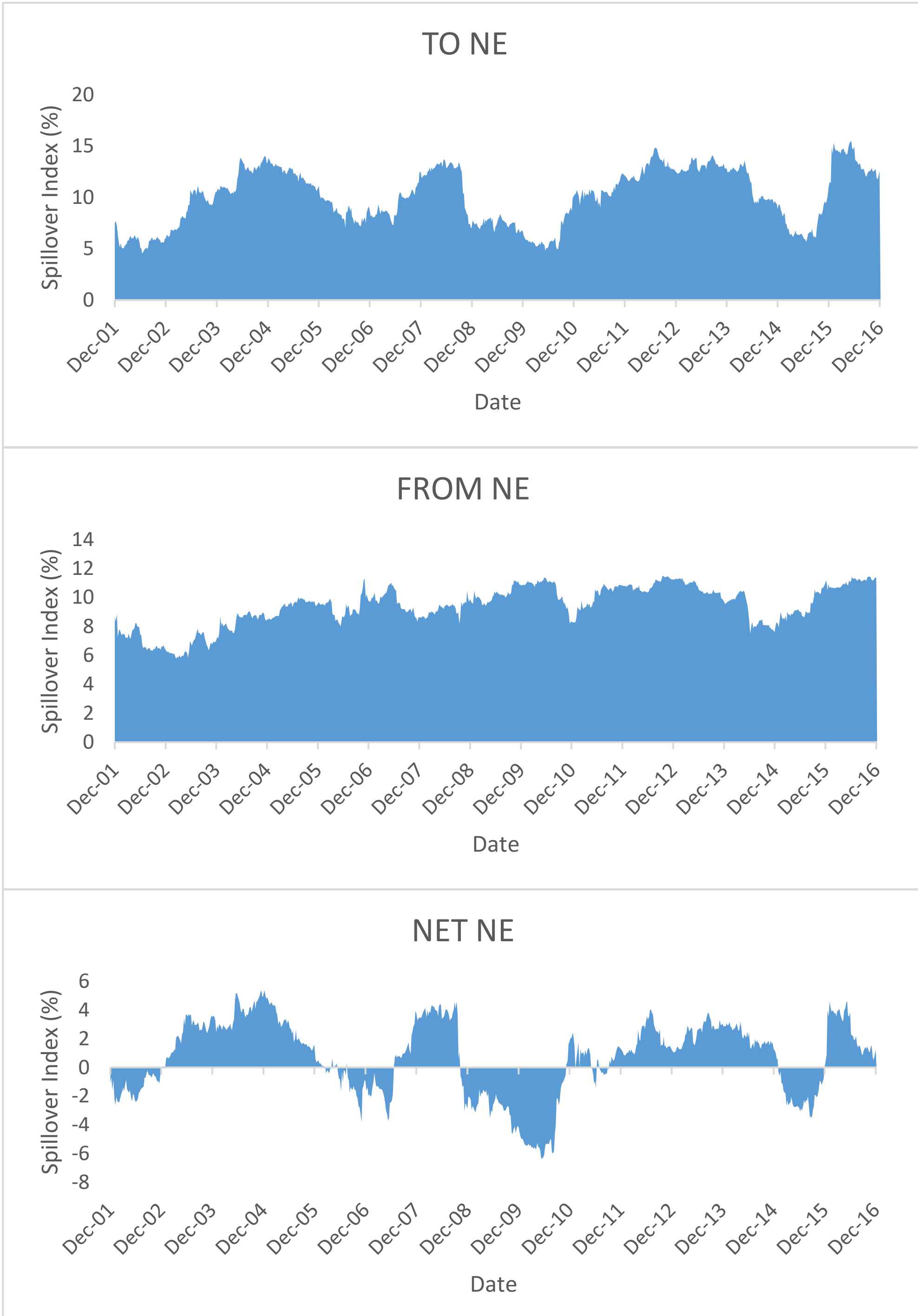

Figure 3.23 Directional and Net Spillover Index – Nebraska.

(a) Price shock from other state markets to Nebraska markets

(b) Price shocks from Nebraska to other state markets

(c) Net price shocks to Nebraska, Nebraska (To-From).

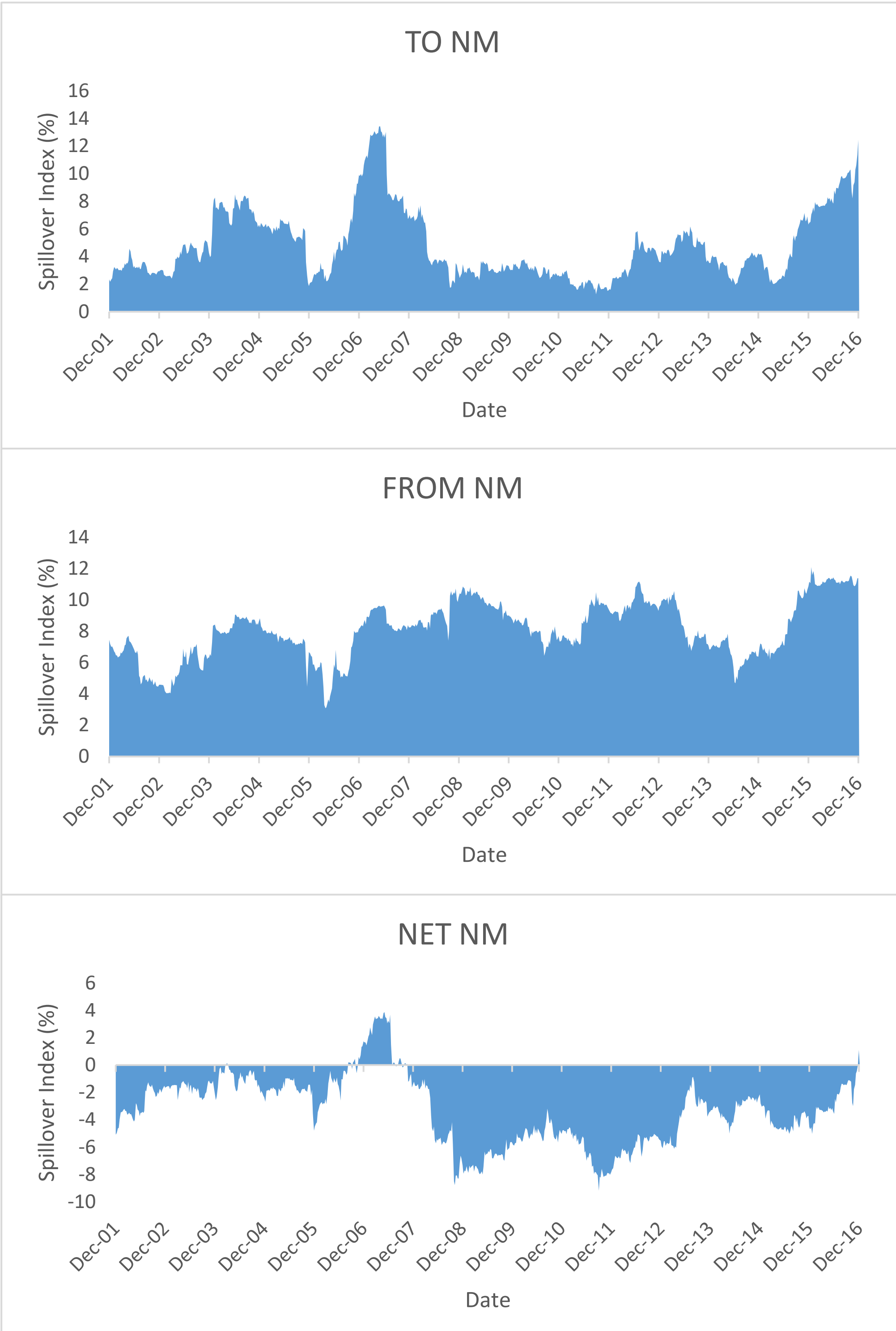

Figure 3.24 Directional and Net Spillover Index – New Mexico.

(a) Price shock from other state markets to New Mexico markets

(b) Price shocks from New Mexico to other state markets

(c) Net price shocks to New Mexico, New Mexico (To-From).

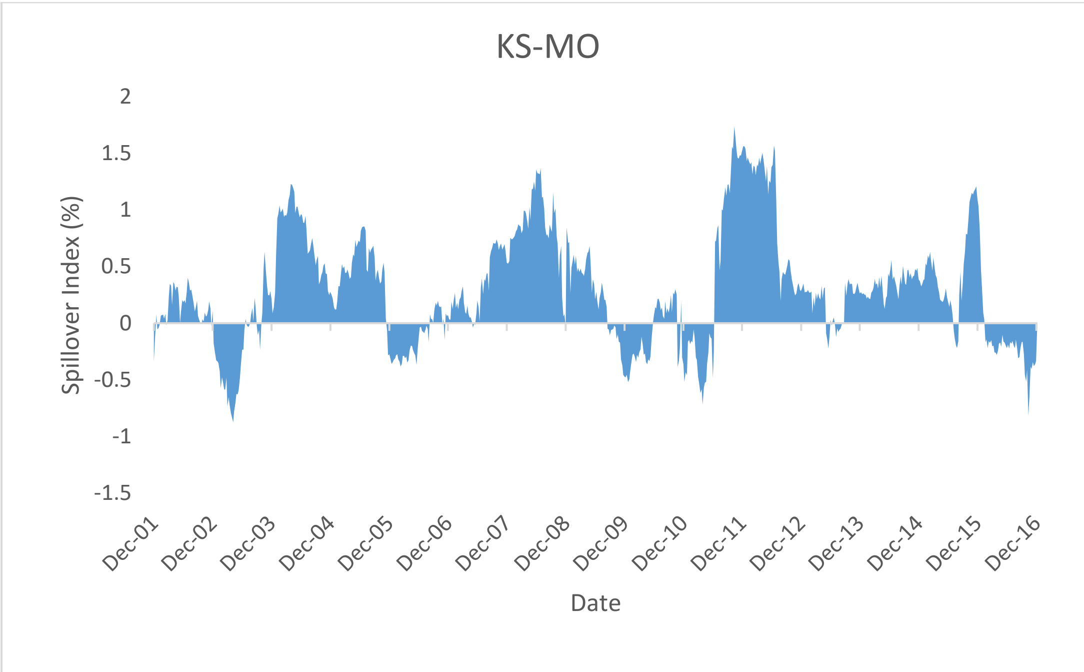

Figure 3.25 Net Spillover from Kansas to Missouri.

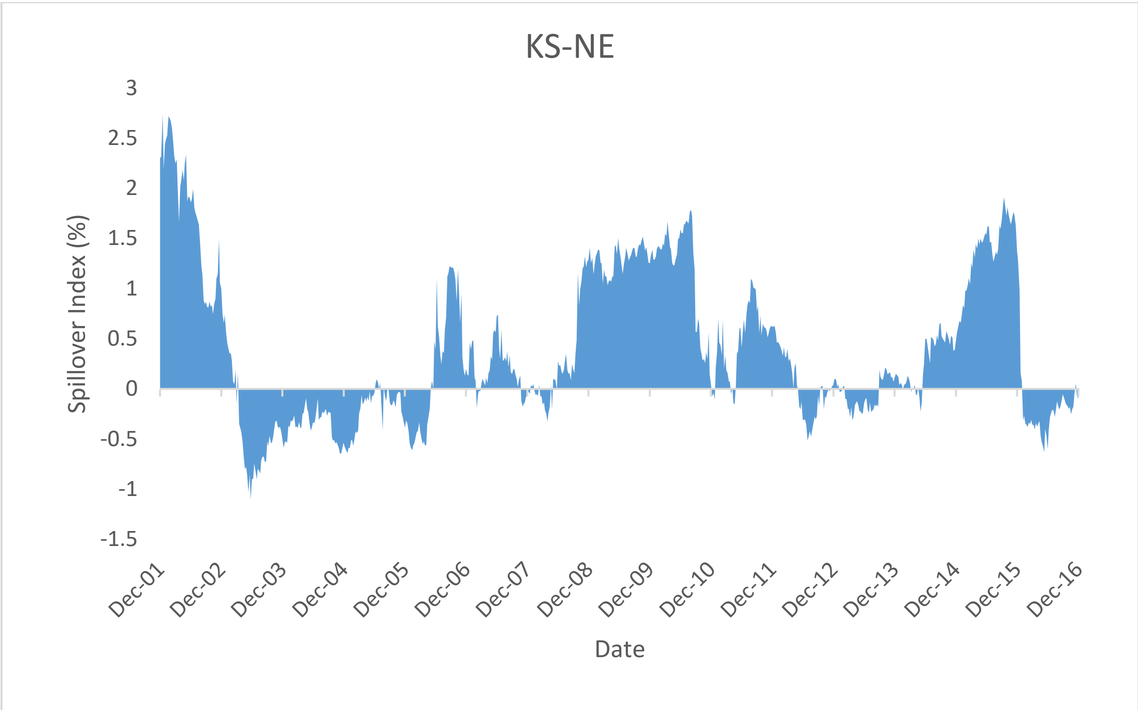

Figure 3.26 Net Spillover from Kansas to Nebraska.

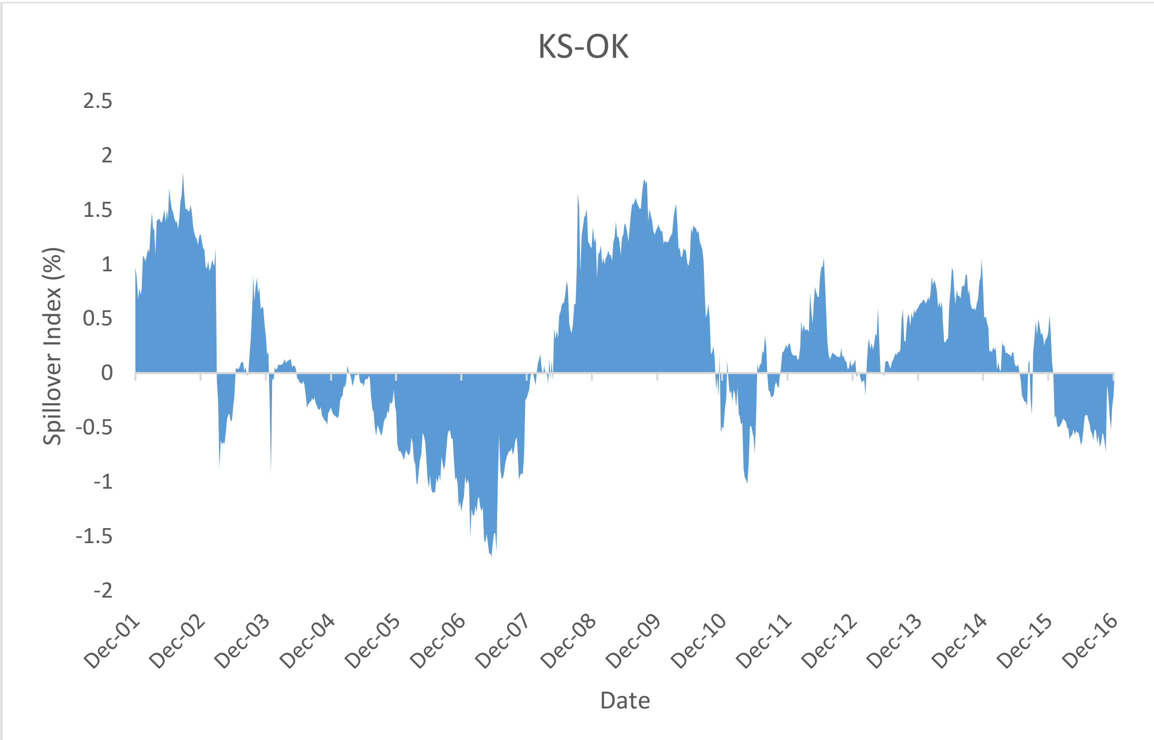

Figure 3.27 Net Spillover from Kansas to Oklahoma.

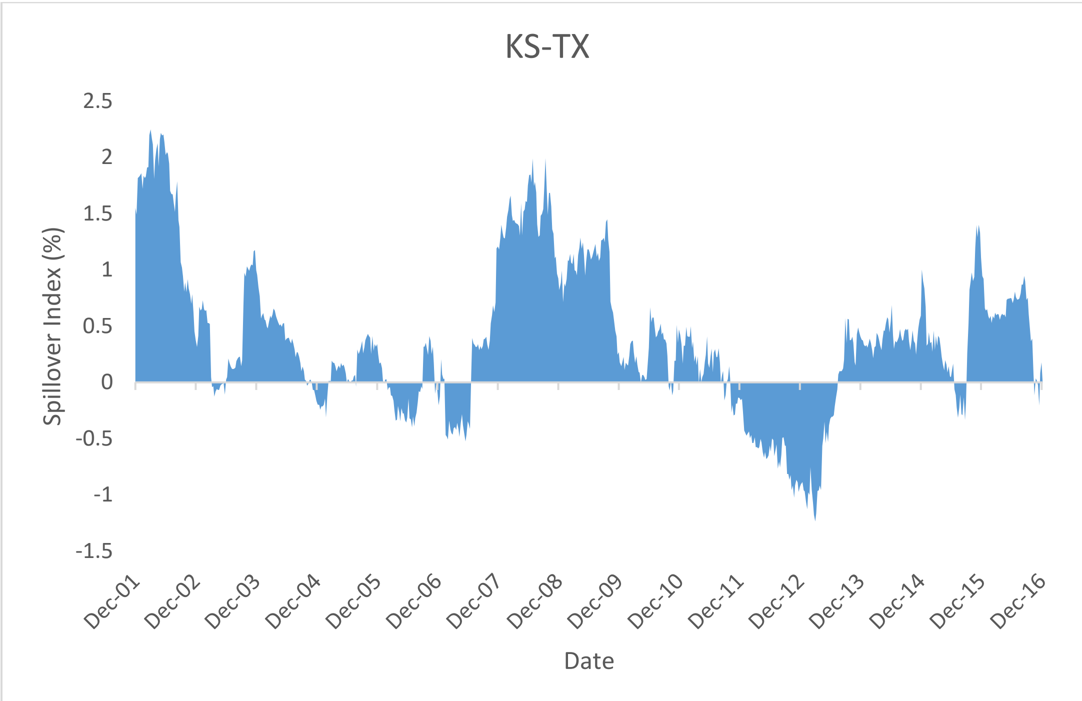

Figure 3.28 Net Spillover from Kansas to Texas.

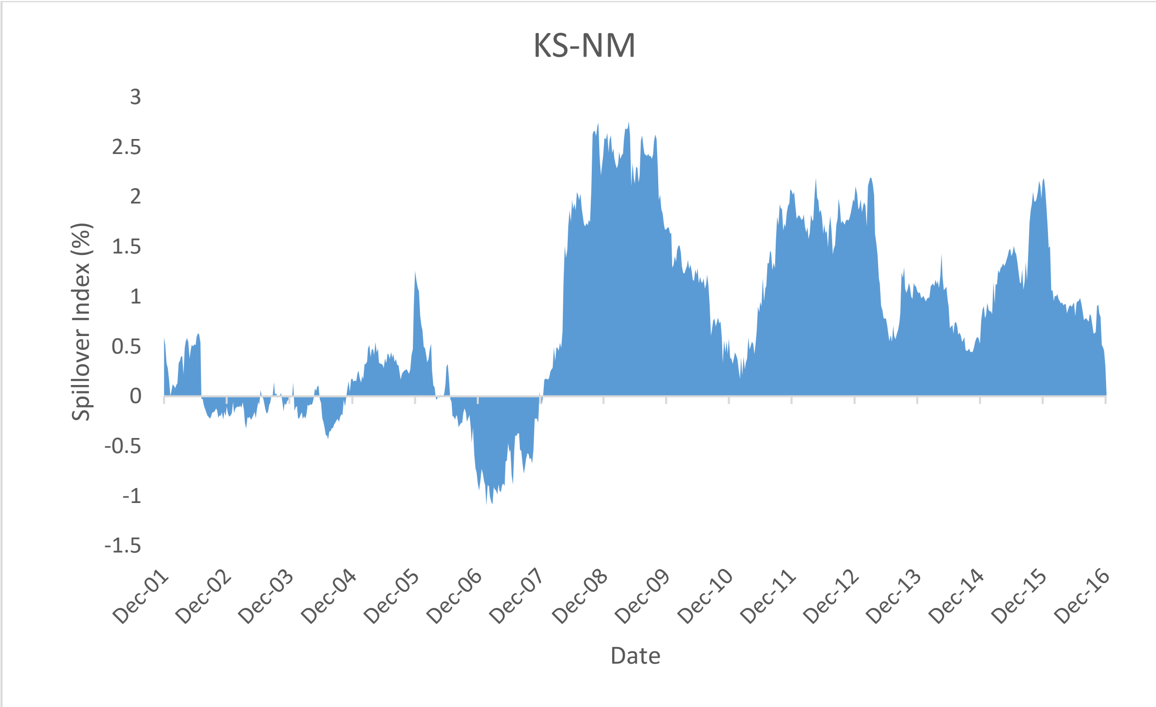

Figure 3.29 Net Spillover from Kansas to New Mexico.

Appendix:

Table 3.A1 Distance (in miles) between selected auction markets.

	Amarillo TX	Joplin MO	Oklahoma OK	Pratt KS	Salina KS	Clovis NM
Joplin MO	491					
Oklahoma OK	260	232				
Pratt KS	294	278	235			
Salina KS	402	287	249	122		
Clovis NM	106	593	362	401	522	
Dodge KS	243	365	253	76	159	349

Table 3.A2 Number of Weeks with Missing Feeder Cattle Prices by Auction market and by Year (Heifer 600-700 lb). This is based on 52 weeks in a calendar year.

Year	Amarillo, TX	Joplin, MO	Oklahoma City, OK	Pratt, KS	Salina, KS	Clovis, NM	Dodge City, KS
2000	3	10	2	2	8	3	0
2001	3	5	2	3	8	9	4
2002	2	5	4	3	8	9	1
2003	1	5	2	4	10	3	6
2004	5	5	2	2	10	2	0
2005	5	4	2	3	8	3	9
2006	8	6	6	4	7	7	5
2007	8	7	6	4	9	8	7
2008	12	4	6	8	9	8	9
2009	9	4	3	5	8	4	6
2010	6	3	7	4	8	4	5
2011	11	6	5	11	8	9	3
2012	12	4	4	9	7	3	6
2013	18	6	7	7	9	6	8
2014	12	7	5	12	7	5	5
2015	19	3	4	8	8	5	6
2016	9	4	4	9	7	3	6
Total	143	88	71	98	139	91	86

Table 3.A3 Number of Weeks with Missing Feeder Cattle Prices by State and by Year (Heifer 600-700 lb).

Year	Alabama	Georgia	Kansas	Missouri	Nebraska	New Mexico	Oklahoma	Texas
2000	4	2	2	0	3	3	2	0
2001	5	3	4	1	5	10	2	0
2002	5	4	4	1	2	11	2	0
2003	6	4	1	2	7	2	2	0
2004	5	4	2	0	2	3	2	1
2005	5	3	3	0	1	2	1	1
2006	4	3	3	1	1	9	2	2
2007	5	4	4	1	0	4	6	1
2008	4	5	3	1	1	4	2	2
2009	4	4	3	1	1	5	3	1
2010	4	4	1	1	0	2	3	1
2011	4	4	4	0	0	5	3	3
2012	3	3	5	1	1	3	2	3
2013	6	6	6	4	2	7	6	5
2014	5	4	4	1	2	4	3	3
2015	7	4	4	0	0	2	3	4
2016	4	4	2	2	0	3	4	6
Total	80	65	55	17	28	79	48	33

Table 3.A4 Summary of Weekly Auction Level Feeder Cattle Prices by Year; 600-700lb Heifer.

	Amarillo, TX		Joplin, MO		Oklahoma, OK		Pratt, KS		Salina, KS		Clovis		Clovis	
Year	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
2000	81.45	2.65	85.67	2.17	84.91	2.58	85.23	2.81	86.33	2.08	80.25	2.36	80.05	1.93
2001	82.35	4.03	85.48	4.62	86.44	4.14	86.74	3.87	86.06	3.93	84.45	4.34	86.03	3.42
2002	76.71	2.71	76.93	3.01	78.11	2.52	78.65	3.05	79.75	2.64	76.52	6.45	78.31	2.63
2003	85.36	7.67	86.71	7.62	87.46	7.58	87.27	8.56	87.96	7.86	83.66	6.05	88.27	9.45
2004	100.33	9.18	102.23	9.62	102.8	9.91	103.14	10.17	102.85	9.13	99.52	8.41	101.75	10.12
2005	106.15	4.34	109.08	4.74	109.85	3.79	111.26	4.76	112.93	5.85	107.24	2.74	109.92	4.23
2006	102.09	7.86	105.86	7.24	106.91	6.07	107.02	7.21	108.32	7.37	99.83	6.64	106.52	6.91
2007	101.23	6.51	101.46	5.78	104.16	6.54	104.35	7.78	104.45	7.21	99.46	5.98	105.8	6.94
2008	95.32	8.23	95.12	7.69	97.31	7.62	99.04	7.23	97.95	8.11	94.53	8.61	99.89	7.84
2009	86.71	4.99	89.38	4.96	91.52	5.19	91.84	5.26	93.07	5.24	88.29	5.13	93.12	4.53
2010	98.32	7.17	102.71	6.81	104.87	6.33	105.28	6.58	106.35	7.14	101.02	7.06	106.69	7.32
2011	119.02	7.24	123.68	5.52	126.85	5.66	128.33	5.63	128.43	4.61	123.61	6.31	129.51	6.58
2012	132.18	12.76	138.51	8.91	141.86	8.14	141.83	8.78	143.83	8.46	139.31	8.59	143.82	7.51
2013	133.08	9.96	140.36	9.21	141.13	9.13	142.61	11.49	146.73	9.88	142.04	18.39	143.56	11.57
2014	187.13	22.31	200.54	26.99	201.86	27.11	206.92	29.31	207.24	29.11	195.65	21.63	204.06	29.17
2015	187.61	25.99	201.64	26.94	205.86	23.55	205.49	23.56	207.91	24.57	196.42	24.87	199.94	26.56
2016	127.78	18.11	136.31	14.84	138.35	15.49	137.88	17.14	141.47	16.27	133.64	20.21	155.01	99.37
Total	109.03	32.67	116.72	37.93	117.89	38.33	117.13	38.01	120.41	39.68	114.69	37.56	119.48	45.52

Table 3.A5 Summary of Weekly State Level Feeder Cattle Prices by Year; 600-700lb Heifer.

	Alabama		Georgia		Kansas		Missouri		Nebraska		New Mexico		Oklahoma		Texas	
Year	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
2000	79.69	2.41	77.54	2.03	85.86	1.55	85.54	2.06	89.25	2.66	80.27	2.27	91.95	49.47	82.51	2.45
2001	87.01	50.77	77.08	4.76	86.65	3.85	94.11	55.09	89.73	4.09	84.37	5.11	86.33	3.65	84.16	3.61
2002	71.92	2.84	69.42	2.78	79.14	2.38	78.13	2.69	81.84	2.82	77.16	3.11	77.93	2.41	76.97	2.77
2003	80.67	5.66	76.51	5.53	88.79	8.82	86.77	7.67	101.28	66.41	84.11	6.48	87.49	8.15	84.76	7.16
2004	96.27	7.75	92.41	7.34	104.22	10.39	103.71	10.38	107.55	10.52	100.42	8.82	102.92	10.43	100.37	8.62
2005	102.93	3.64	98.38	3.34	111.36	4.41	112.14	5.37	116.25	5.57	107.72	2.27	109.72	3.93	107.26	2.71
2006	99.32	6.54	94.43	5.86	108.29	5.96	108.49	7.04	112.59	7.82	102.39	6.53	106.85	5.93	103.18	6.51
2007	94.76	6.12	90.02	5.75	105.61	7.26	104.93	6.97	108.21	7.69	98.83	5.61	105.14	6.34	101.35	6.32
2008	87.09	7.15	82.36	7.42	100.57	7.43	98.66	7.34	102.02	9.09	91.37	7.16	99.35	7.42	95.81	8.03
2009	81.18	5.16	78.63	4.22	93.94	4.52	92.92	4.46	96.67	4.54	84.48	4.91	93.19	4.14	89.38	5.26
2010	93.09	7.12	89.75	5.74	106.87	7.11	106.61	6.92	110.45	7.43	97.25	6.62	105.88	6.21	101.87	6.37
2011	112.94	5.41	109.02	5.38	129.44	5.68	128.45	5.49	133.31	5.95	116.27	7.39	128.47	5.39	124.83	6.16
2012	128.56	10.99	126.95	8.42	144.33	7.01	142.77	8.19	147.65	7.77	133.48	9.46	143.37	7.11	141.96	7.94
2013	127.68	6.47	123.36	9.97	145.31	11.56	141.56	12.44	149.61	11.72	134.26	7.97	142.33	10.02	139.53	8.94
2014	184.91	23.63	181.96	27.44	205.88	28.95	204.64	28.84	213.71	28.55	191.76	22.97	202.18	27.38	197.21	26.21
2015	189.05	31.59	188.56	28.16	208.19	22.13	205.38	25.52	214.91	26.39	194.38	24.88	206.24	20.89	196.31	23.16
2016	118.96	16.99	118.84	18.4	142.44	13.78	138.32	13.87	144.53	14.95	131.15	17.52	140.82	13.55	132.71	18.27
Total	107.76	36.76	104.31	35.83	120.01	38.88	119.59	40.59	125.16	42.79	112.94	36.32	119.15	39.83	114.36	36.77

Table 3.A6 Unit Root Test for Feeder Cattle Auction Prices and Prices Pairs; 600-700 lb Heifer

	Dickey-Fuller test		Phillips-Perron test		
Market	Z(t)	p-value	Z(rho)	Z(t)	p-value
Amarillo TX	-3.14	0.02	-7.21	-1.97	0.31
Joplin MO	-2.05	0.26	-4.47	-1.55	0.51
Oklahoma OK	-1.74	0.41	-3.91	-1.47	0.55
Pratt KS	-2.31	0.17	-4.81	-1.61	0.48
Salina KS	-1.99	0.29	-4.27	-1.53	0.52
Clovis NM	-1.84	0.36	-4.31	-1.55	0.51
Dodge KS	-1.65	0.45	-4.07	-1.51	0.53
	1st Difference				
Amarillo TX	-48.48	0.00	-1151.53	-55.34	0.00
Joplin MO	-41.86	0.00	-1153.46	-42.39	0.00
Oklahoma OK	-37.15	0.00	-1079.97	-37.23	0.00
Pratt KS	-43.09	0.00	-1114.59	-45.4	0.00
Salina KS	-40.02	0.00	-1094.05	-40.9	0.00
Clovis NM	-35.86	0.00	-997.83	-36.35	0.00
Dodge KS	-33.88	0.00	-989.30	-33.93	0.00

Table 3.A7 Unit Root Test for Feeder Cattle State Prices and Prices Pairs (600-700 lb Heifer)

	Dickey-Fuller test		Phillips-Perron test		
Market	Z(t)	p-value	Z(rho)	Z(t)	p-value
Alabama	-1.45	0.55	-14.8	-1.41	0.57
Georgia	-2.31	0.16	-5.5	-1.93	0.31
Kansas	-2.62	0.08	-6.86	-2.62	0.08
Missouri	-7.26	0.00	-55.86	-5.6	0.00
Nebraska	-7.81	0.00	-70.65	-6.28	0.00
New Mexico	-2.08	0.25	-4.35	-1.5	0.52
Oklahoma	-6.54	0.00	-41.57	-4.87	0.00
Texas	-1.92	0.32	-3.57	-1.21	0.66
	1st Difference				
Alabama	-7.27	0.00	-912.95	-8.31	0.00
Georgia	-37.62	0.00	-905.31	-38.69	0.00
Kansas	-29.89	0.00	-841.98	-29.79	0.00
Missouri	-48.91	0.00	-1015.11	-72.65	0.00
Nebraska	-79.99	0.00	-1300.63	-63.99	0.00
New Mexico	-38.56	0.00	-908.83	-39.65	0.00
Oklahoma	-47.07	0.00	-939.06	-69.76	0.00
Texas	-47.54	0.00	-1081.97	-45.98	0.00

Table 3.A8 Description of the Variables in Table 5&6. The dependent variables are the spillover indexes.

Variable	Description
Total Spillover	Total Spillover index
Amarillo - Pratt	Spillover index of shock transmission from Amarillo to Pratt
Amarillo - Salina	Spillover index of shock transmission from Amarillo to Salina
Amarillo - Dodge City	Spillover index of shock transmission from Amarillo to Dodge City
Clovis - Pratt	Spillover index of shock transmission from Clovis to Pratt
Clovis - Salina	Spillover index of shock transmission from Clovis to Salina
Clovis - Dodge City	Spillover index of shock transmission from Clovis to Dodge City
Kansas – Nebraska	Spillover index of shock transmission from Kansas to Nebraska
Kansas – Texas	Spillover index of shock transmission from Kansas to Texas
Nebraska - Texas	Spillover index of shock transmission from Nebraska to Texas
Corn	Weekly corn futures. This is the moving average over 100 weeks period.
Drought Index	This is the aggregated drought severity and coverage index at time t. The drought index is aggregated over 100 weeks.
Diesel	This is the weekly moving average of diesel prices. The moving average is on 100 weeks window.
Replacement Cattle	This is the aggregated replacement cattle value in the United States. The values are aggregated over a 100-week window
Spring	This is a seasonal dummy variable representing the spring season.
Summer	This is a seasonal dummy variable representing the Summer season.
Winter	This is a seasonal dummy variable representing the Winter season.
Drought Differences	This is the absolute differences in the drought severity between two locations, aggregated over a 100-week window.
Kansas – Texas	Drought difference between Kansas and Texas
Kansas – New Mexico	Drought Difference between Kansas and New Mexico.
Trend	Trend variable to capture the trend in the time series.

Table 3.A9 Average Market Connectedness with Inclusion of Alabama (AL) and Georgia (GA) State Prices.

	AL	GA	KS	MO	NE	NM	OK	TX	FROM
AL	34.220	11.683	11.775	8.709	8.103	5.762	12.024	7.724	65.780
GA	13.283	37.119	10.592	8.275	7.806	4.989	10.862	7.074	62.881
KS	8.608	7.140	35.590	9.755	11.023	4.495	14.293	9.096	64.410
MO	8.513	7.471	11.300	36.172	11.967	4.736	13.342	6.498	63.828
NE	7.378	7.289	13.120	10.151	38.169	4.955	12.037	6.901	61.831
NM	8.533	7.585	8.294	6.857	7.590	43.681	10.021	7.440	56.319
OK	10.620	8.749	15.165	11.294	11.669	5.050	27.566	9.888	72.434
TX	10.458	8.459	11.231	7.963	7.945	5.114	12.986	35.843	64.157
Contribution TO others	67.393	58.376	81.477	63.004	66.103	35.100	85.566	54.620	511.639
Contribution including own	101.613	95.494	117.067	99.176	104.273	78.782	113.132	90.462	TCI
Net spillovers	1.613	-4.506	17.067	-0.824	4.273	-21.218	13.132	-9.538	63.955

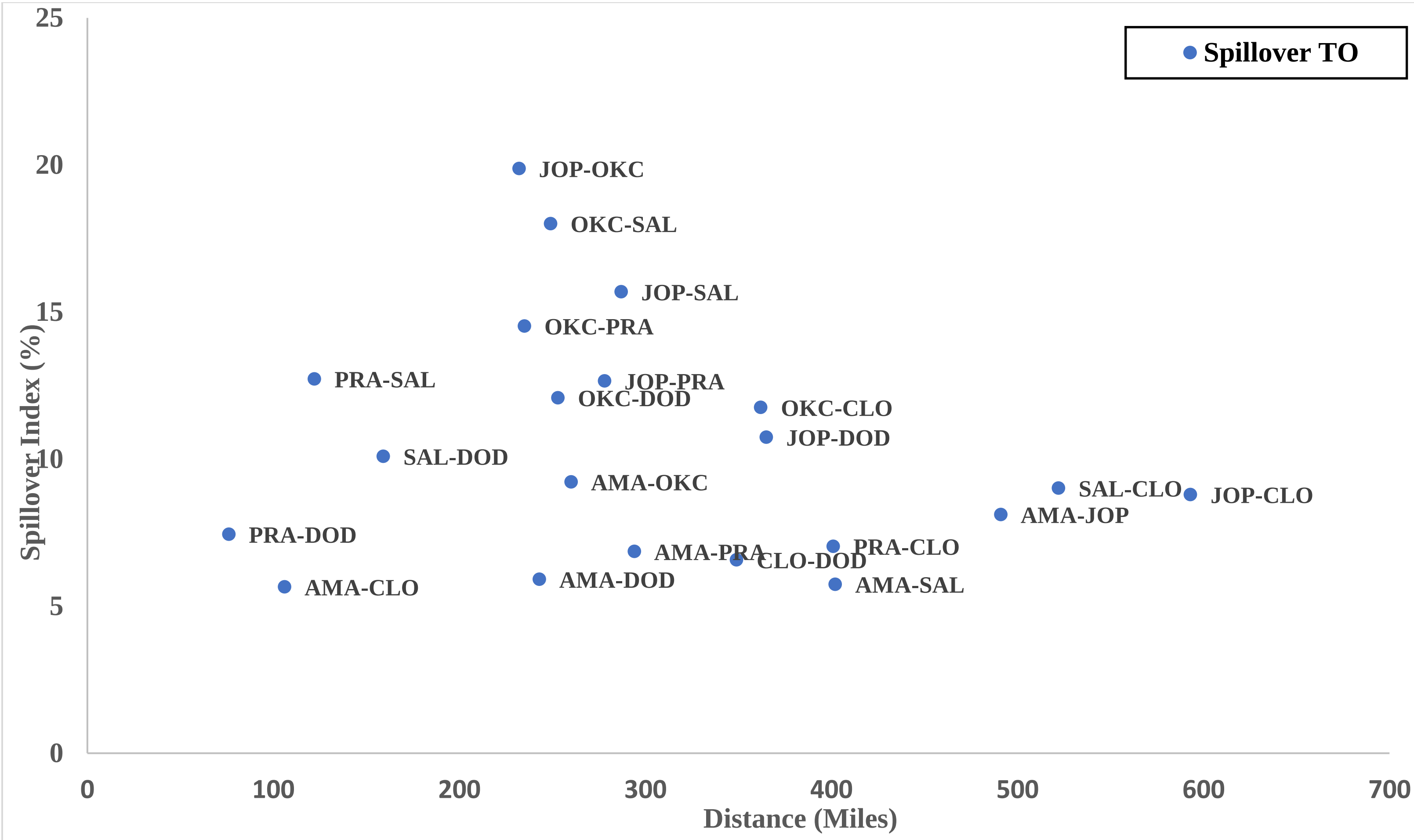

Figure 3.A1 Plot of spillover index by distance indicating where individual market pair stands. This is plotted using the "spillover TO" (e.g. JOP-OKC means that the spillover index of shock from Joplin to Oklahoma City).

Note: AMA – Amarillo; JOP -Joplin; OKC – Oklahoma City; PRA – Pratt; SAL – Salina; CLO- Clovis; DOD – Dodge City.

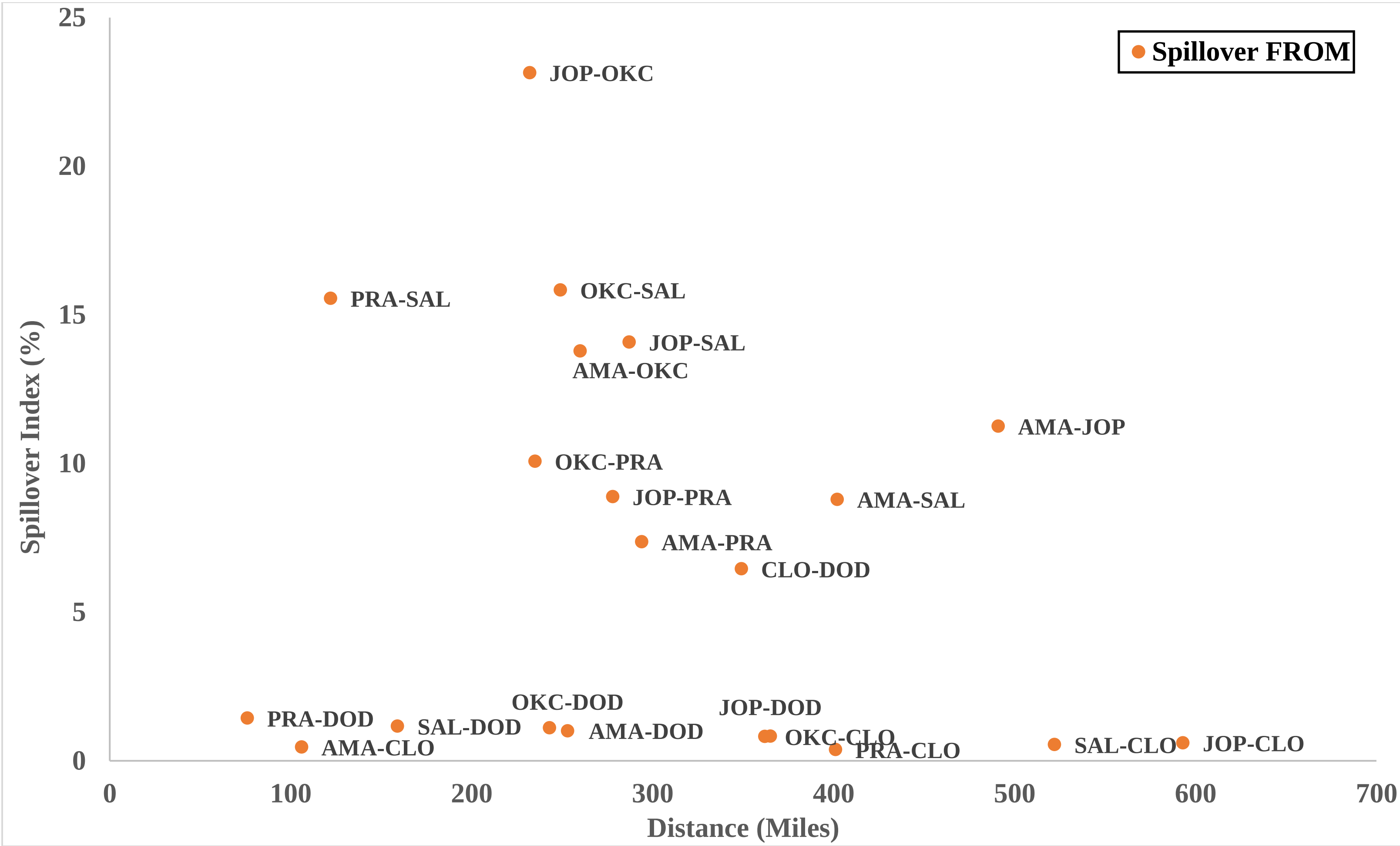

Figure 3.A2 Plot of Spillover Index by Distance (indicating where individual market pair stands). This is plotted using the "spillover FROM" (e.g. JOP-OKC means that the spillover index of shock from Oklahoma City by Joplin).

Note: AMA – Amarillo; JOP -Joplin; OKC – Oklahoma City; PRA – Pratt; SAL – Salina; CLO- Clovis; DOD – Dodge City.

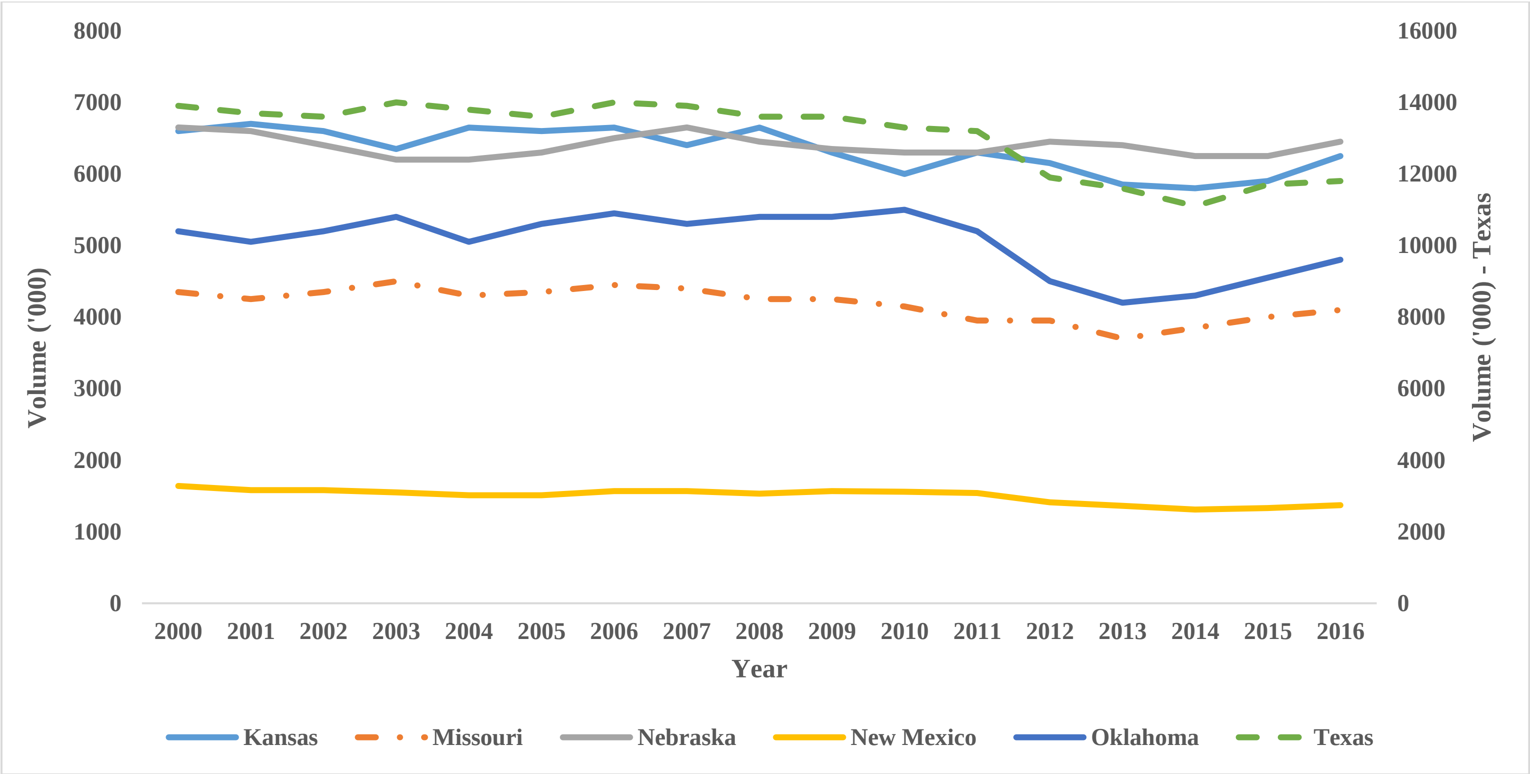

Figure 3.A3 All Cattle and Calves Inventory by year (in thousands).

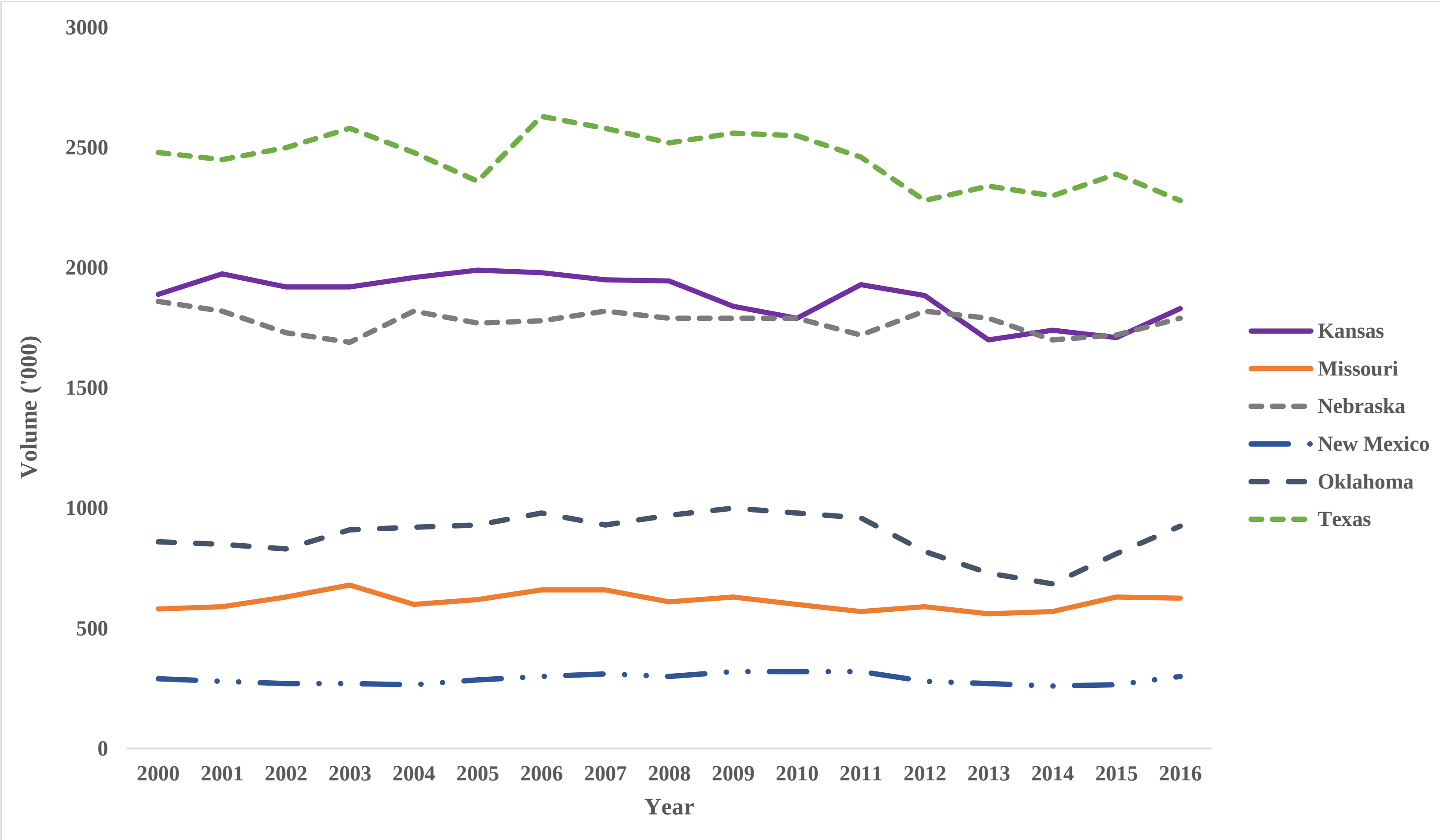

Figure 3.A4 All Heifer Inventory by Year (in thousands).

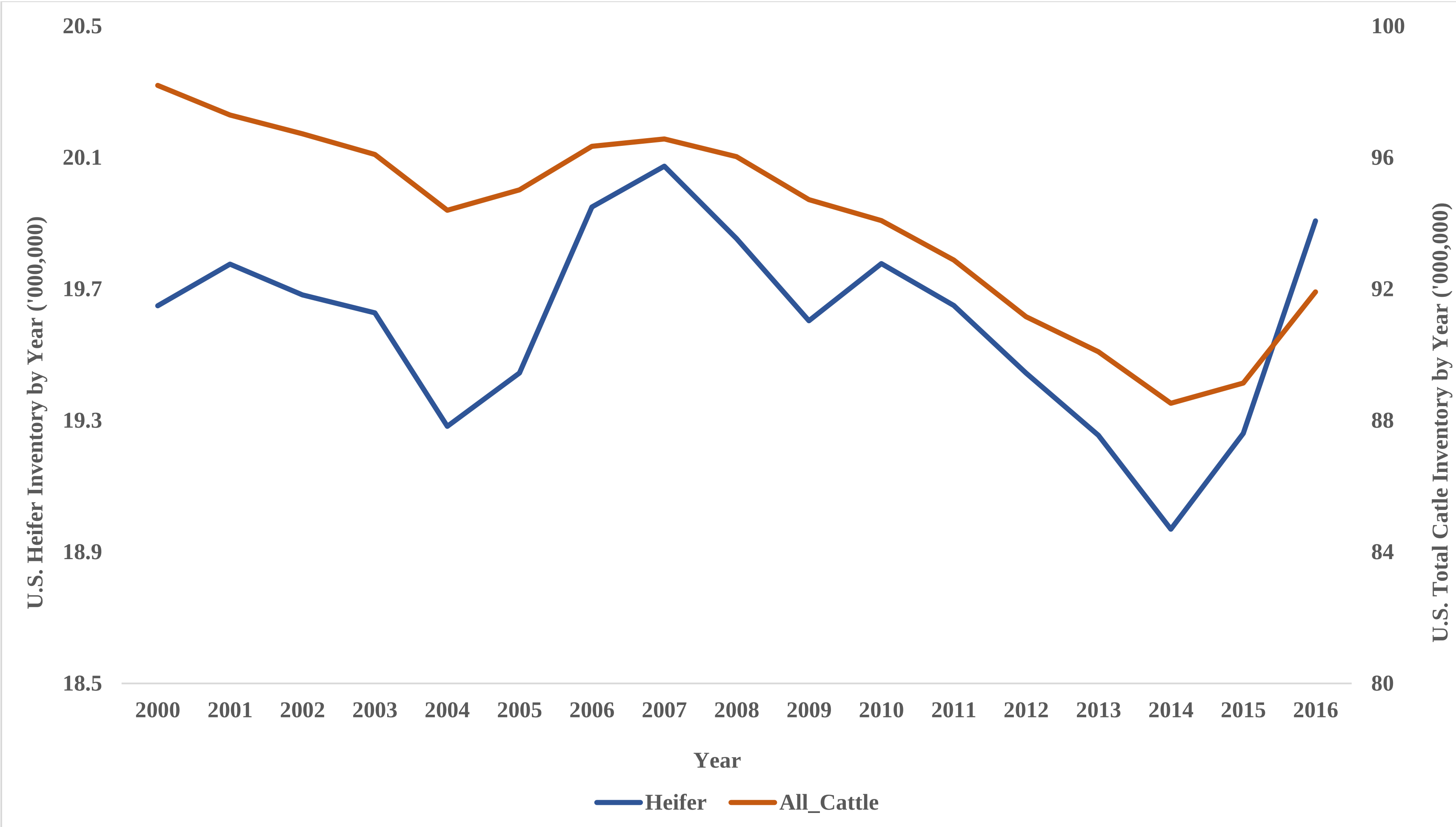

Figure 3.A5 U.S. Total Cattle and Heifer Inventory by Year (in millions).

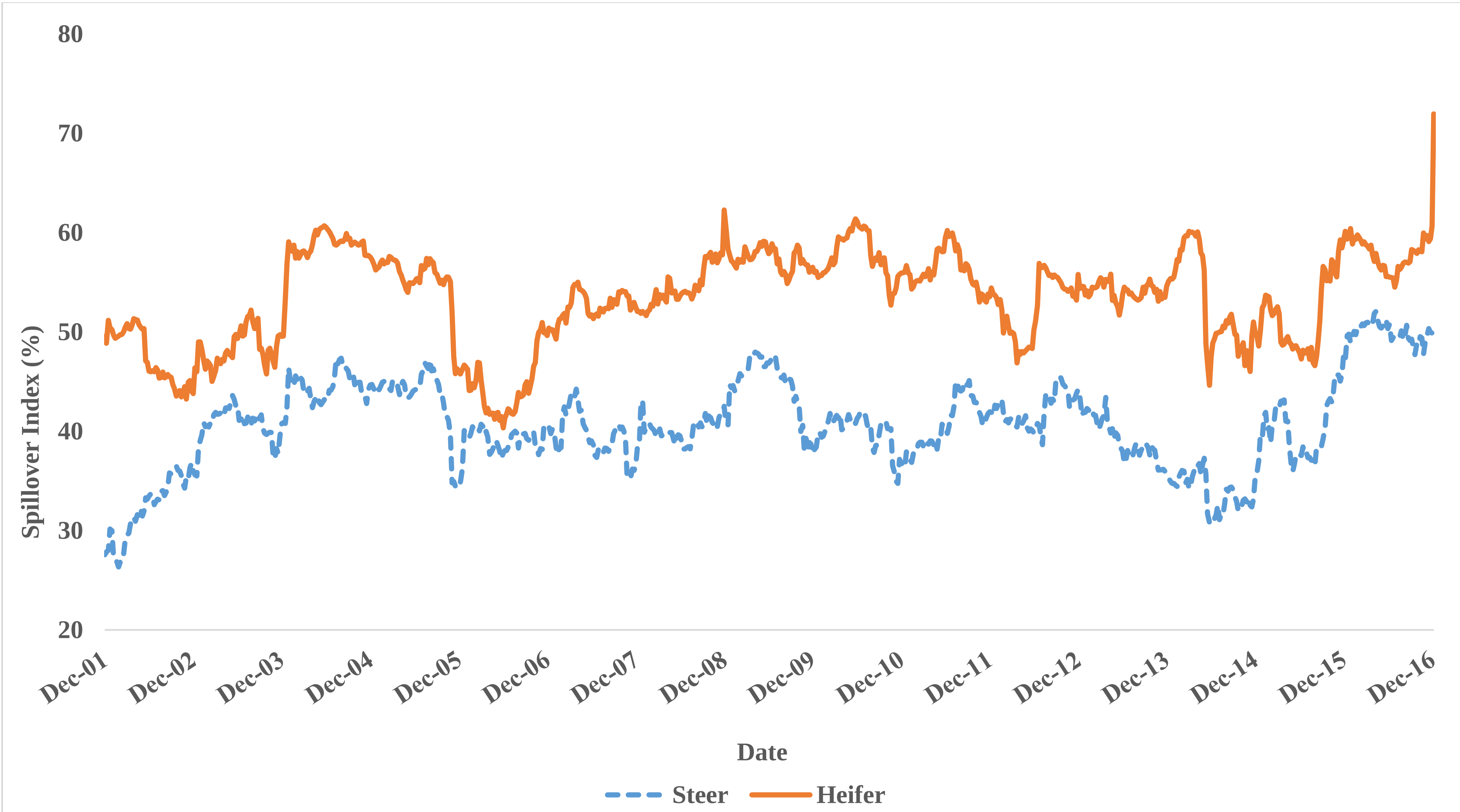

Figure 3.A6 Comparison of the Heifer's and Steer's Dynamic Total Connectedness with 100-week rolling window, 10-week-ahead Predictive Horizon for Variance Decomposition (Auction Level Prices).

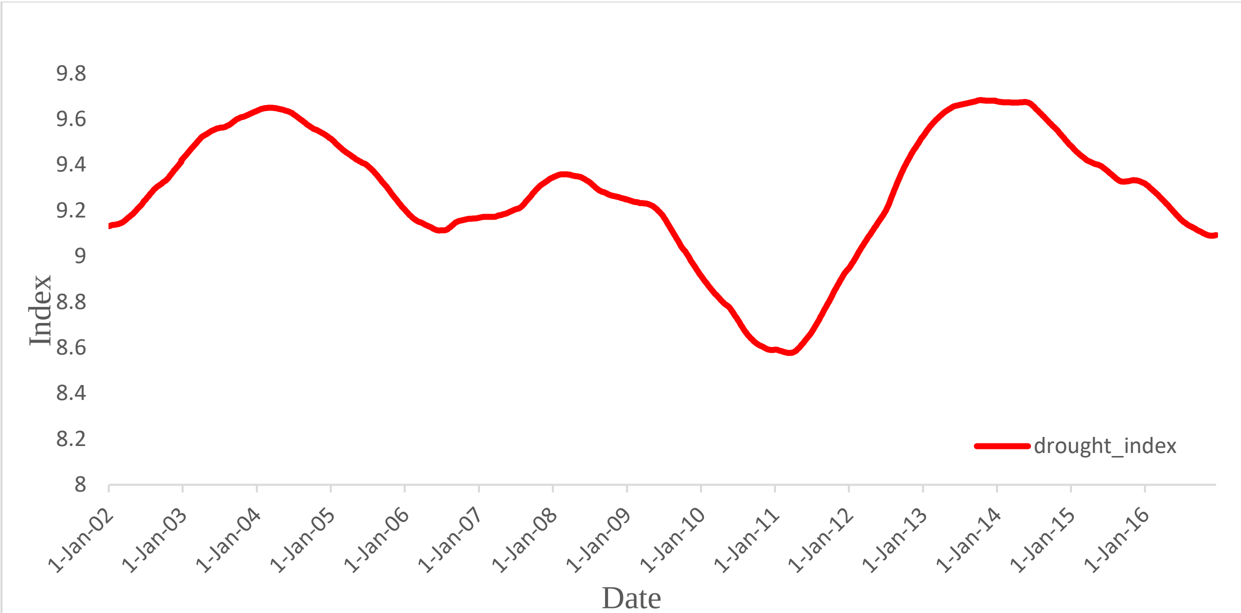

Figure 3.A7 Drought Index.

Chapter 4 - Does Energy Transmit Shocks to the Feeder Cattle Market? A Time-Varying Analysis

Elevated volatility in agricultural commodity markets has been prominent in industry and policy discussions in recent years. The Energy Policy Act of 2005 redefined the corn market and created a direct link between corn and energy markets. As a result, the prices of corn and gasoline are more strongly related than before the Act as the price of crude oil signals ethanol production (Du, Yu, and Hayes, 2011). Given the strengthened price relationships between corn and energy, other agricultural prices are affected because of spillover from corn markets. One of the markets that could have a direct link with the corn market is the feeder cattle market. Though the feeder cattle market does not solely rely on the corn market, shocks can be transmitted from the corn market to the feeder cattle market directly or indirectly through the live cattle market. Crude oil prices are highly volatile because of the complex and irregular nature of the crude oil market (Yu, Wang, and Lai, 2008). Thus, as crude oil and agricultural markets became more directly connected, volatility in agricultural market prices is likely elevated. The result is a greater need for price risk management instruments by grain and livestock producers and associated market participants and higher costs associated with managing increased price risk. This study is designed to test whether price volatility linkages across energy, grain, and cattle markets have changed over time as policies have affected the relationships among these markets.

Commodity prices more than tripled between 2006 and mid-2008, plummeted in late 2008, and sustained unusually high volatility over much of the past decade. We incorporate time-varying empirical methods in our investigation of the impact of the energy mandate on volatility in agricultural markets, most especially the feeder cattle market. Our objective of introducing time variation into the coefficients is to determine if the transmission of volatility shocks between the energy, grain and livestock markets is time-dependent. In accordance with our expectation, market volatility relationships have evolved over time.

Economists have provided explanations for the dramatic increase in agricultural market instability experienced since 2005, but there is no consensus quantifying causal factors. Fundamental drivers of increased market volatility include changes in biofuel policy, exchange rate movements, speculative price bubbles, increased globalization, income expansion in developing countries, European agricultural policy changes, and weather shocks (Wright 2011; Devlin, Woods, and Coates 2011; Gilbert and Morgan 2010; Irwin and Good 2009; Sumner 2009; Headey and Fan 2008; Sanders and Irwin, 2017). Changes in energy policy, including the Energy Policy Act of 2005, restructured the biofuels industry and had direct impacts on agricultural markets. Fluctuations in commodity market volatility alter risk exposure of agricultural producers, processors, and biofuel refineries and affect production, marketing, and investing decisions. Of considerable interest to participants throughout the food and fuel industries is how volatility in one market affects volatility in other markets. That is, understanding the magnitude of volatility spillover across commodities is essential for risk management and policy analysis.

In several studies, the focus has been to examine the relationship before and after the energy mandate. One important question; is the relationship constant over the selected periods? How do we capture the effect of other policies or unexpected circumstance on the relationship? For instance, we expect the energy mandate to link the crude oil and corn market but did other such, e.g., the food crisis, change the relationship? Does the instability in the Middle East contribute more to the changes in the linkage between the energy and the agricultural commodities? This motivates the introduction of time-variation into the parameters of our time series model. The time-variation shows not only the effect of the energy mandate on commodity markets but also allows for dynamics in the connection over time.

Determining the dynamics and lead-lag relationships of implied volatilities (IVs) among major agricultural commodity markets will provide useful information for producers, traders, market analysts, and policymakers. Producers and market analysts benefit from understanding volatility spillovers as they formulate risk management strategies. Traders and speculators can use this information to predict how immediate changes in implied volatilities in one market may affect future option premiums in another market. Similarly, policymakers should consider this information when proposing policies for one industry that could impact risk management in another industry. Additionally, this study will motivate further research as implied volatility spillover has not been widely explored in the livestock markets.

Implied volatility

Two basic methods of estimating market volatility include calculating the volatility implied by the market based on the other known factors in an option pricing model or calculating the variance of historical prices. Option pricing models enable calculating the market-determined expected commodity price risk by evaluating the present option premium (Black and Scholes, 1972). The option premium quantifies option buyer uncertainty based on their willingness to pay to defer price risk. The increasing availability of financial market data at intraday frequencies has led to improvement in the volatility measurements (Koopman et al., 2005). Implied volatility provides a measure of market participants' expectations regarding market uncertainty and directly determines premiums for risk mitigation by market participants. Standard option pricing formulas derived from Black and Scholes (1972); Cox, Ross, and Rubinstein (1979); and Boyle (1988) have been subjected to critique of assumptions underlying the various models. However, despite recognized limitations, these types of option pricing formulas are the most commonly used and referenced forms of forwarding-looking market-based implied volatility calculations. Because of industry demand, implied volatility derived from these types of formulas on futures option market commodities is made widely available through major information services such as CRB, Bloomberg, Reuters, and DTN ProphetX® as well as major commodity exchanges such as CME Group. Implied volatility spillover has received little attention in the literature relative to historical volatility and given its importance in commodity price insurance and general commodity market information, further analysis of IV spillover is warranted.

Earlier Research

Several studies have documented the nature of increased commodity prices and associated price variability, and a few studies have assessed price spillovers across agricultural commodities (Etienne *et. al*., 2016; Trujillo-Barrera *et. al.*, 2012; Saghaian 2010; Zhang *et. al.*, 2009; Muhammad and Kebede 2009). However, little has been done to determine how market variability translates across agricultural commodities. Most of the volatility spillover work that has been completed focuses on financial markets (e.g., Christiansen 2007; Baele 2005; Soytas and Sari 2003; Hong 2001; Ng 2000) or price relationships between energy markets and agricultural markets (e.g., Kang et. al., 2017; Cabrera and Schulz, 2016; Nicola et. al., 2016; Nazlioglu et. al., 2013; Mensi et. al., 2013; Ji and Fan, 2012; Du, Yu, and Hayes, 2011; Harri and Hudson, 2009; Saghaian, 2010; Zhang et al., 2009; Myers et al., 2014). Additionally, most studies have examined the spillover effects of historical variation in prices rather than implied volatilities. Generally, previous research has used Bollerslev's generalized autoregressive conditional heteroskedasticity (GARCH) or stochastic volatility (SV) methods to model historical volatility. Granger causality tests (Granger, 1969) are typically employed using vector autoregressive (VAR) models to analyze causal relationships between volatilities.

The use of causality tests to determine a relationship among two or more commodities has been well documented, but not much focus has been placed on variability in implied volatility transmissions between commodity markets. Akinfenwa and Qasmi (2014) revealed that ethanol production Granger-caused agricultural net value added, agriculture's share of U.S employment, net returns to operators, and rural income per capita in the short run. Saghaian (2010) found that correlation and causal relationships between the energy sector and commodity prices, but the causal link from oil to commodity prices was mixed. Sanders and Irwin (2011) examined whether index fund positions lead agricultural commodity futures market returns, implied volatility, and realized volatility. Using both time-series and cross-sectional correlation, Sanders and Irwin (2017) confirmed a contemporaneous correlation between changes in the US Commodity Futures Trading Commission (CFTC) *Supplemental Commitments of Traders* (SCOT) index positions and nearby futures returns, but they failed to find price behavior consistent with the Masters (2008)[19] Hypothesis.

Results of previous literature vary based on the period chosen to analyze and the method used to calculate volatility. To date, limited research has been published evaluating spillover in the energy and agricultural markets using implied volatilities from standard Black-Scholes models. There are also no known previous studies that have considered IV spillovers across energy, grain, and livestock commodities together. This study also contributes to literature with the introduction of time variation into the estimation of the relationship between energy and

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[19] Masters, M. W. (2008). Testimony of Michael W. Masters before the Committee on Homeland Security and Governmental Affairs United States Senate. *May 20th*. https://www.hsgac.senate.gov/download/062408masters

agricultural commodities. This study is the first to examine time variation in implied volatility spillover between energy and livestock markets.

Empirical Methodology

The econometric procedure in this study follows the path of previous studies examining causal relationships between time series (e.g., Ji and Chung, 2012; Trujillo-Barrera, Mallory, and Garcia 2012; Saghaian, 2010; Zhang et al., 2009; Harri and Hudson, 2009). The major contribution is the introduction of the time variation in our estimate. We apply a time-varying parameter vector autoregressive model (TVP-VAR) introduced by (Primiceri, 2005) to investigate the influence of the energy market on feeder cattle markets and other agricultural markets. Nakajima (2011) introduced TVP-VAR with stochastic volatility (SV). The TVP-VAR-SV model is estimated using the Monte chain Monte Carlo (MCMC) method in the context of Bayesian inference. The influence of IV of one commodity on that of another commodity can easily be compared over time. The TVP-VAR model enables us to account for possible variation in the IV relationships across time. Our objective here is to examine the dynamic relationship between the energy IVs, grain IVs, and the livestock IVs before and after the 2005 energy mandate. Despite that structural break plays a vital role in the introduction of the time-varying impulse response function, applying TVP-VAR will also enable us to observe changes in the relative degree of impact of one commodity on another, over time. The identification of a structural break in corn IV led us to further examine differences in the relationship during the pre- and post-ethanol mandate.

Specifying the TVP-VAR model in a multivariate form and following the approach by Primiceri (2005) and Nakajima (2011) can be summarized as;

$$y_t = c_t + \beta_{1,t} y_{t-1} + \ldots + \beta_{k,t} y_{t-k} + A_t^{-1} \textstyle\sum_t \varepsilon_t \qquad \text{Eq (1)}$$

Equation (1) above can easily be represented as

$$y_t = X_t\beta_t + A_t^{-1}\textstyle\sum_t \varepsilon_t \qquad \text{where } t = s+1,\dots,n. \qquad Eq(2)$$

where the coefficients β_t and the parameters A_t and $\sum_t$ are all time varying. A_t is a lower triangular matrix of elements represented as $\alpha_{i,j,t}$ $(i = 2,\dots n,\ and\ j = 1,\dots,n-1)$, while $\sigma_{i,j,t}$ $(i = 2,\dots n,\ and\ j = 1,\dots,n-1)$ are the elements of the diagonal matrix $\sum_{t,}$ with $h_{it} = \log\sigma_{it}^2$ $(structural\ shocks)$, and $V(\varepsilon_t) = I_n$. Following Primiceri (2005), the parameters in the time-varying equation follows a random walk process as specified:

$$\beta_{t+1} = \beta_t + v_t \qquad Eq(3)$$

$$\alpha_{t+1} = \alpha_t + u_t \qquad Eq(2)$$

$$h_{t+1} = h_t + \eta_t \qquad Eq(3)$$

.where,

$$\begin{pmatrix}\varepsilon_t\\ v_t\\ u_t\\ \eta_t\end{pmatrix} \sim N\left(0, \begin{pmatrix} I_n & 0 & 0 & 0\\ 0 & \sum_\beta & 0 & 0\\ 0 & 0 & \sum_\alpha & 0\\ 0 & 0 & 0 & \sum_h \end{pmatrix}\right) \qquad Eq(4)$$

for $t = s+1,\dots,n$, where $\sum_\beta, \sum_\alpha, and\ \sum_h$ are block diagonal matrices. The parameters are distributed as $\beta_{s+1}\sim N(v_0, \sum_{\beta 0})$, $\alpha_{s+1}\sim N(u_0, \sum_{\alpha 0})$ and $h_{s+1}\sim N(\eta_0, \sum_{h0})$. As summarized by Prieto et. al. (2016), the system of equations in our TVP-VAR model contains four sources of uncertainty: the structural shocks (ε_t), the innovations to the time-varying parameters $\beta_t(v_t)$, the contemporaneous relations (u_t), and the stochastic volatilities (η_t). The model is estimated using Markov chain Monte Carlo (MCMC) algorithm. See Nakajima (2011) for the details of the MCMC algorithms.

In TVP-VAR model, there are many parameters to estimate, reducing the number of parameters increases the efficiency of the model. We followed the estimation procedure developed by Nakajima (2011) in estimating the market relationships. Optimal lag selection is an integral part of time series data analysis as it reduces chances of obtaining spurious causal relationships (Akinfenwa and Qasmi, 2014). We used the average lag lengths from the trio of Akaike information criterion[20] (AIC), Schwarz Bayesian information criterion (SBIC), and the Hannan and Quinn information criterion (HQIC) lag-order selection statistics. In most cases, the selection criteria gave common optimal lags.

Time-varying generalized impulse response functions (GIRFs) were constructed using the estimates from the TVP-VAR model. The GIRFs help us to determine the average magnitude and persistence of shocks to implied volatility for the different commodities. Multiple structural shocks were detected in most of the commodities' IVs. Impulse responses are constructed over 1-, 6-, and 12-week periods at different dates using orthogonal shocks. These three periods were selected to check short-term impact (one week), the impact after six weeks (medium range), and a longer-term impact (12 weeks). The impulse response functions examine the deviation in the usual trend for IV of the commodities due to a one-standard deviation shock to itself or another commodity's IV. In ordering the variables for estimation, assumptions are made on the effect of one variable on another. in all the estimations, crude oil is placed first because we believe that shock to crude oil will affect all both the grain IVs and livestock IVs.

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[20] L$\ddot{u}$tkepohl information criteria versions are:

$$AIC = \ln(\textstyle\sum_u |) + \frac{2pK^2}{T}, SBIC = \ln(\textstyle\sum_u |) + \frac{\ln(T)}{T} pK^2, \; HQIC = \ln(\textstyle\sum_u |) + \frac{2\ln\{\ln(T)\}}{T} pK^2$$

Where T is the number of observations, K is the number of equations, p is the VAR order, and Σ_u is the maximum likehood. For details, see L$\ddot{u}$tkepohl (2005).

Data

The data used in this study were obtained from Bloomberg Professional service data terminals. Daily implied volatilities for corn, soybeans, live cattle, feeder cattle from the CME Group, and light sweet crude oil and natural gas from the New York Mercantile Exchange (NYMEX) were collected over January 3, 1995, through December 31, 2015 period. Option implied volatilities were calculated using the implied trinomial method for American options (Boyle, 1988). The IV is a weighted average of the implied volatilities of the two put or call options closest to the at-the-money strike.

Weekly averages of the daily IVs were used for analysis in this study. For each commodity, the implied volatility analyzed was that associated with the futures contract expiring in four or five months depending on the contract months traded for each commodity.[21] We selected the 4-5 month deferred contracts so the IV would be forward several months into the future reflecting future expected risk, but not too distant into the future to have contracts represented with thin trading volume.

The markets selected were major U.S. agricultural markets that are related in that one is a standard input for another (e.g., corn and cattle) or they are substitutes in production (e.g., corn and soybeans). We would have preferred to include the ethanol market as well. However, ethanol futures contracts were not traded until 2005, and due to low trade volume, prices and IVs for this contract are not consistently reported.

Prior to analyzing our models, a unit root test was performed to determine if the individual implied volatility series were stationary. When nonstationary was found, the data

[21] In the event that the commodity had a contract expiring in four months and a contract expiring in five months, the contract expiring in four months was used. In only a few instances, there were no contracts expiring in four or five months, and in these cases the contract expiring in six months was used.

series were first-differenced to create stationary series. An augmented Dickey-Fuller (ADF) test was conducted to test for stationarity. In addition to the Dickey-Fuller test, we also conducted the Phillips-Perron test. Four lagged differences were included in the estimation in Dickey-Fuller as suggested by the lag length selection tests. Phillips–Perron tests used the Newey-West lags with suggested default of $int\left\{4\left(\frac{N}{100}\right)^{\frac{2}{9}}\right\}$, where N is the number of observations (Myers et al., 2014).

Across the aggregate period, there were 1022 total weekly average observations (one observation per week over the 20 years). Subsets of the aggregate data were analyzed in the pre-ethanol boom and post-ethanol boom eras (the division supported by the presence of an identified structural break[22]) to enable us to see the difference between using a time-varying VAR approach compared to the constant VAR approach. Descriptive statistics are presented in table 1. Over time, the live cattle and feeder cattle markets have had the smallest IVs averaging less than 15%. In contrast, energy markets have been the most volatile with IV in crude oil often exceeding 30% and natural gas frequently surpassing 45%.

In comparing the pre-ethanol boom and post-ethanol boom periods corn, soybeans, wheat, and cotton all exhibit average IVs increasing by more than 25% with corn realizing the most substantial increase of 35%, rising from 23% to 31%. Most of the commodity prices, except for natural gas, began trending upward as well in the mid-2000s.

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[22] The structural break test was performed using the cumulative sum test for parameter stability (supremum Wald test) in StataCorp (2015). We detected a structural break in corn IV on first week of March, 2006. Likewise, we detected structural break on wheat IV in February 2006. With these two detected break, we were able to divide our estimation into pre- and post-ethanol mandate, using 2006 as the break point. https://www.stata.com/manuals/tsestatsbsingle.pdf

Results

Plots of the implied volatilities are informative in themselves. Figures 4.1-4.3 illustrate patterns of implied volatilities over the 1995-2015 period. For better illustration, the commodities are presented in groups; livestock (feeder cattle and live cattle) in Figure 4.1, grains (corn and soybean) in Figure 4.2, and energy (crude oil and natural gas) in Figure 4.3. The live cattle and feeder cattle futures implied volatility spiked during specific events (Figure 4.1). For example, the discovery of the bovine spongiform encephalopathy (BSE) infected cow in December 2003 was associated with an extreme increase in volatility reaching upwards of 40% for both feeder cattle and live cattle. More generally, feeder cattle IV hovers around 10 to 20%. Corn IV and soybean IV have experienced notable changes over time (Figure 4.2). Evident is the increased volatility during 2006-2009. Crude oil IV (Figure 4.3) has the largest variation over time of the commodities analyzed.

Contemporaneous correlations of the IVs across all six markets for the overall time, pre- and post-ethanol boom periods are presented in Table 4.2. Nearly all the IV series for the agricultural commodities are positively correlated in both the pre-ethanol boom and post-ethanol boom periods. Across the study periods, the strongest volatility correlations occur between the live cattle and feeder cattle markets with correlations exceeding 0.80 in both pre-ethanol boom and post-ethanol boom periods. Corn and soybeans IVs are also highly correlated at generally greater than 0.70 during the 1995-2005 period. Correlations between crude oil market and grain market IVs transformed from near zero during the pre-ethanol boom to strongly positive during the post-ethanol boom. Following enactment of the Energy Policy Act of 2005, correlations of crude oil IV strengthened noticeably with corn, soybeans, live cattle, and feeder cattle implied volatilities.

Unit root tests (Table 4.3) indicate that all the IV series are stationary at the 90 percent confidence level over the 1995 to 2015 aggregate time and during the pre-ethanol boom period (1995-2005). As expected, based on upward trends in prices and IVs that began in the mid-2000s, some of the volatility series were nonstationary in the 2006 to 2015 period. The ADF statistics showed that the IV series in the later period were stationary after the first-differencing.

Stochastic volatility?

We confirm time variation in the relationship between the energy and the agricultural commodities' IVs. We start by first presenting the time-varying standard deviation of the orthogonalized commodity shocks in selected commodities. Figure 4.4 shows the posterior means and the 16th and 84th quantile intervals of the standard deviation of the estimates of the stochastic volatility ($\sigma_t^2 = \exp(h_t)$) for crude, corn, and soybean and feeder cattle IVs. The posterior means and one standard deviation percentile of the estimated time-varying standard deviations of innovations in each of the variables are the blue and orange dotted lines respectively. The purpose of the plot is to confirm if the existence of time variation in the relationship between the commodities is due to the transmission of shock from the energy IV to the agricultural IVs or only due to the changes in the size of the energy IV shocks. It is obvious that each commodity IV posts several shocks across the study period. The most significant structural shock in the crude oil IV is between 2007 and 2009. Crude oil IV is also upward trending at the end of the study period. Both corn and soybean IVs have undergone many structural shocks during the study period. Feeder cattle IV had the least shocks.

The time-varying relationship

Using a three variable TVP-VAR model, we investigate the time-varying structure of the relationship between the energy and the agricultural commodities IVs. The time-varying volatility helps in the VAR estimation by identifying the structural shocks with the appropriate variance in the shock size (Nakijima et. al., 2011). With high degree of variability across the commodity IVs, standard VAR model is not likely to fit well with the dataset because standard VAR assumes shocks are homoscedastic across the study period. Figures 4.5-4.10 display intertemporal generalized impulse response functions among the commodities over 12-week horizons and for each moment in the sample period (1995 to 2015). The z axis of each plot represents the degree of the impulse responses, in percentages. Figures 4.11-4.16 show the time varying impulse response function over the study period using three selected shock horizons; 1-week, 6-week, and the 12-week horizons. The shock horizons are selected to reveal the immediate impact (a week) and impact after several weeks of a shock to the market.

We have several sets of combinations of the commodities in our analyses, but those presented here broadly illustrate the relationships between feeder cattle IVs and the rest of the commodities. Unlike the time-invariant VAR, the impulse responses are computed using the estimated time-varying parameters. Starting from Figure 4.4, the plot illustrates feeder cattle IV response to a shock from crude oil IV across horizons and sample period. Across the sample period, the response of feeder cattle IV to crude oil IV shock is not persistent. Using the 12-week horizon, the shock of crude IV contributes to the decrease (1998 to 2002) and subsequently increase in the feeder cattle IV afterward. As mentioned earlier, the discovery of the BSE had an impact on the cattle industry, which translated to the changes in the relationship between the two markets. The relationship between the natural gas IV and the feeder cattle market has been consistent over time until after 2007. There is a similar trend between crude and feeder cattle relationship (Figure 4.5), and corn and feeder cattle relationship (Figure 4.7). This is an evidence that energy shocks are transmitted to the feeder cattle market through the corn market. Corn is essential in the cattle feeding industry, and we expect crude oil shock to the corn to spillover to the cattle market. Because of this, there should be a spillover from corn to the cattle market.

We also examine the impact of shocks from both crude IV and corn IV on feeder cattle IV. The relationship was downward sloping at the beginning of the sample period until 2001 where there is trajectory upward shift in the relationship between corn and feeder cattle. Looking at the relationship from the energy perspective, there has been a lot of policies or disaster shocks to the energy market. We should note that the Iraq war caused a significant shift in the world energy supply that led to an increase in energy prices in the United States. The increase in crude price volatility due to the war likely led to a change in the relationship between the agricultural and the energy markets. The relationship between crude oil IV and corn IV is becoming more negative (positive for feeder cattle IV) before 2005, but the introduction of the Energy Policy Act of 2005 likely caused the change in the relationship. Figure 5 shows that there is a continuous upward shift in the relationship after 2005. There is a noticeable structural change in the plot after 2007. The region on the plot shaded red or deep blue is the region with the highest response to shock. The most substantial cumulative effect of crude oil of feeder IV is slightly above 0.4% around 2013. We can ascertain the relation between crude IV and feeder IV has been varying, which means that the impact of the energy mandate only affected the relationship for a few years.

The most significant changes in soybean IV and feeder cattle IV relationship occurred between 1999 and 2001 (Figure 4.8). Though the shock transmission from the soybean market to the feeder cattle market has been relatively low, it has been consistent with the price path of soybeans. There is similarity between the time-varying shock transmission from the soybean market to the feeder cattle market and historical soybean prices (Figure 4.14 & Figure 4.A1). Soybean also plays an important role in the cattle feeding industry through soybean meal.

One surprising relationship here is that feeder cattle and live cattle IVs reacts differently to the crude oil IV. Figure 4.10 shows an evidence of time-variation in the relationship between crude IV and live cattle IV. This relationship is elaborated in Figure 4.16. Live cattle IV has not been responsive to crude IV shocks for most of our sample period. The two significant shifts in the relationship occurred between 1997 and 1999, and 2012 to 2014. Examining the relationship between feeder cattle and live cattle, the relationship between both has been stable most of the sample period. The shock response of feeder cattle IV to cattle IV has been relatively stable between 0.1 and 0.3, except between 1999 and 2001. The BSE crisis started around the late 1990s in Europe (Wood, 2005), which contributed to increased uncertainty in the cattle industry. The outbreak of BSE in Europe led to increase in demand for U.S. cattle which eventually translates to the feeder cattle market. The cattle IV response to a shock in the feeder cattle market follows a similar path (Figure 4.A2). It shows that both markets transfer shocks to each other, and they are tied together. Shock to one market will have an impact on the other market.

With the detection of structural break in the relationship between the crude IV and corn IV during the period of the enactment of energy policy act, we follow the concepts of Gali and Gambert (2009) and Prieto et. al., (2016) to plot the average impulse response function over the selected period using a constant VAR model (Figure 4.17- 4.21). The plots compare the average impulse response before and after the 2005 energy mandate. The objective is to examine the potential asymmetries in the transmission of energy shocks to the selected three agricultural commodities' IVs. The plots also emphasize the importance of introducing time variation in the spillover analysis of shocks between commodities. All plots show a difference in the feeder cattle shock response to the selected commodities before and after the energy mandate. Comparing the constant VAR and the TVP-VAR plots, we see variation in the response of these agricultural commodities IVs can only be revealed with introduction of time variation into our VAR coefficients. The constant coefficient VAR can only show the short-term impact of a change in one commodity to another.

Our focus here is to examine the changes to the relationship between the crude oil market and the feeder cattle market after the energy mandate. Results reveal the energy mandate had only marginal impact on the feeder cattle market. The relationship between feeder cattle and crude oil has been varying over the years. Between corn and crude oil (Figures 4.A3 & 4.A4), several years after the mandate, the market readjusted, and crude and corn became less connected. Probably the energy mandate impact of crude on gasoline was transmitted to feeder cattle market through the corn market.

Our study confirms that there is variation in the relationships between the energy and the agricultural markets, especially between the crude oil and the feeder cattle IVs. We detected a structural change in the relationship around the beginning of the implementation of the energy mandate. There is a reduction in the spillover effect of the energy market to the commodity market a few years after the ethanol mandate but more correlation relationship. This result is different from other studies because most studies have focused on only prices or historical volatility. For instance, Ji and Fan (2012) study examined the relationship between energy and crop commodity after the ethanol mandate, and their result showed that there is no Granger causality relationship between energy (crude oil) market and crop market. In the post-ethanol boom era, crude oil and corn IVs were highly correlated and natural gas volatility led to corn volatility.

Significant correlation and causal relationships exist between energy and agricultural markets. The Energy Policy Act of 2005 was likely a driver of this fundamental change in the markets that occurred around 2005. The policy resulted in increased correlation among the commodity IVs but reduced causal relationships across some commodities. Not to misinterpret the high correlation after the energy policy, the food price crisis during the 2006-2008 period is said to trigger the high correlation between the oil and agricultural commodities (Nazlioglu et al., 2013). An unanswered question here is; what impact did the energy mandate had on the 2006-2008 food crisis?

Although our study is among the few to introduce time-variation into the relationship between energy and the agricultural commodities' IVs, our results are supported by many past findings with constant coefficients. Focusing on the impact of the energy mandate on the relationship between crude oil and corn few years after the mandate, Hertel and Beckman (2011) found that the relationship between crude oil and corn strengthened after the passage of the Energy Policy Act of 2005. Similarly, Du, Yu, and Hayes (2011) found that in the first period of their study (November 1998 to October 2006), crude oil and the agricultural commodities had a negative correlation and little spillover (our results also identified a downward relationship between crude and corn before the energy mandate). However, in the second period (October 2006 to January 2009) there was high correlation and positive spillover coefficients between variability in crude oil and corn and variability in crude oil and wheat.

For robustness check, we analyzed the constant parameter VAR (C-VAR) models and tested for Granger Causalities between the commodities' pairs. We compare the shock distribution from our TVP-VAR model with those of C-VAR. We divided the estimation of the C-VAR into three categories; the entire sample period, pre-ethanol mandate period, and post-ethanol mandate period. The C-VAR models supported more connection between the energy and some grain markets (specifically corn and soybean) after the energy mandate than before the mandate. This relationship was confirmed by Wu, Guan, and Myers (2011). Their study confirmed that after the introduction of the Energy Policy Act of 2005, the connection between crude oil and corn markets strengthened and volatility spillover was present from crude oil to corn. One significant difference of our study from Wu, Guan, and Myers (2011) is that our TVP-VAR model reveals that the connection between the crude and corn markets did not last long, only on a short period.

Conclusion

Sources of risk and translation of volatility across commodity markets have been an issue of intense interest. Because the Energy Policy Act of 2005 redefined the corn market and created a direct link between corn and energy markets, recent literature has focused on the relationship between those markets. It is of great importance not to classify the relationship between the energy and agricultural commodities not in a constant measure before and after the energy mandate. In this study, we applied a time-varying VAR model to provide empirical evidence on the time-varying relationship between the energy markets and the agricultural markets (specifically the feeder cattle). We were able to capture the dynamics in the relationship between the energy markets and the feeder cattle markets over the study period.

This research contributes to existing literature by addressing the previously unexplored dynamics in implied volatility spillover across the energy, grain, and livestock markets. Presenting the time variation in the commodities relationship is economically important because it provides an accurate measure of the risk variation in the markets. By using implied volatility, this analysis considers IV derived from market-determined price insurance premiums rather than historical variance typically evaluated.

Despite the increase in the correlation between the grain and the livestock markets from the pre-ethanol to the post-ethanol period, there was less causal relationships. Furthermore, with increased volatility, the variability within each commodity appeared to become more independent or less linked to the other commodities. This suggests there are less linkage and spillover during the more volatile market period of late compared to more stable markets during 1995-2005 time-frame.

The relationships between crude and feeder cattle IVs, feeder cattle and soybean IVs, and corn and feeder cattle IVs, have been time dependent. The variation in impulse response from one commodity to another over time, especially between crude oil IV and feeder cattle IV, emphasizes the importance of allowing for time variation in the coefficients indicating the relationships between the commodities. The use of regular VAR such to test causality can be sensitive to omitted variables, misspecification errors, time-varying effects, and functional form assumptions (Grosche, 2014). Time variation in our analysis makes a significant contribution to the literature by revealing the degree of connectedness between the energy, grain and the feeder cattle markets over time.

A few general implications may be established from the results of this study: Since increases in implied volatility cause options prices to rise, uncertainty in some markets may affect options prices in other markets. Producers and market analysts should be aware of volatility spillover as they form risk management decisions. Implied volatility spillover also has implications for basis risk since increased fluctuations in the futures markets can cause more basis variability. The market stakeholder should not worry about the link created by the 2005 energy mandate between crude oil and the feeder cattle volatilities because the linkage only lasted for short period.

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Table 4.1 Descriptive Statistics for Weekly Implied Volatilities, 1995-2012.

	Units	Mean	Std. Dev.	Min	Max
1995-2015, Obs.=1022					
Corn	%	26.65	7.71	6.98	53.44
Soybeans	%	24.29	7.38	2.43	54.39
Live Cattle	%	14.89	3.78	7.12	34.83
Feeder Cattle	%	13.63	3.74	4.57	32.84
Crude Oil	%	34.87	11.34	12.91	94.76
Natural Gas	%	50.22	14.85	26.02	130.8
Pre-Ethanol Boom, 1995-2005, Obs.=535					
Corn	%	23.03	5.92	11.75	42.09
Soybeans	%	23.04	6.44	10.69	48.31
Live Cattle	%	14.94	4.01	9.19	34.83
Feeder Cattle	%	12.89	3.58	4.57	32.84
Crude Oil	%	34.94	8.28	14.25	66.25
Natural Gas	%	52.46	15.06	28.69	130.8
Post-Ethanol Boom, 2006-2015, Obs.=487					
Corn	%	30.62	7.49	6.98	53.44
Soybeans	%	25.65	8.07	2.43	54.39
Live Cattle	%	14.84	3.51	7.12	26.7
Feeder Cattle	%	14.44	3.75	7.41	27.64
Crude Oil	%	34.80	13.96	12.91	94.76
Natural Gas	%	47.76	14.23	26.02	102.53

Table 4.2 Correlations of Weekly Implied Volatilities.

	Corn	Soybeans	Live Cattle	Feeder Cattle	Crude Oil	Natural Gas
1995-2015						
Corn	1	-	-	-	-	-
Soybeans	0.764	1	-	-	-	-
Live Cattle	0.277	0.319	1	-	-	-
Feeder Cattle	0.361	0.322	0.802	1	-	-
Crude Oil	0.225	0.281	0.421	0.393	1	-
Natural Gas	-0.154	-0.033	0.146	-0.026	0.356	1
Pre-Ethanol Boom, 1995-2005						
Corn	1	-	-	-	-	-
Soybeans	0.770	1	-	-	-	-
Live Cattle	0.182	0.236	1	-	-	-
Feeder Cattle	0.254	0.245	0.818	1	-	-
Crude Oil	-0.118	-0.096	0.056	-0.066	1	-
Natural Gas	-0.403	-0.363	-0.038	-0.169	0.378	1
Post-Ethanol Boom, 2006-2015						
Corn	1	-	-	-	-	-
Soybeans	0.805	1	-	-	-	-
Live Cattle	0.477	0.428	1	-	-	-
Feeder Cattle	0.348	0.341	0.834	1	-	-
Crude Oil	0.461	0.490	0.733	0.712	1	-
Natural Gas	0.197	0.326	0.393	0.202	0.372	1

Table 4.3 Unit root test.

Commodity	Test	1995-2015 Statistics	1995-2015 P-value	1995-2005 Statistics	1995-2005 P-value	2006-2015 Statistics	2006-2015 P-value
Feeder Cattle	ADF	-5.411	0.000	-4.110	0.001	-3.709	0.004
	PP	-6.706	0.000	-5.083	0.000	-4.655	0.000
Corn	ADF	-4.860	0.000	-5.038	0.000	-3.121	0.025
	PP	-5.464	0.000	-5.317	0.000	-3.910	0.002
Natural Gas	ADF	-5.147	0.000	-4.320	0.001	-3.095	0.027
	PP	-6.453	0.000	-5.162	0.000	-3.948	0.002
Live Cattle	ADF	-4.964	0.000	-3.811	0.003	-3.126	0.025
	PP	-6.055	0.000	-4.848	0.000	-3.449	0.009
Crude Oil	ADF	-4.075	0.001	-3.931	0.002	-2.381	0.147
	PP	-4.507	0.000	-4.306	0.000	-2.704	0.073
Soybean	ADF	-4.840	0.000	-4.618	0.000	-2.436	0.132
	PP	-5.718	0.000	-5.205	0.000	-3.151	0.023

ADF - Augmented Dickey-Fuller test
PP - Phillips–Perron test

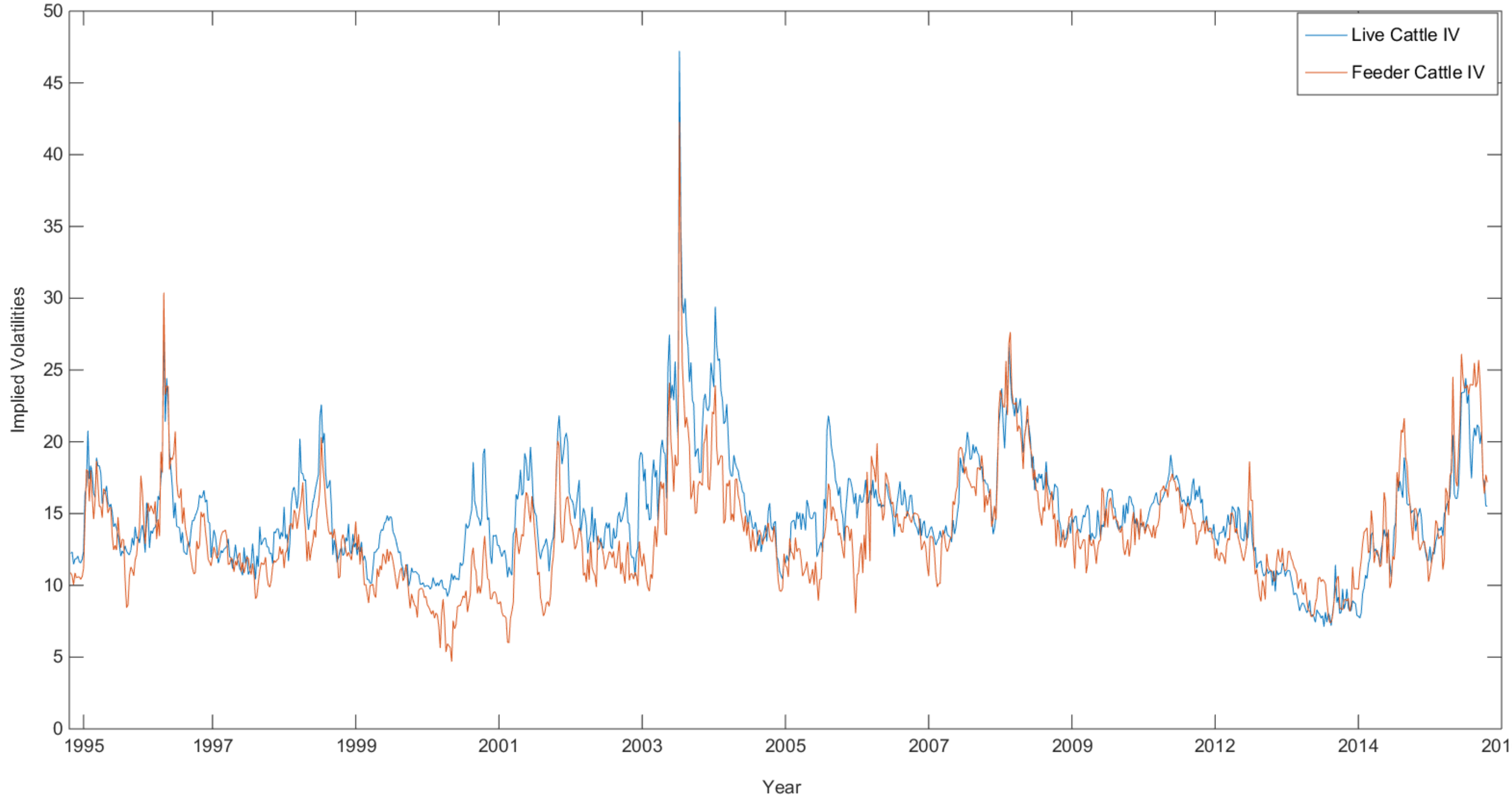

Figure 4.1 Weekly Implied Volatilities for Live cattle and Feeder Cattle.

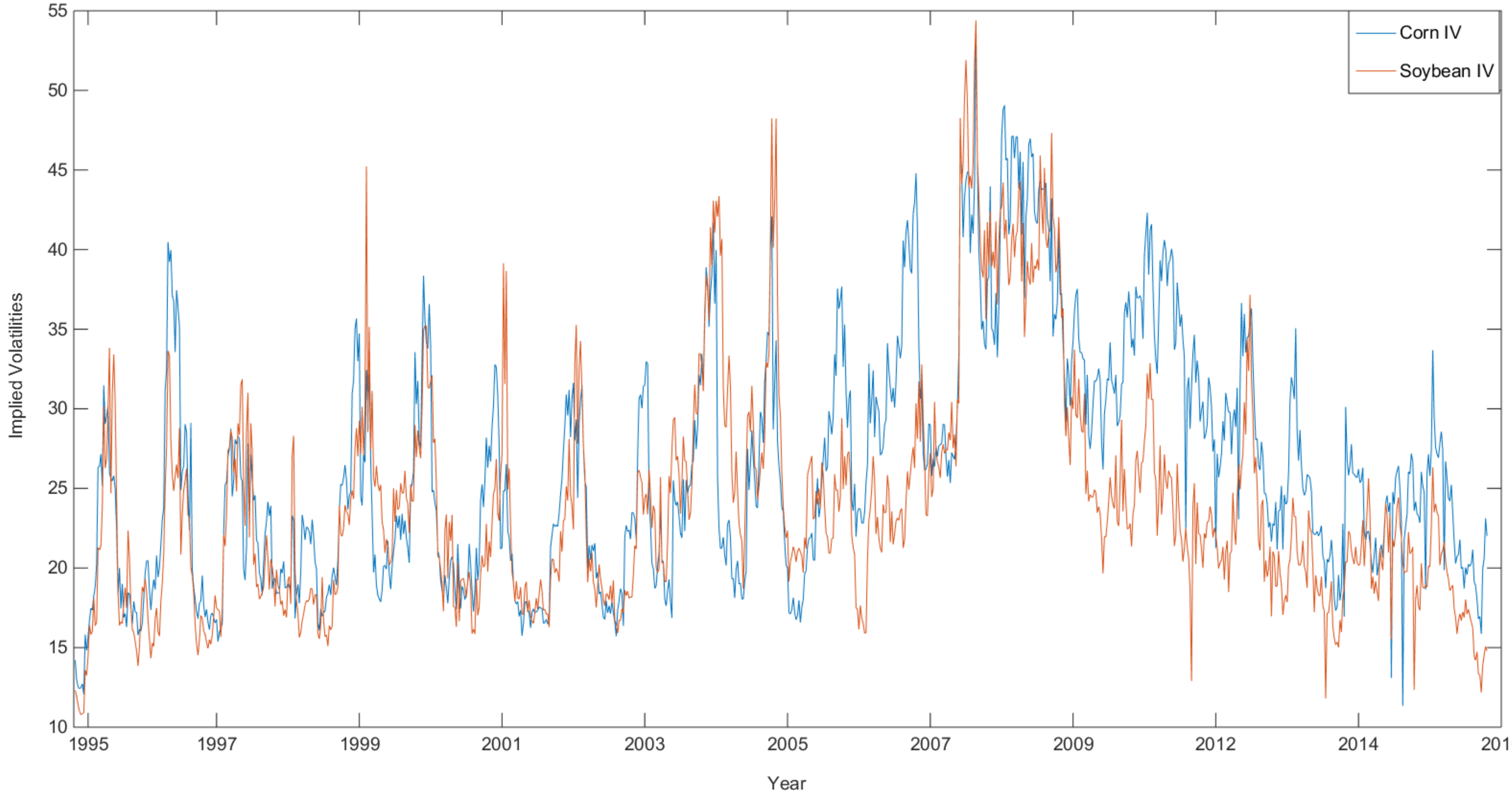

Figure 4.2 Weekly Implied Volatilities for Corn and Soybean.

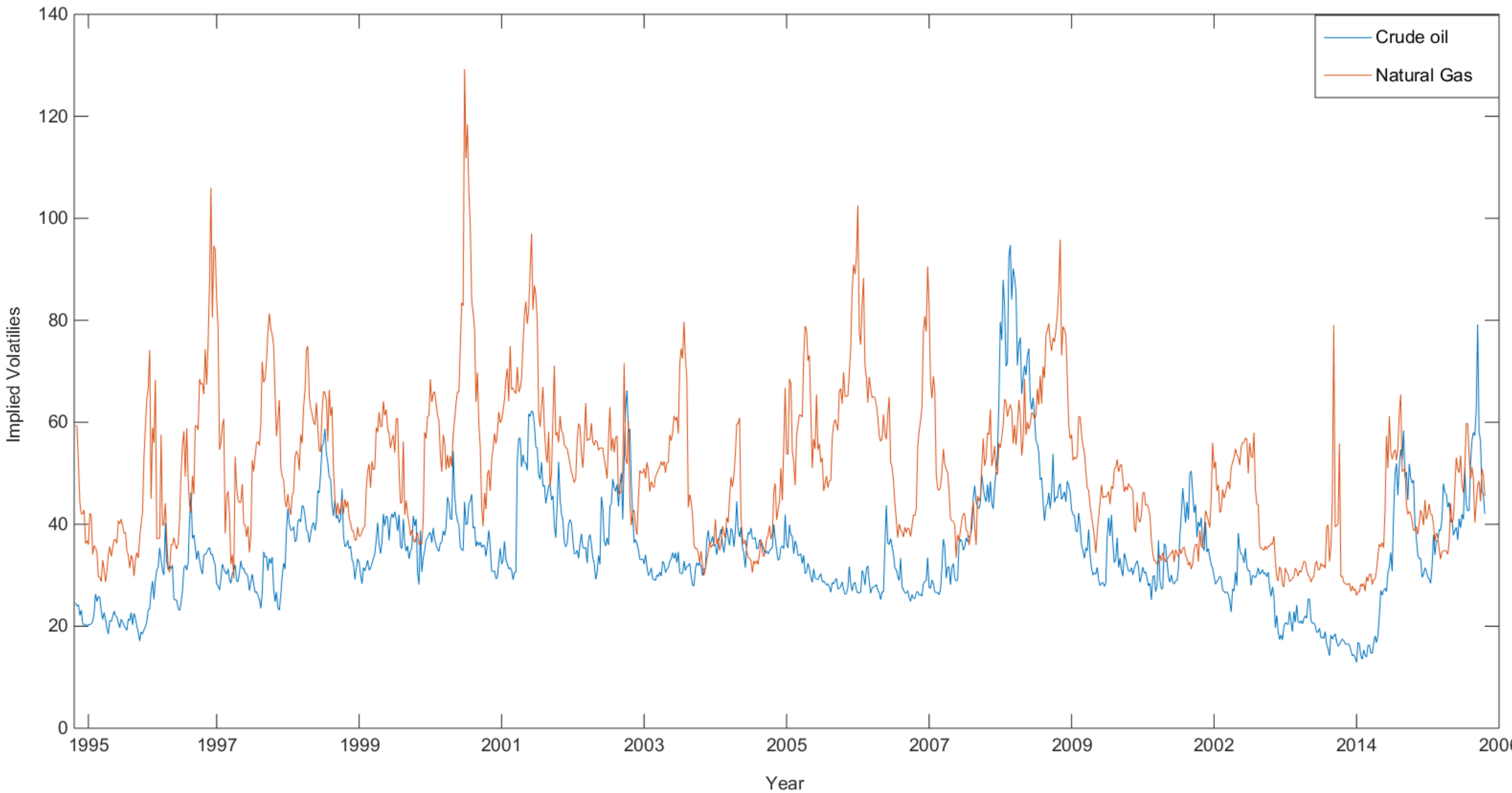

Figure 4.3 Weekly implied volatilities for crude oil and natural gas.

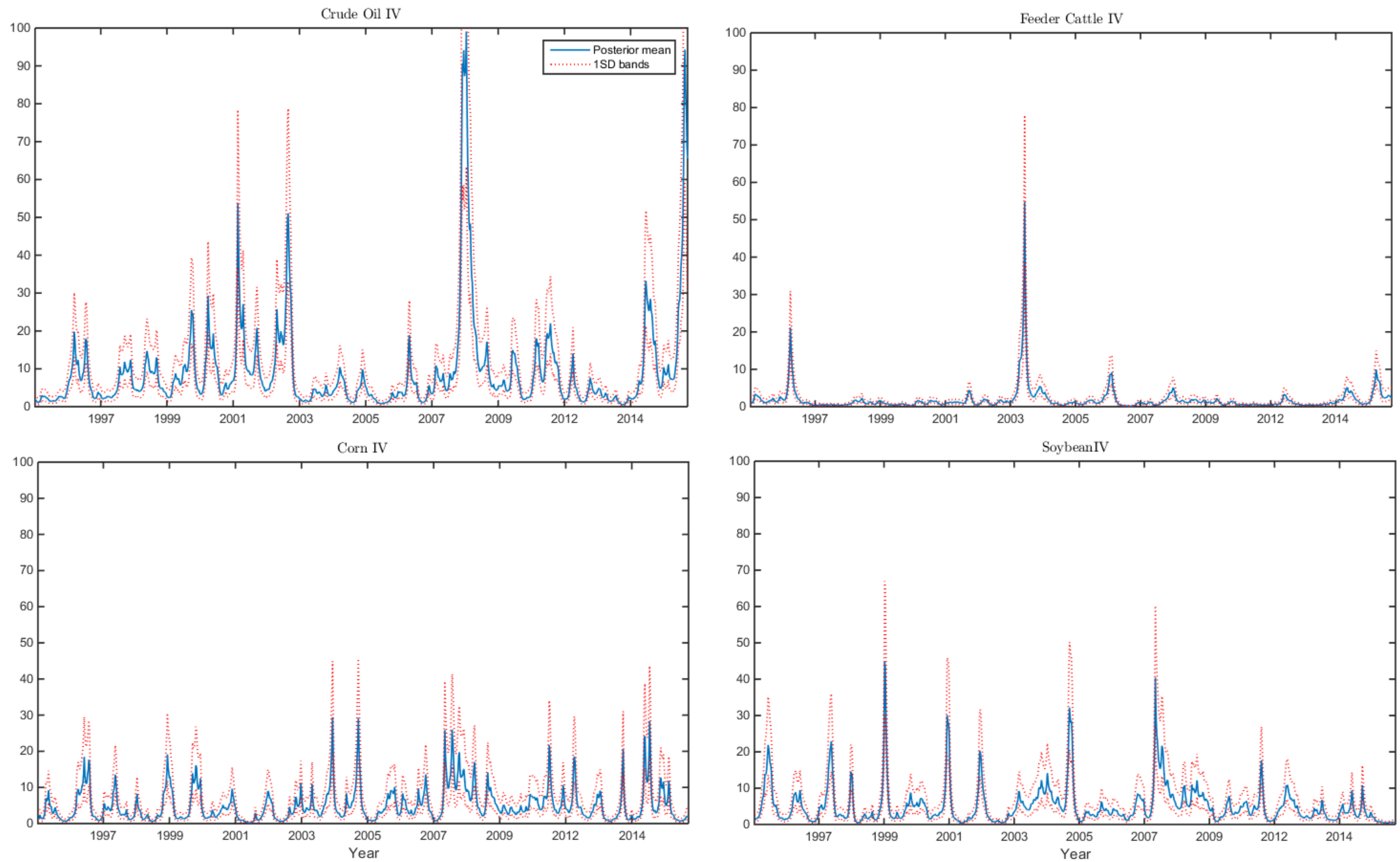

Figure 4.4 Posterior estimates for stochastics volatility of the structural shocks.

Note: Posterior mean (solid black line), 16th quantile (orange dotted line) and 84th quantile (blue dotted line).

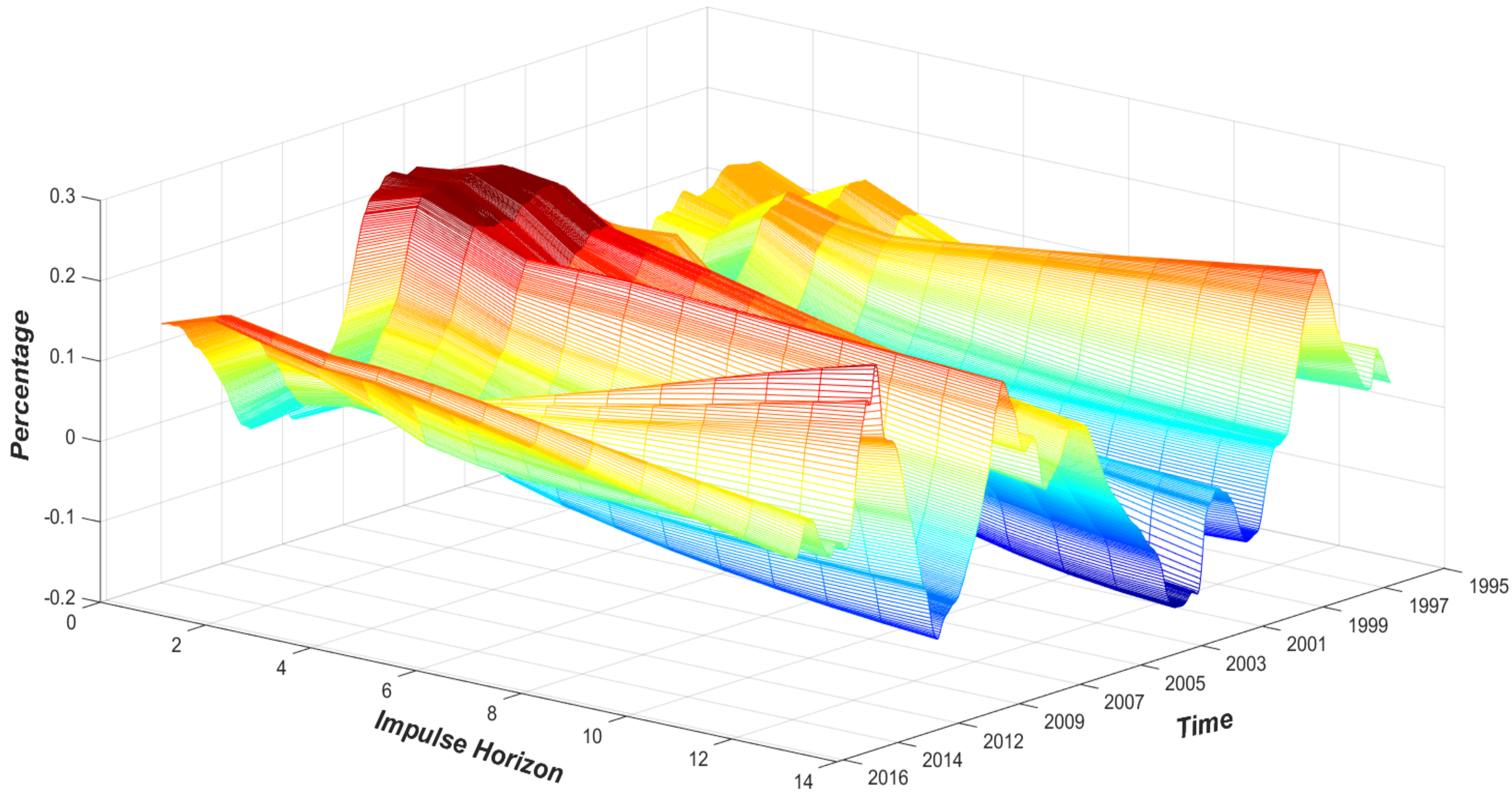

Figure 4.5 Generalized impulse response functions for response of feeder cattle to crude oil shocks. The figure shows the response of feeder cattle to the crude oil shocks.

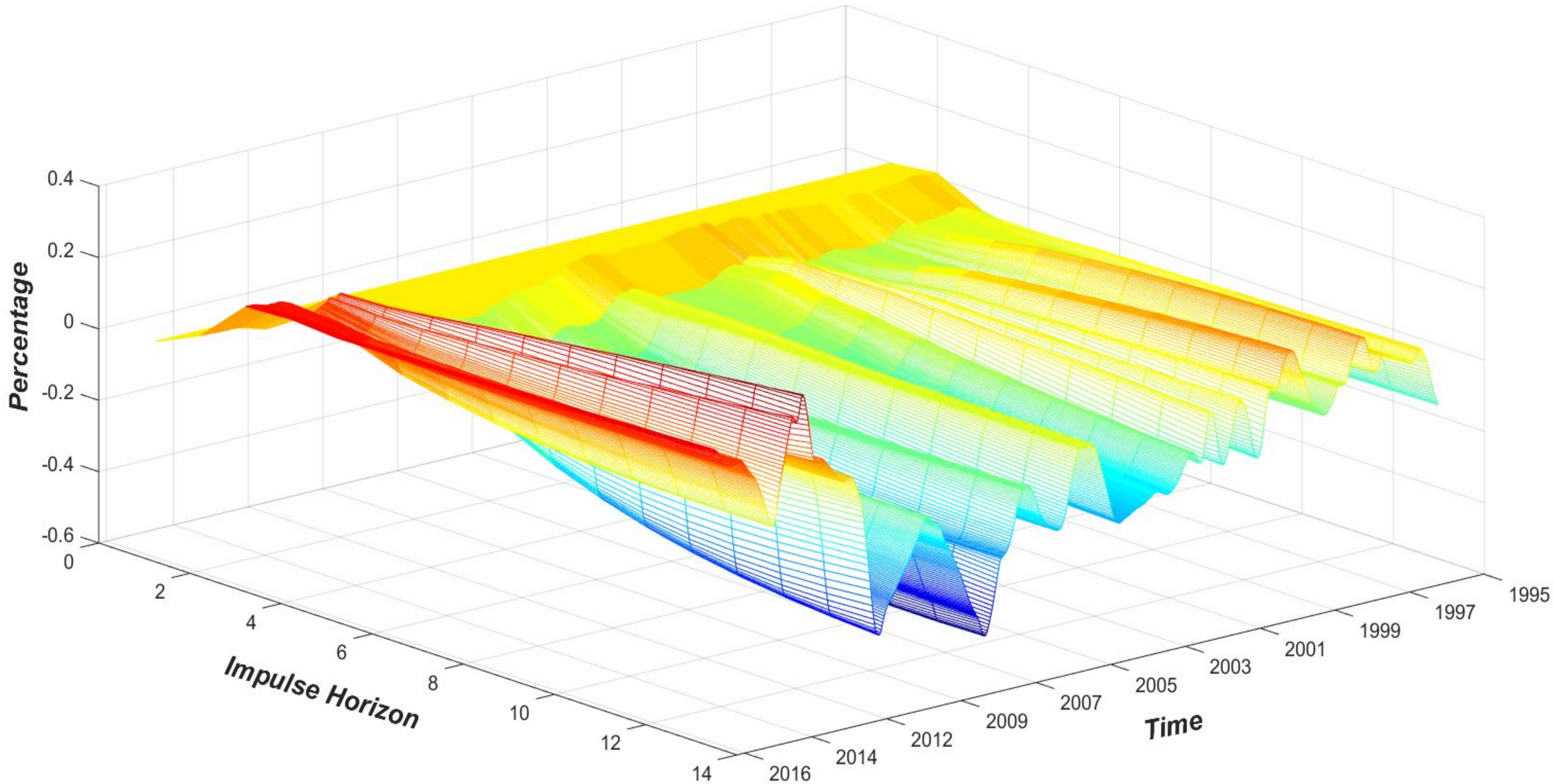

Figure 4.6 Generalized impulse response functions for response of feeder cattle to natural gas shocks. The figure shows the response of feeder cattle to the natural gas shocks.

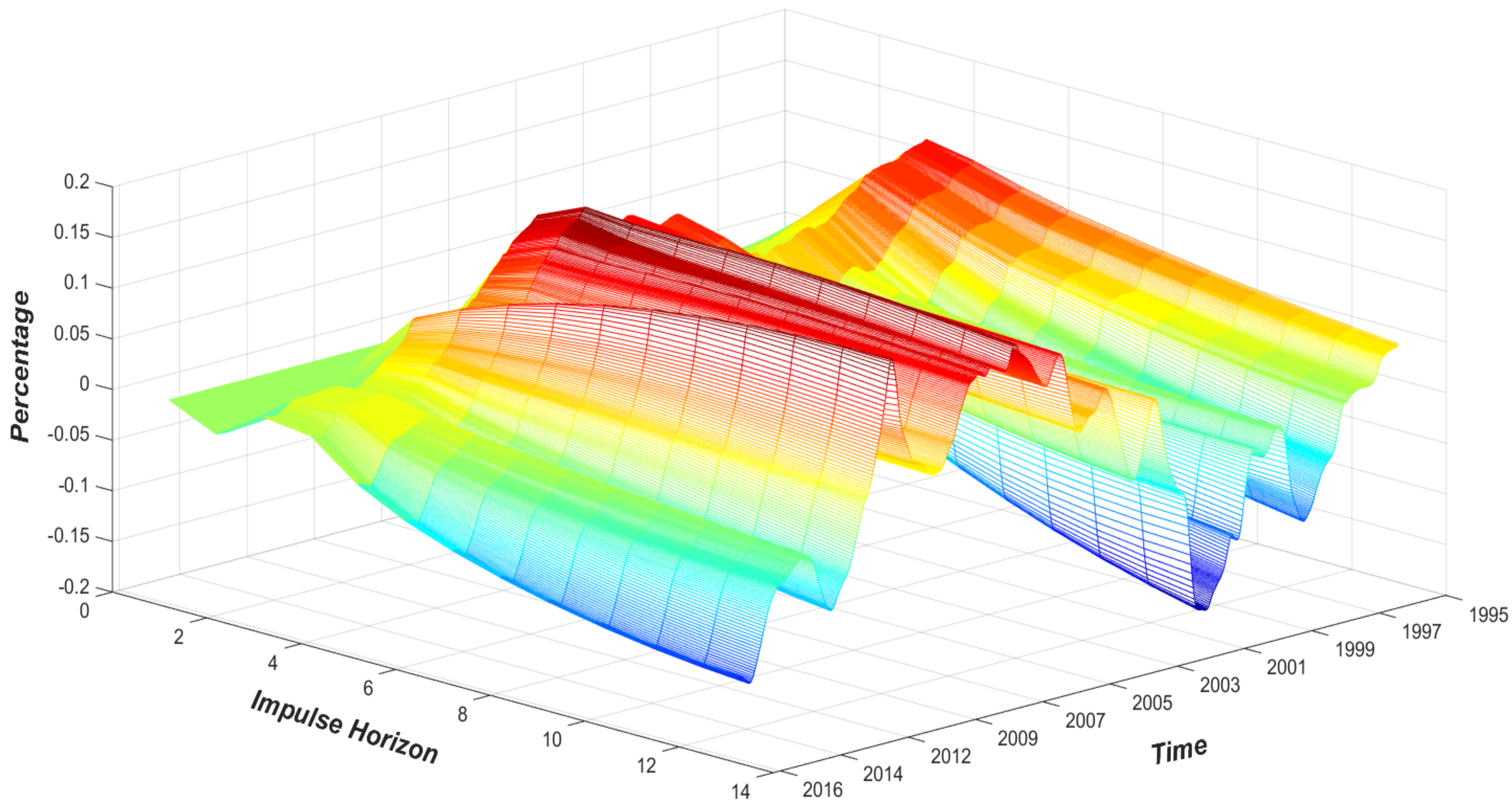

Figure 4.7 Generalized impulse response functions for response of feeder cattle IV to corn IV shocks.

The figure shows the response of feeder cattle to the corn shocks.

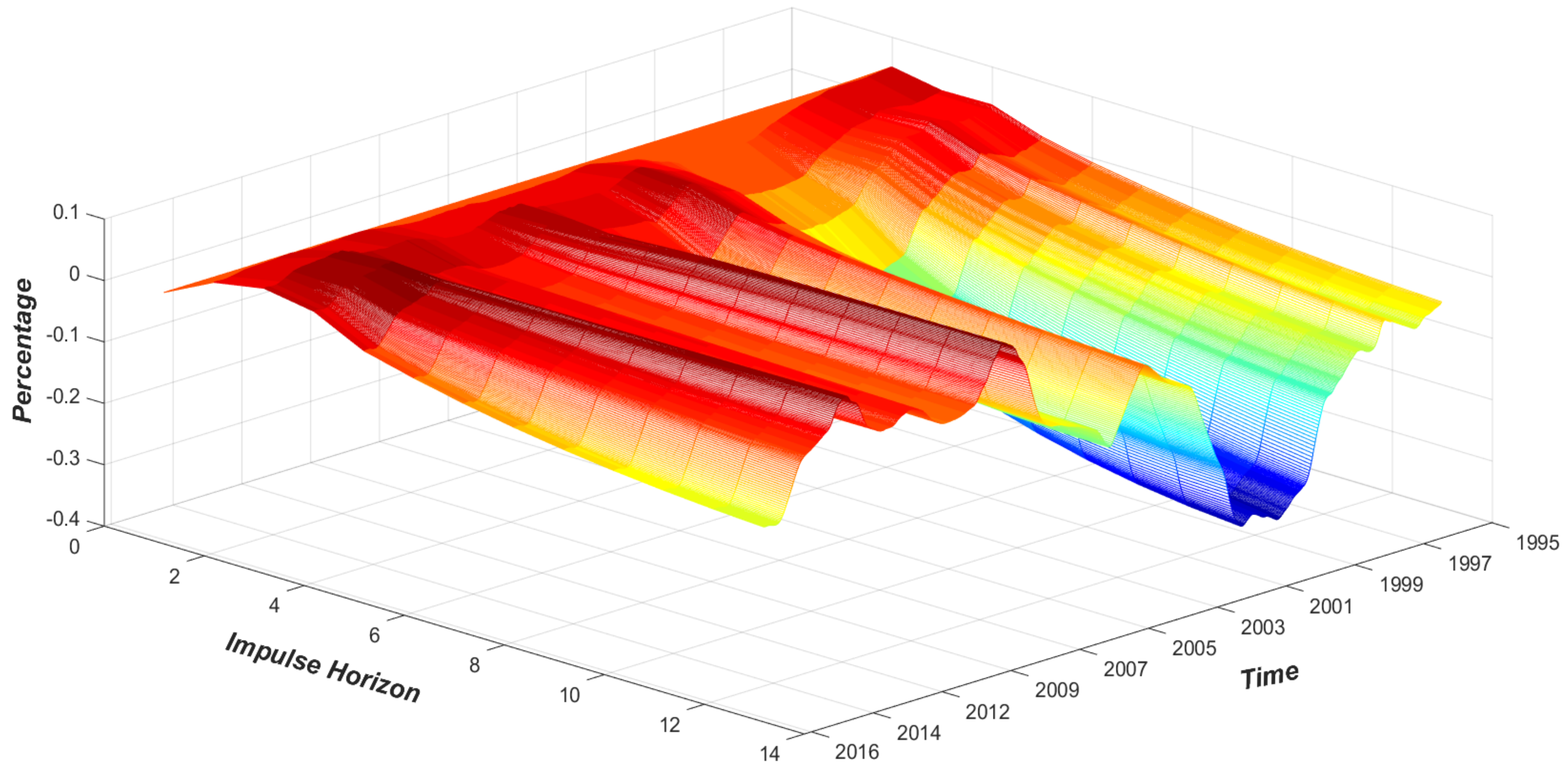

Figure 4.8 Generalized impulse response functions for response of feeder cattle to soybean IV shocks. The figure shows the response of feeder cattle to the soybean shocks.

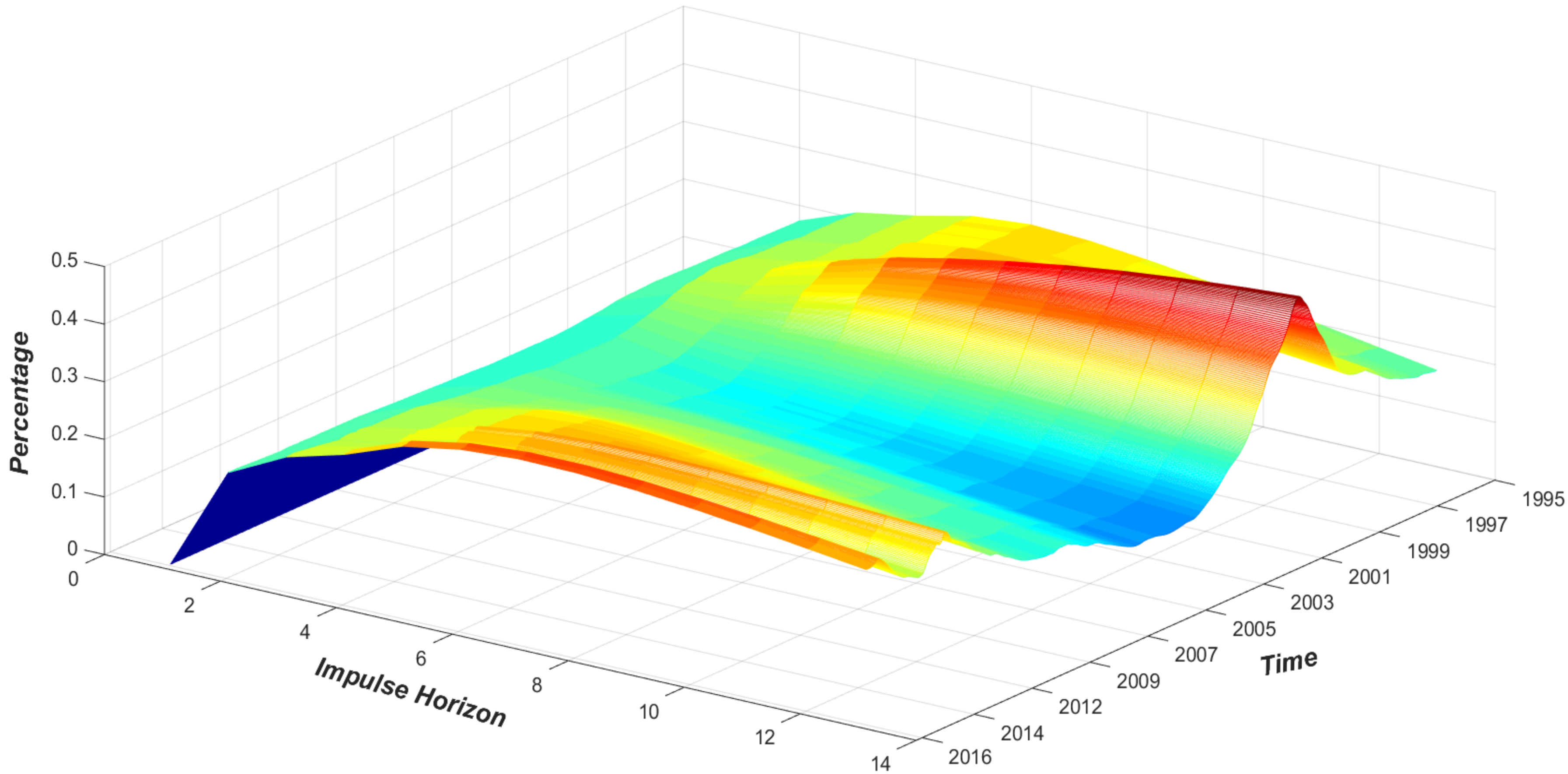

Figure 4.9 Generalized impulse response functions for response of feeder cattle to cattle shocks. The figure shows the response of feeder cattle to the cattle shocks.

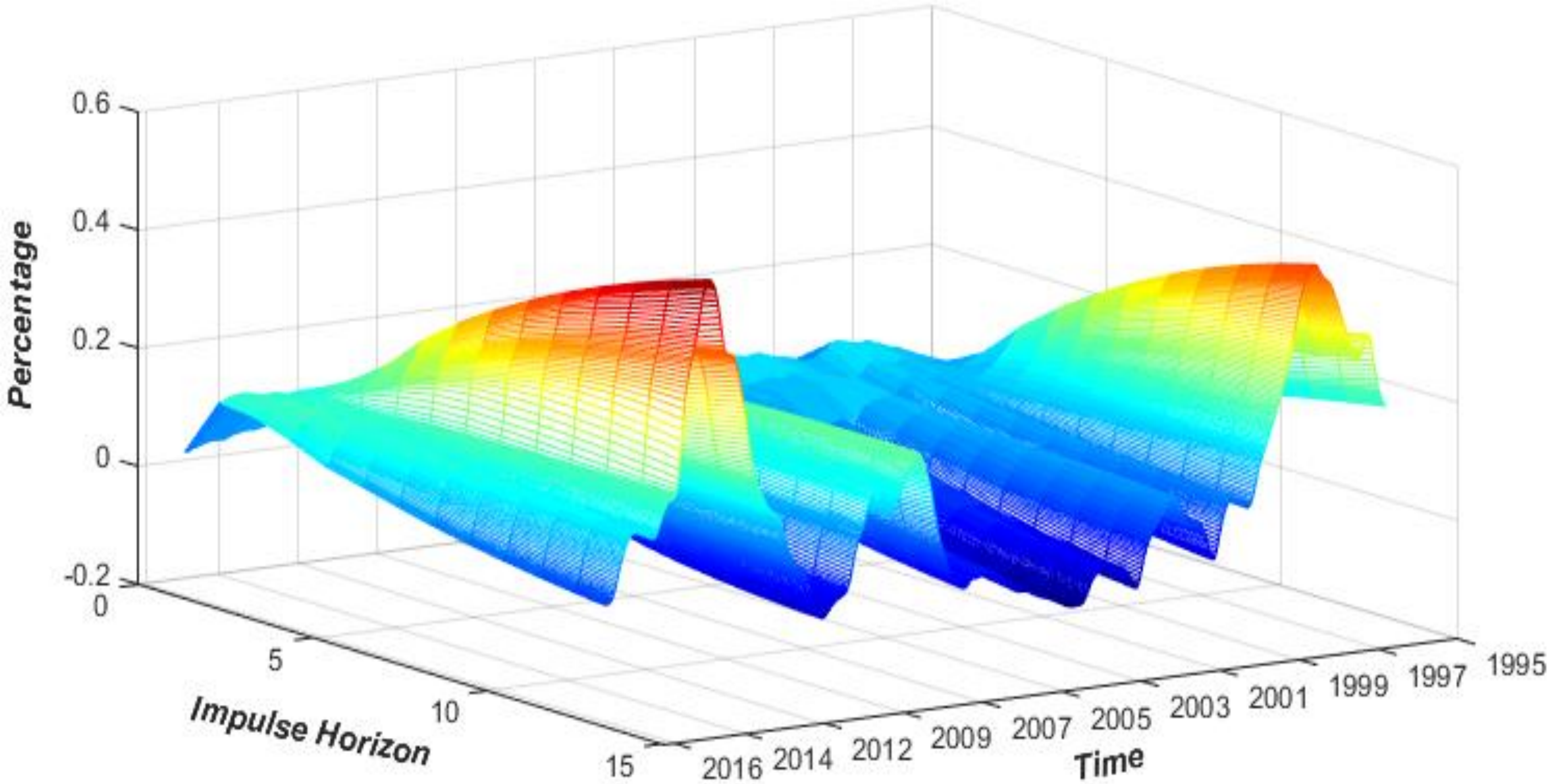

Figure 4.10 Generalized impulse response functions for response of live cattle to crude oil shocks.
The figure shows the response of live cattle to the crude oil shocks.

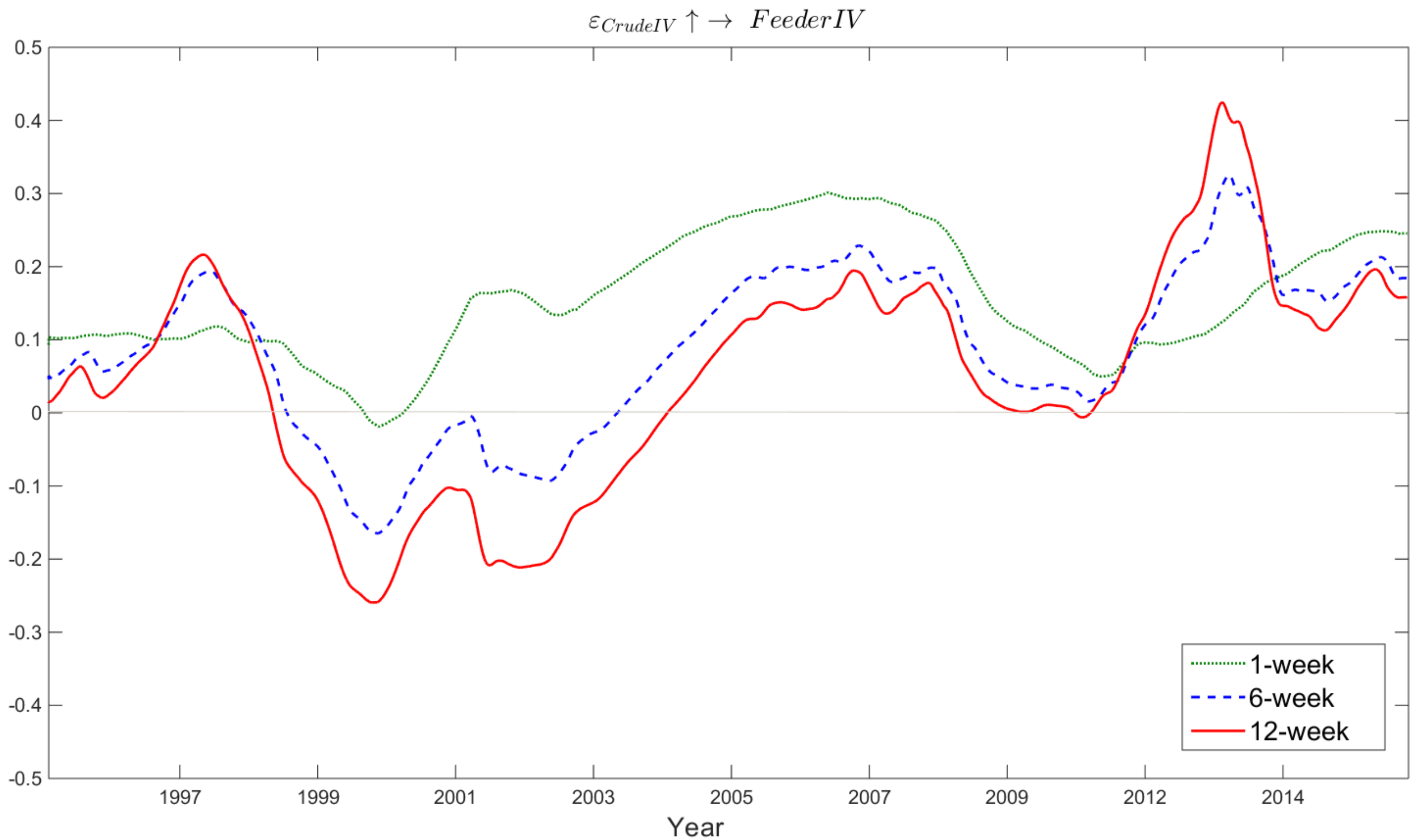

Figure 4.11 Impulse responses of TVP-VAR.

The figure shows the one-week (green dotted line), 6 weeks (blue dashed line) and 12 weeks (solid red line) time-varying responses of feeder cattle to the crude oil shocks.

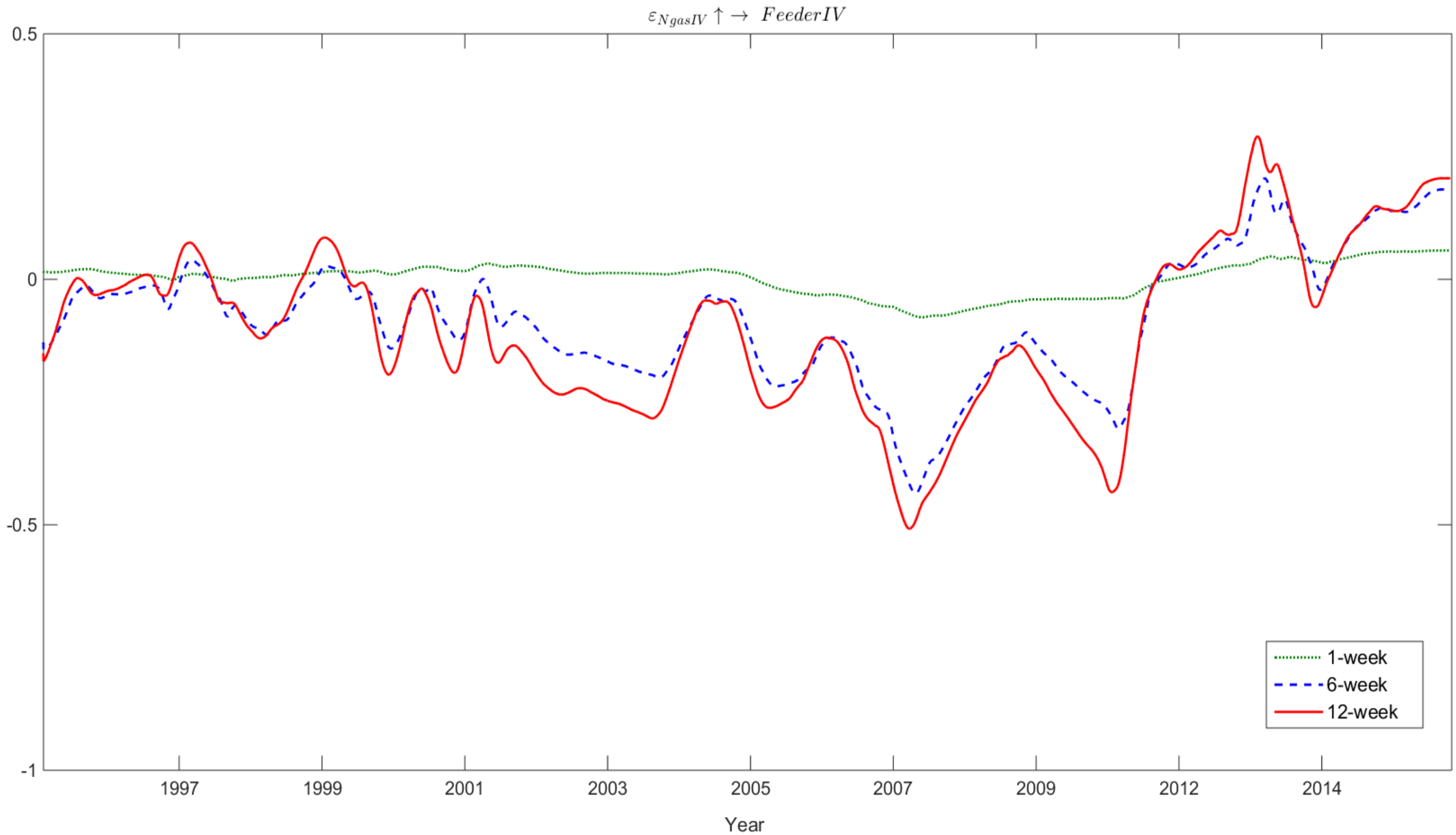

Figure 4.12 Impulse responses of TVP-VAR.

The figure shows the one-week (green dotted line), 6 weeks (blue dashed line) and 12 weeks (solid red line) time varying responses of feeder cattle to the natural gas shock.

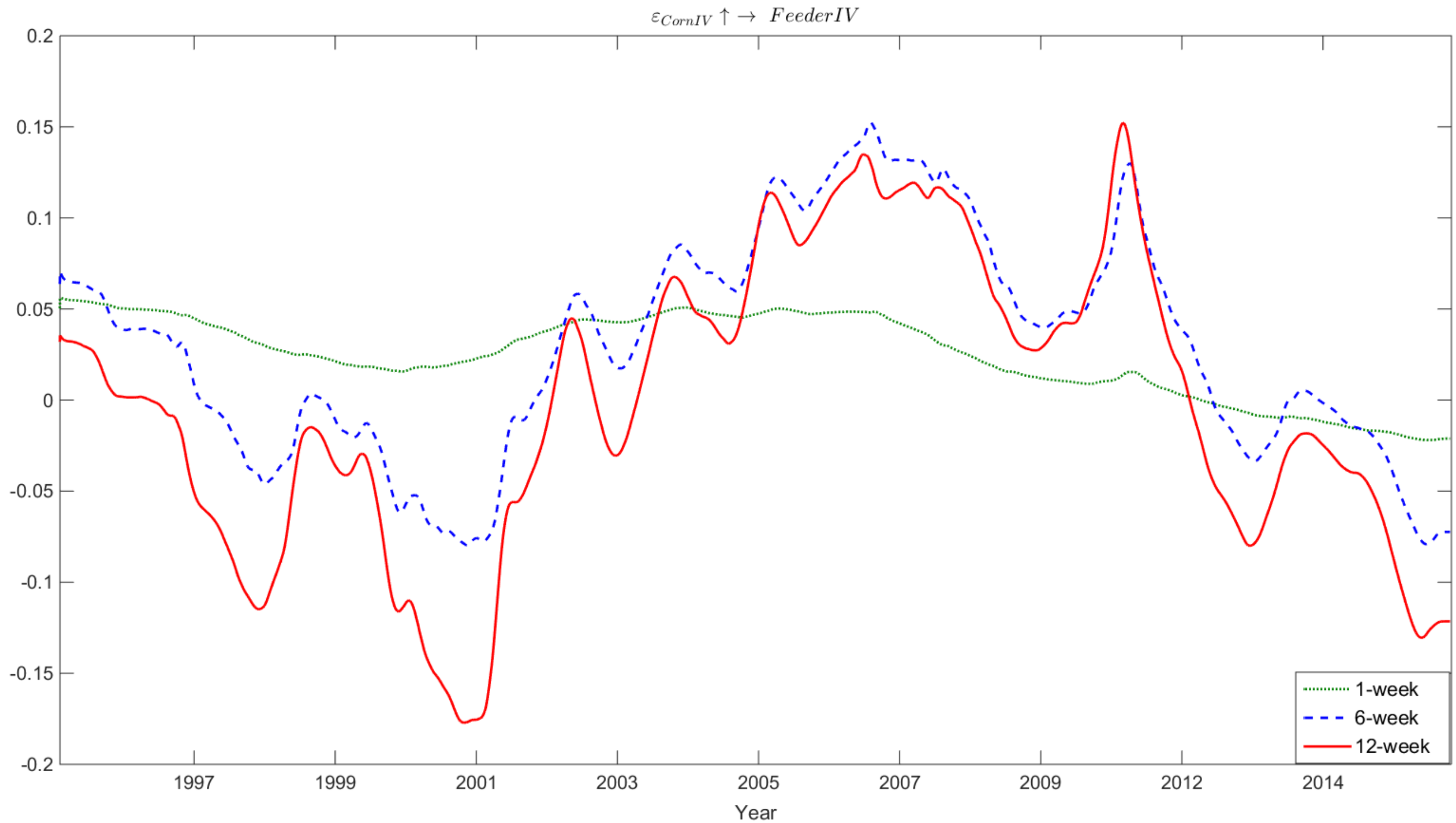

Figure 4.13 Impulse responses of TVP-VAR.

The figure shows the one-week (green dotted line), 6 weeks (blue dashed line) and 12 weeks (solid red line) time-varying responses of feeder cattle to the corn shocks.

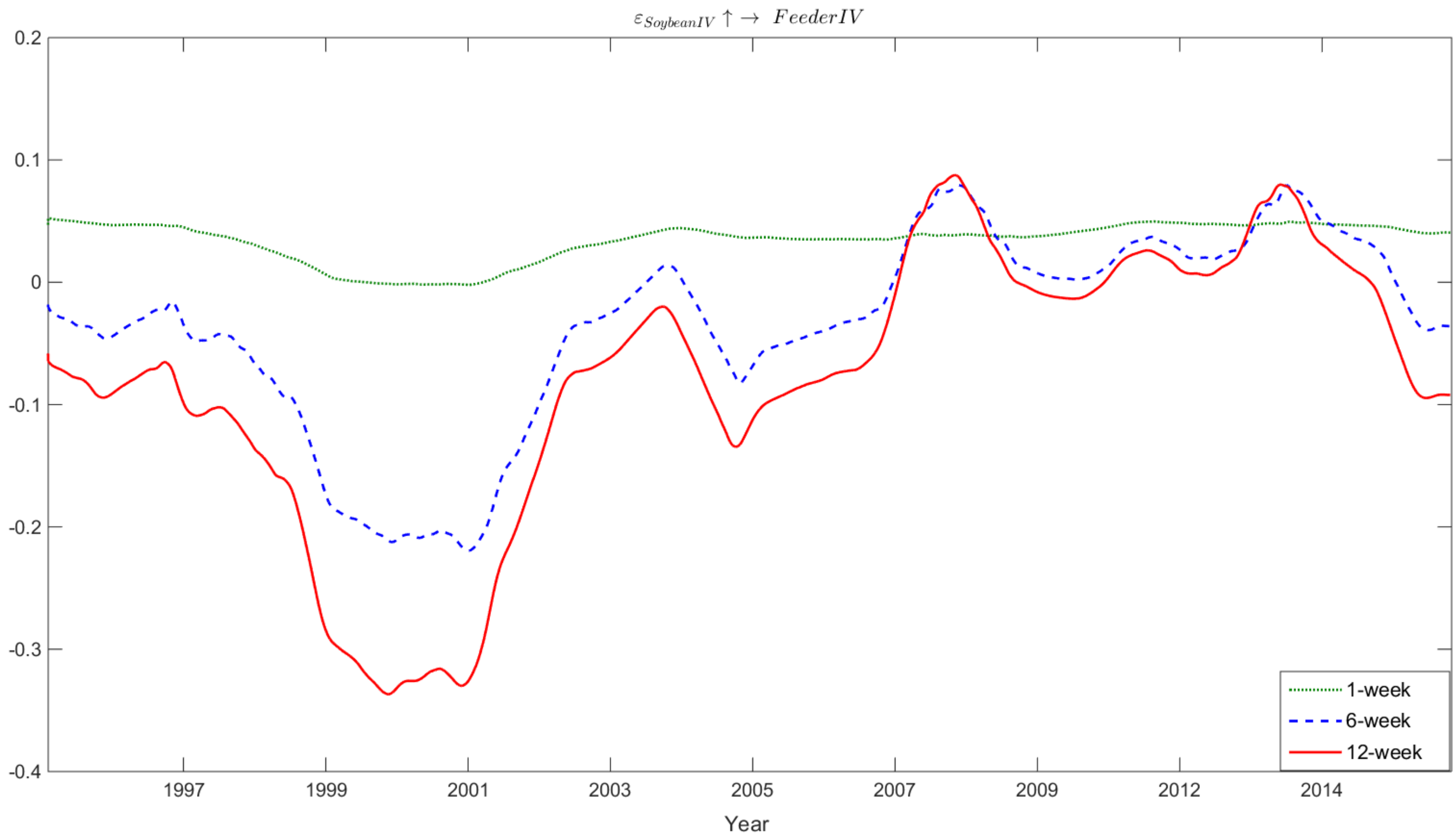

Figure 4.14 Impulse responses of TVP-VAR.

The figure shows the one-week (green dotted line), 6 weeks (blue dashed line) and 12 weeks (solid red line) time-varying responses of feeder cattle to the soybean shocks.

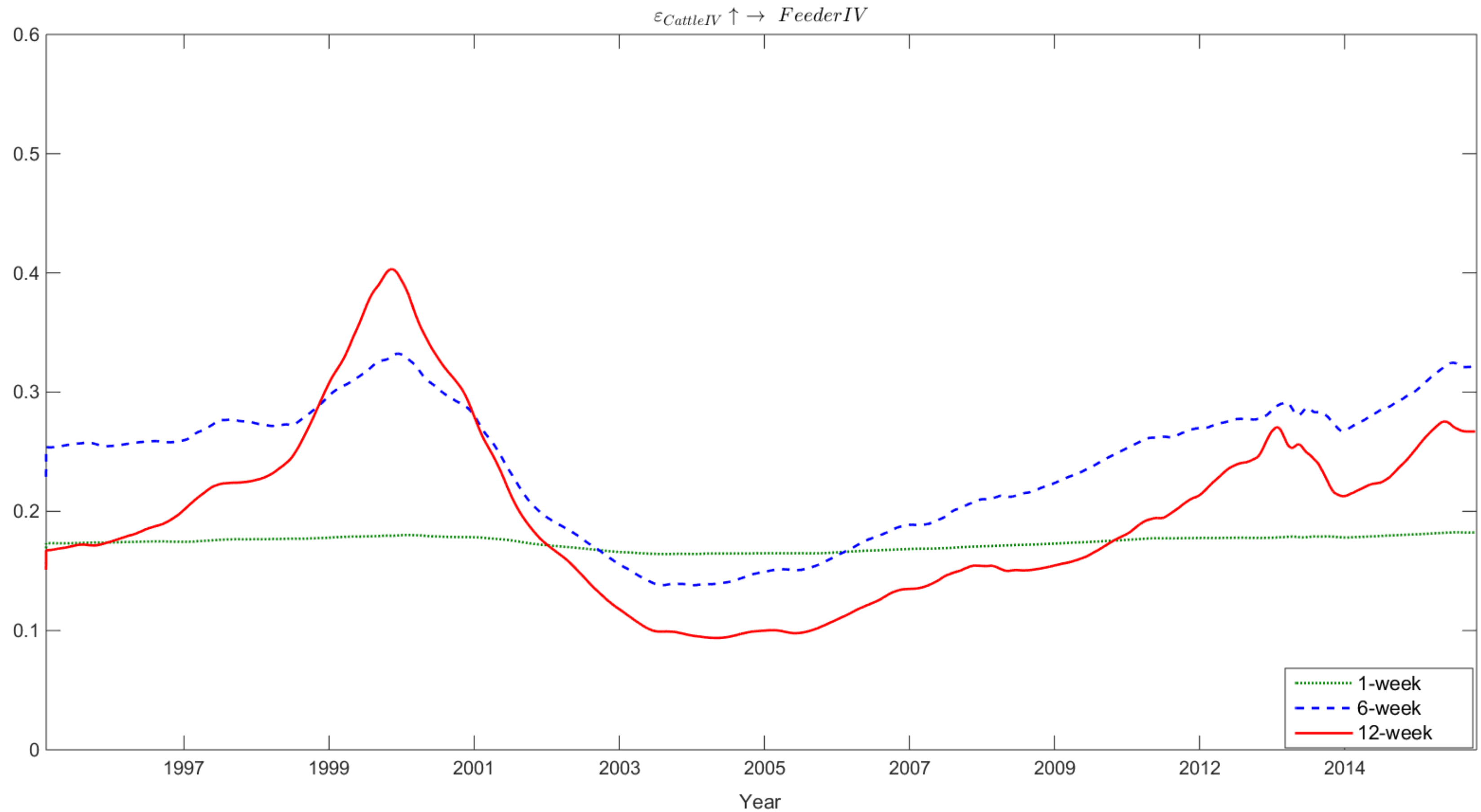

Figure 4.15 Impulse responses of TVP-VAR.

The figure shows the one-week (green dotted line), 6 weeks (blue dashed line) and 12 weeks (solid red line) time-varying responses of feeder cattle to the live cattle shocks.

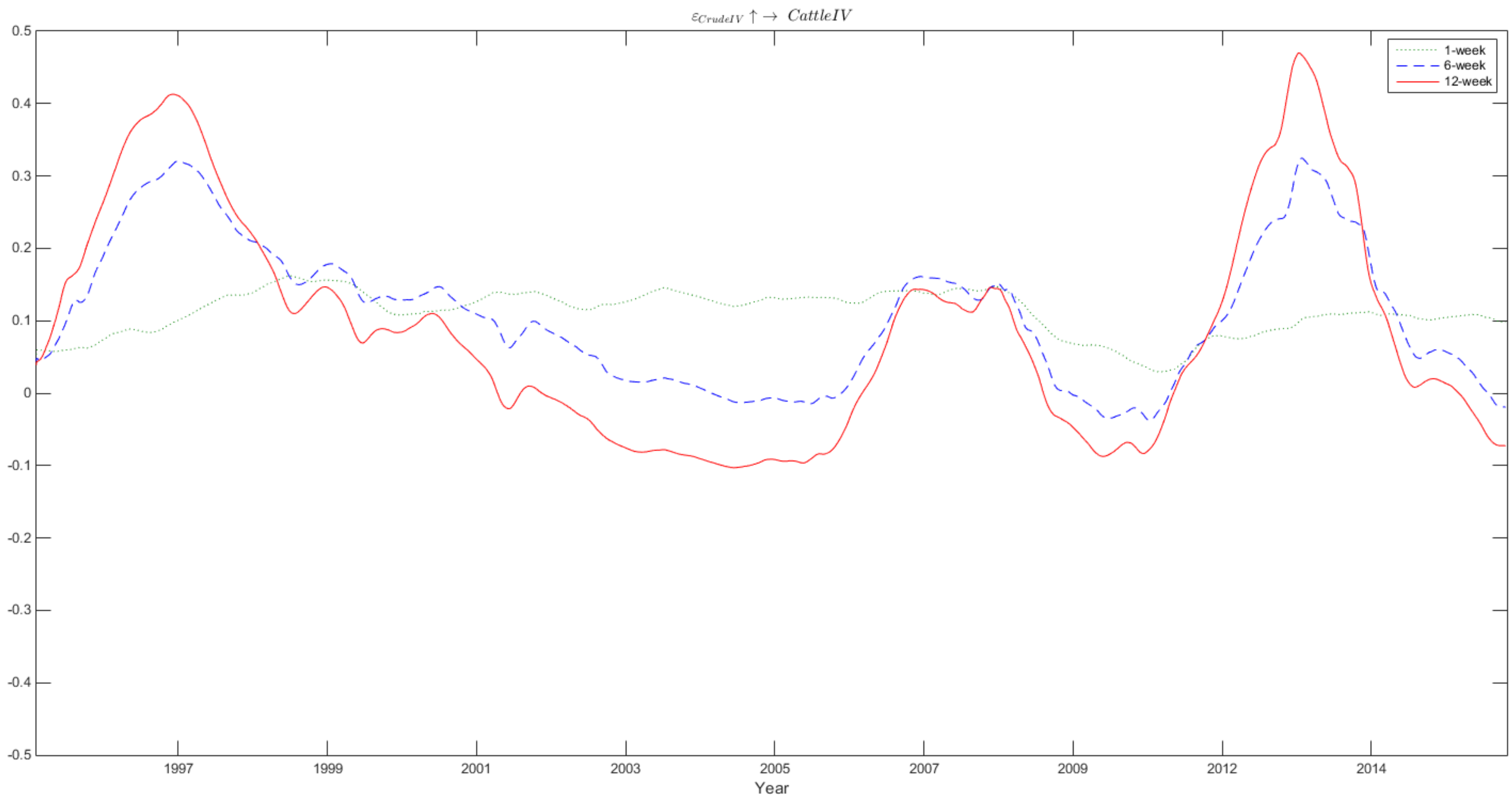

Figure 4.16 Impulse responses of TVP-VAR.

The figure shows the one-week (green dotted line), 6 weeks (blue dashed line) and 12 weeks (solid red line) time varying responses of live cattle to the crude oil shocks.

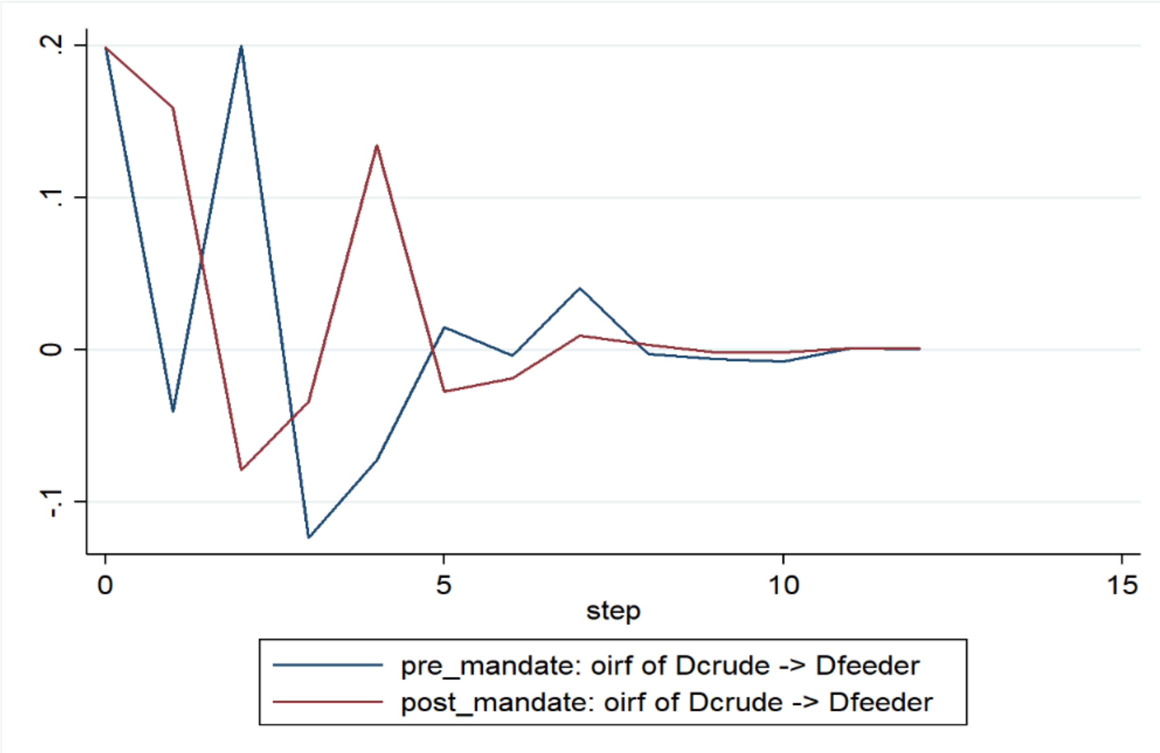

Figure 4.17 Impulse responses of (constant VAR) of feeder cattle to crude.

The blue line represents the posterior mean response to crude shock before 2006 (the energy mandate breakpoint) and the solid red line represents the posterior mean response after the enactment of the energy mandate.

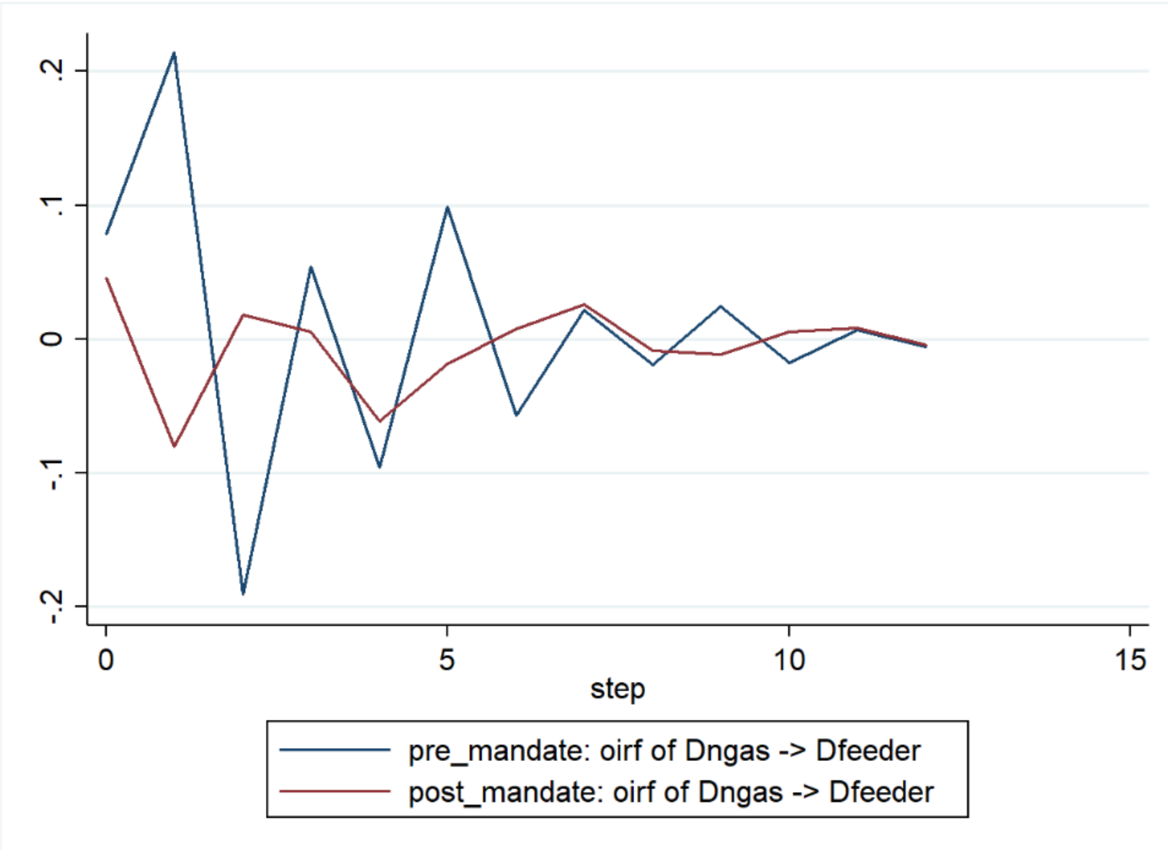

Figure 4.18 Impulse responses of (constant VAR) of feeder cattle to crude.

The blue line represents the posterior mean response to crude shock before 2006 (the energy mandate breakpoint) and the solid red line represents the posterior mean response after the enactment of the energy mandate.

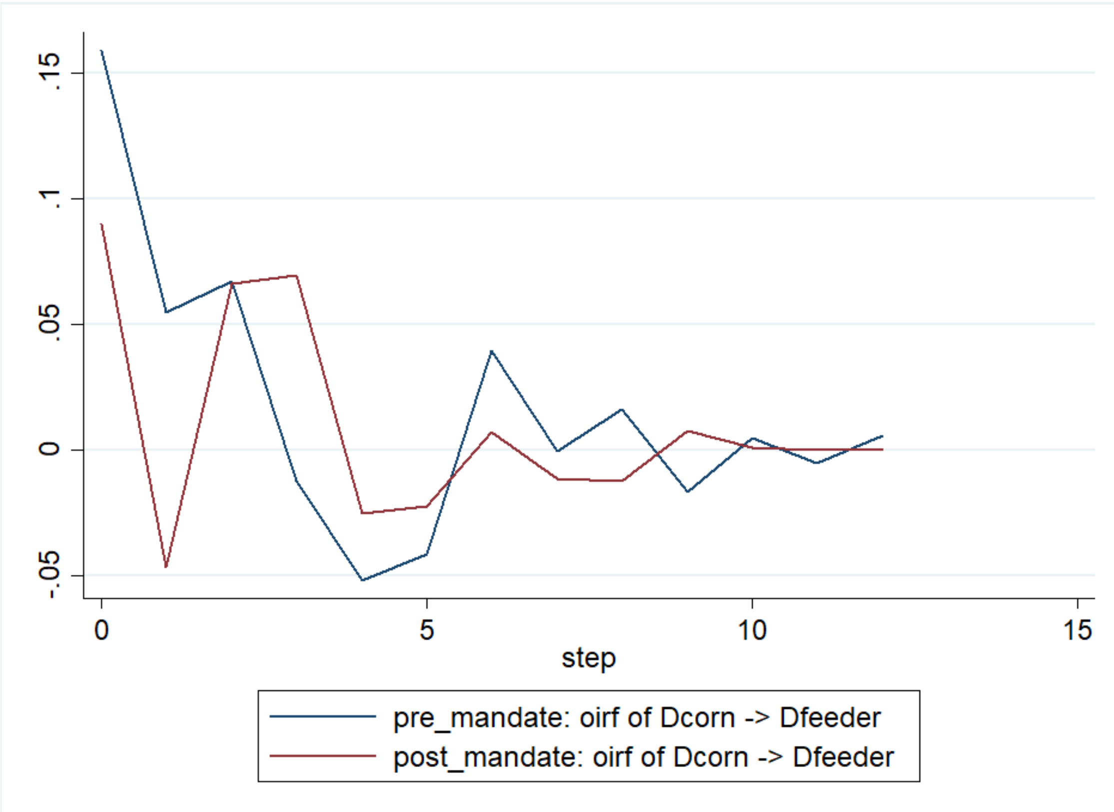

Figure 4.19 Impulse responses of (constant VAR) feeder cattle to corn.

The blue line represents the posterior mean response to crude shock before 2006 (the energy mandate breakpoint) and the solid red line represents the posterior mean response after the enactment of the energy mandate.

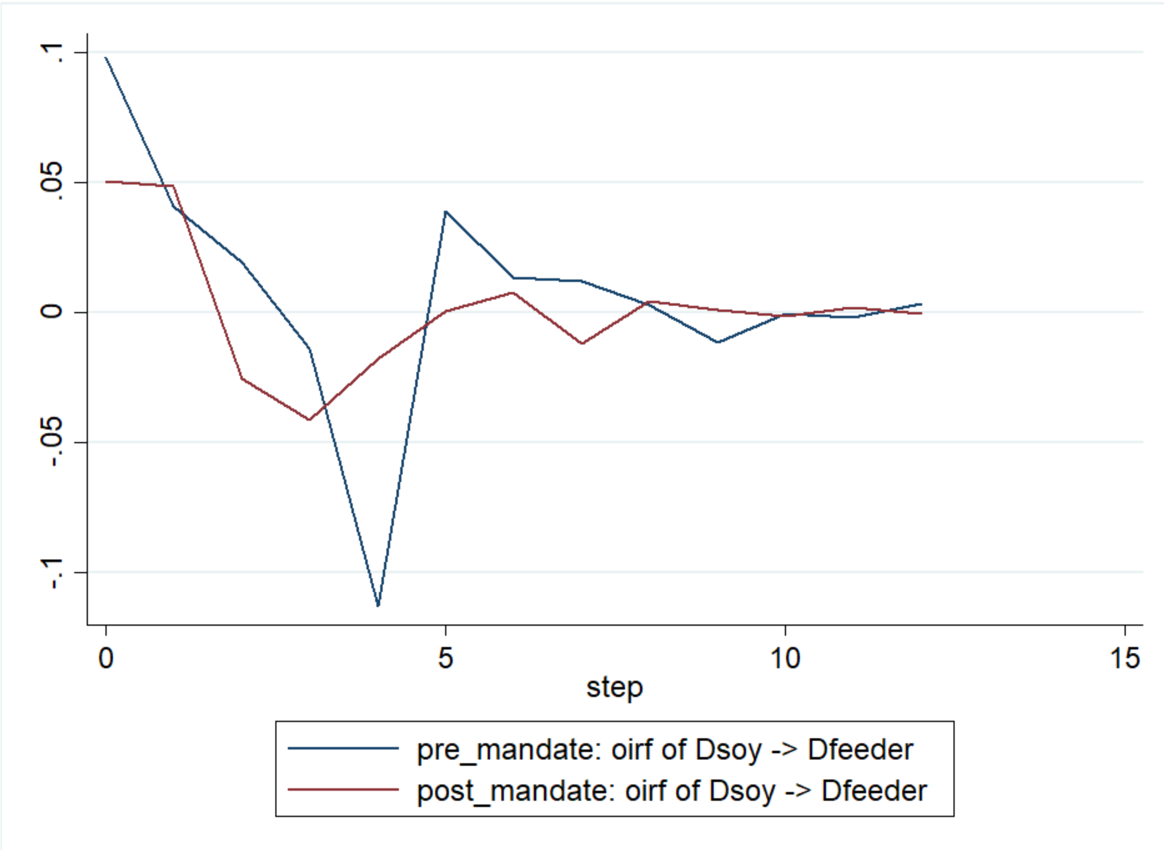

Figure 4.20 Impulse responses of (constant VAR) feeder cattle to soybean.

The blue line represents the posterior mean response to crude shock before 2006 (the energy mandate breakpoint) and the solid red line represents the posterior mean response after the enactment of the energy mandate.

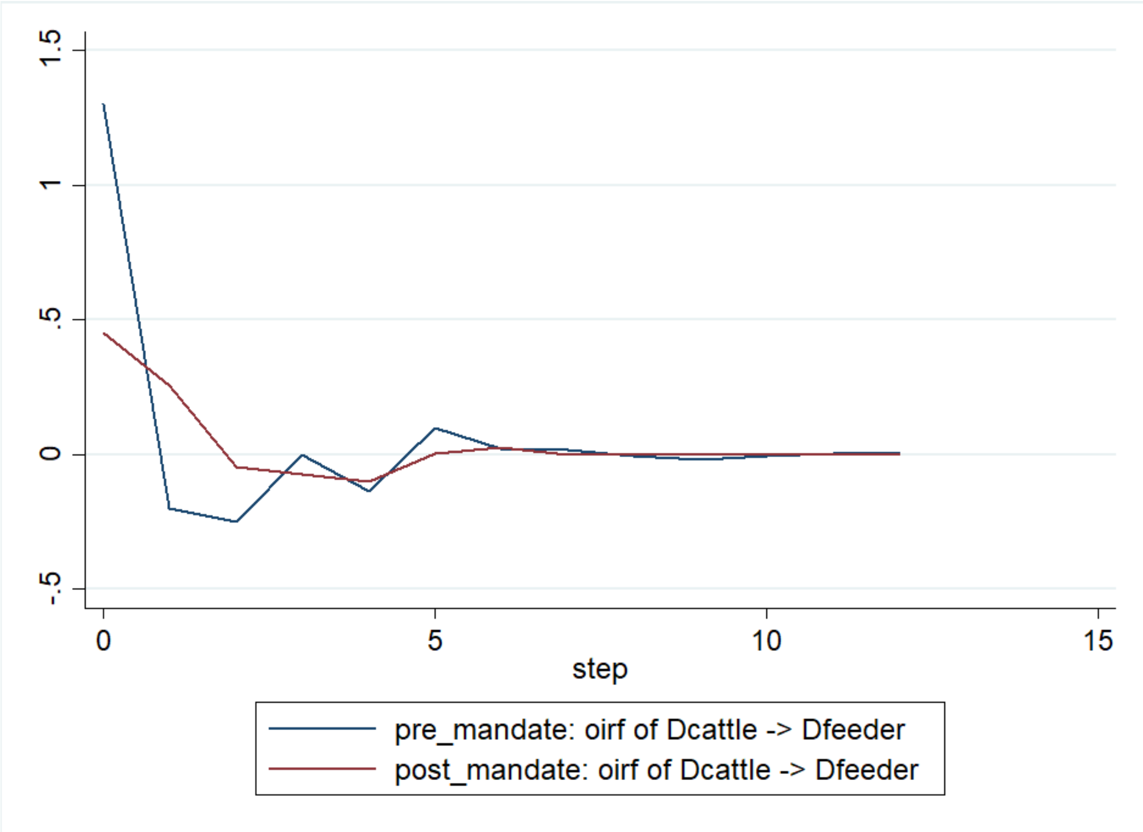

Figure 4.21 Impulse responses of (constant VAR) feeder cattle to cattle.

The blue line represents the posterior mean response to crude shock before 2006 (the energy mandate breakpoint) and the solid red line represents the posterior mean response after the enactment of the energy mandate.

APPENDIX

Figure A1 Historical prices of Soybean (shaded regions are the region of structural changes).

Source: https://www.macrotrends.net/2531/soybean-prices-historical-chart-data

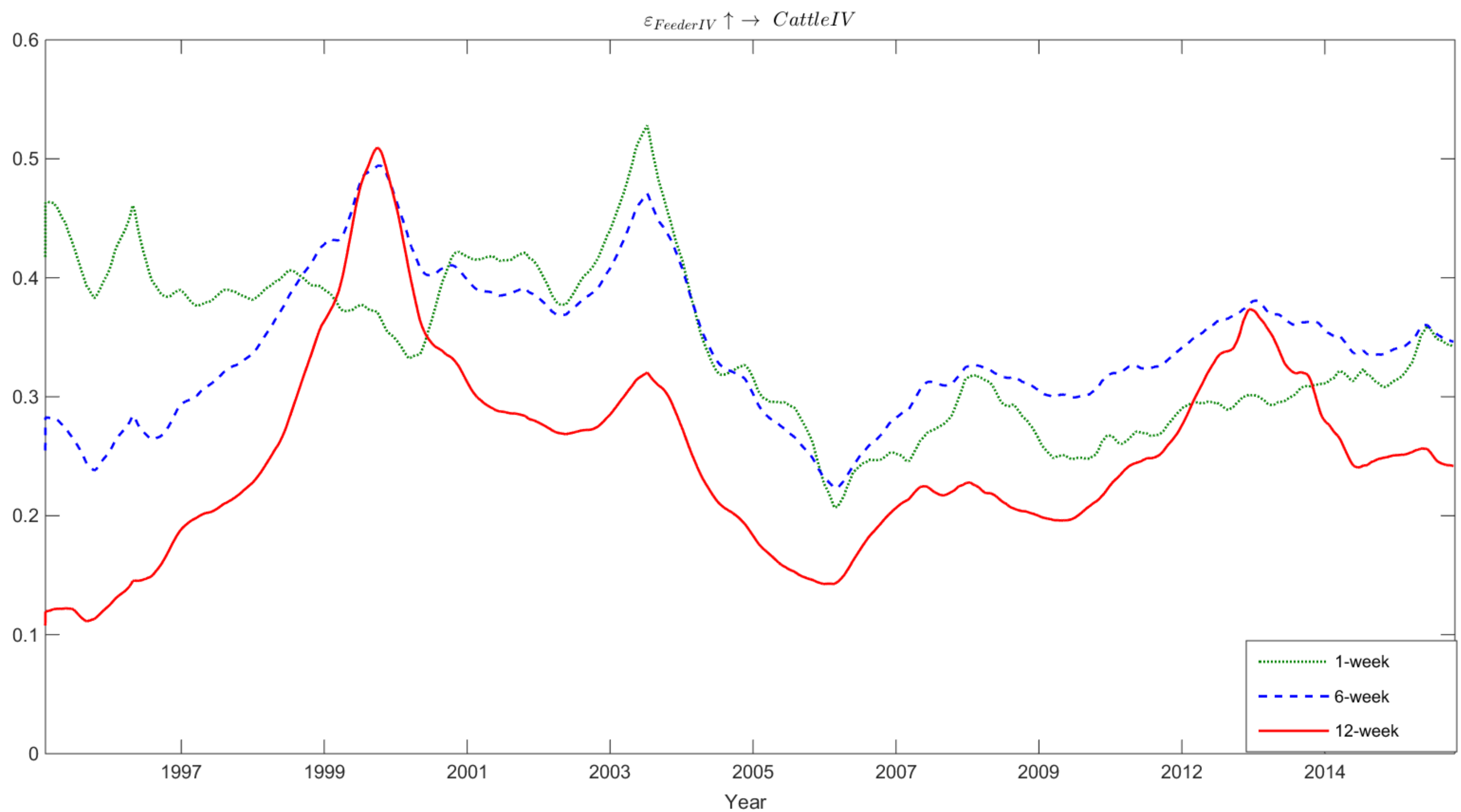

Figure A2 Impulse responses of TVP-VAR. The figure shows the one-week (green dotted line), 6 weeks (blue dashed line) and 12 weeks (solid red line) time-varying responses of live cattle to the feeder cattle shocks.

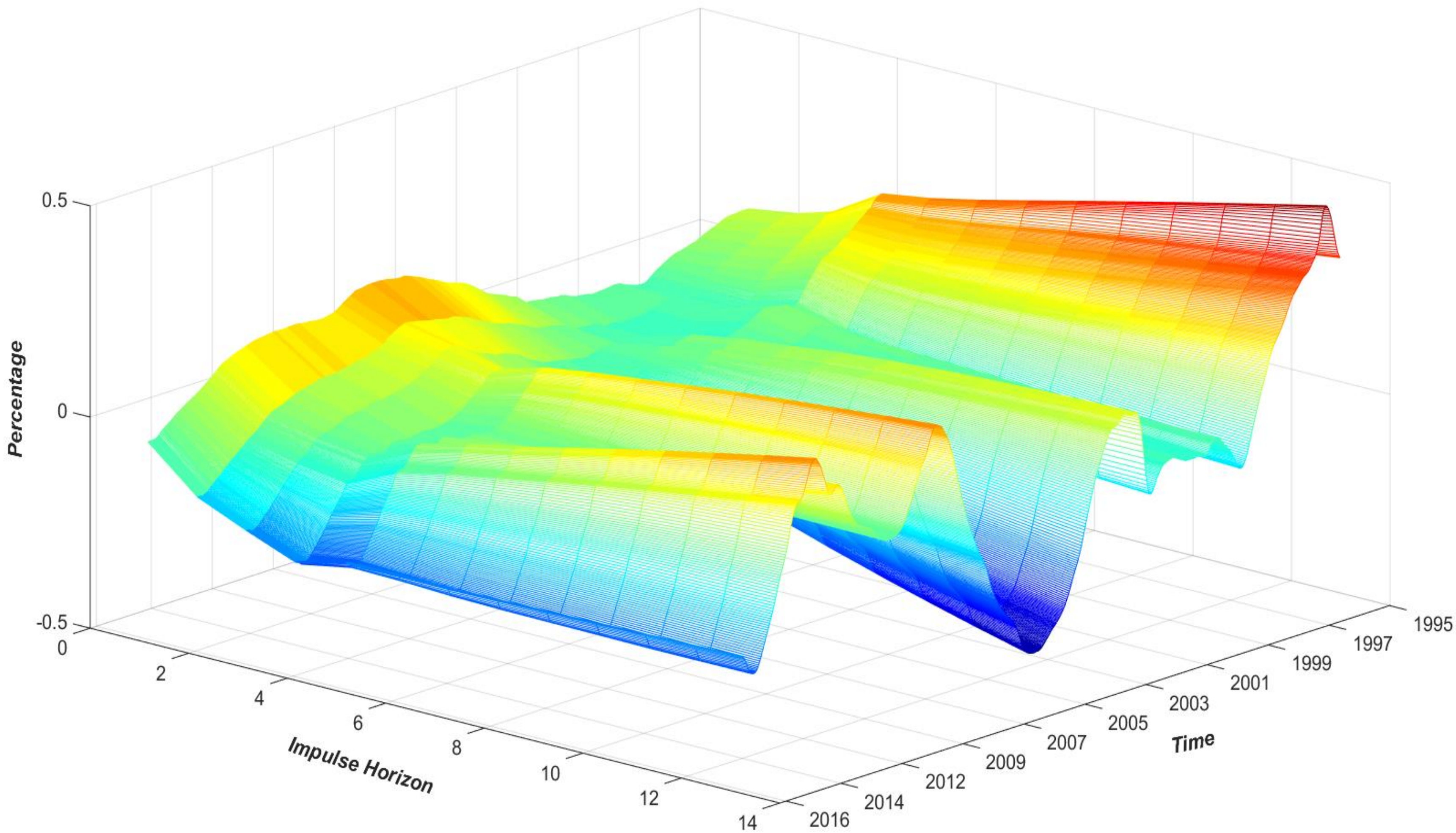

Figure A3 Generalized impulse response functions for response of corn to the crude oil shocks. The figure shows the response of corn to the crude oil shocks.

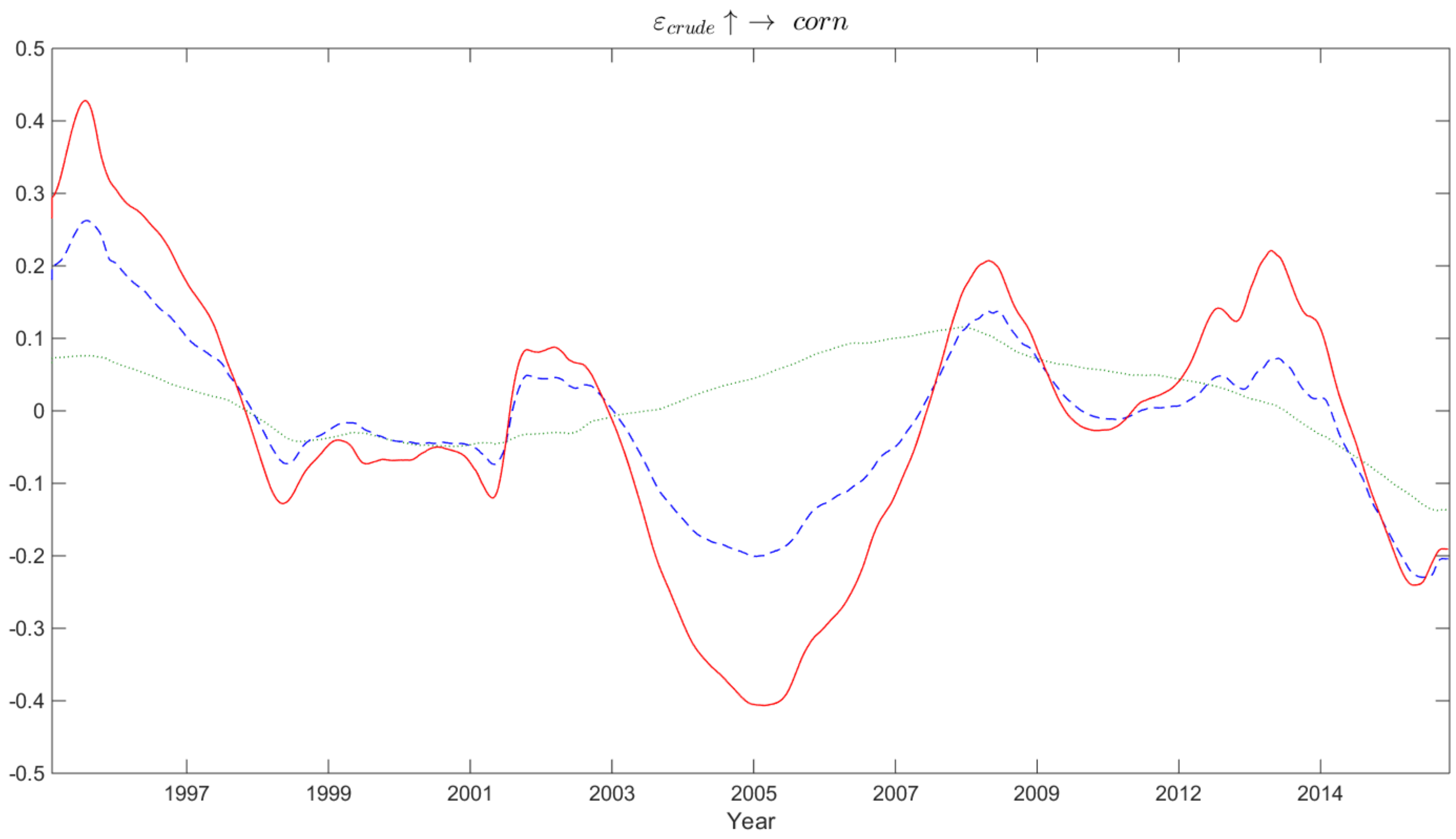

Figure A4 Impulse responses of TVP-VAR. The figure shows the one-week (green dotted line), 6 weeks (blue dashed line) and 12 weeks (solid red line) time-varying responses of corn to the crude oil shocks.