Essays on beef economics: an updated understanding of cowherd supply response and wholesale meat demand

by

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Abstract

The beef supply chain in the United States consists of many actors from the farm to retail level; with approximately 730,000 beef farms moving cattle to feedlots to slaughter plants and finally to various wholesale, retail, and export channels (USDA NASS, 2017). Thus, the U.S. beef industry is known to be one of the most complex segments of the agricultural sector. Periods of increased volatility and uncertainty related to economic, environmental, and social factors have further highlighted the dynamic nature of the U.S. beef industry and supply chain. This thesis contains two articles. The first article analyzes cowherd supply response in the United States and 14 major cow-calf states in the country. The second article estimates wholesale beef demand parameters. In Article 1, partial-adjustment supply models are estimated to quantify how changes in feeder cattle prices impact beef cow inventories at state and national levels. In Article 2, seeming unrelated regression (SUR) models are estimated to obtain updated wholesale beef demand elasticities. Both Articles 1 and 2 provide updated research related to two current knowledge gaps in the U.S. beef industry. Findings in both articles support the notion that price sensitivity may be decreasing in the U.S. beef-cattle industry.

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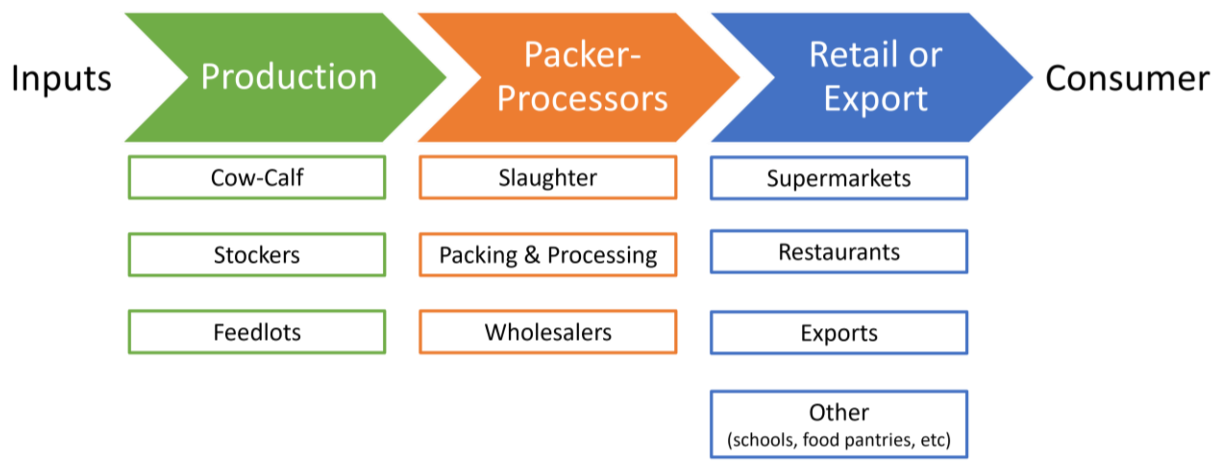
Executive Summary

Overview

The beef supply chain in the United States, shown in Figure 1.1, consists of many actors spanning from input suppliers to final consumers. In the live-animal stage of production, cow-calf producers sell calves that either move first to backgrounding and stocker operations then to feedlots, or directly to feedlots, depending on region, producer preferences, and market conditions. Feedlots move live cattle to slaughter plants and resulting beef moves to various wholesale markets before ultimately reaching consumers through retail (for at-home domestic consumption), food service (for away-from-home domestic consumption), or export channels. Thus, the U.S. beef industry is known to be one of the most complex segments of the agricultural sector. Events of increased volatility and uncertainty related to economic, environmental, and social factors have further highlighted the dynamic nature of the U.S. beef industry and supply chain. In recent years, a global pandemic, extreme drought conditions, and other unexpected events have disrupted supply chains and created elevated periods of economic, environmental, and social uncertainty at every level of the beef supply chain.

Figure 1. The U.S. beef supply chain



Note: The figure was adapted from Cowley (2020) and Lowe & Gereffi (2009)

A common area of interest in economic research is related to the dynamic nature of the U.S. beef industry and the relationships among the various segments of the supply chain. However, there are currently knowledge gaps related to the complex and evolving nature of the beef supply chain in the United States. This thesis aims to address two of the existing knowledge gaps related to the cow-calf and wholesale segments of the beef supply chain.

First, cowherd supply responses at both the national and state levels are analyzed in Article 1. Changes over time related to production efficiencies, producer demographics, climate events, and other industry factors may alter price sensitivity of cow-calf producers and their herding decisions. Therefore, an undated understanding of cowherd supply response would benefit industry participants and analysts. Second, wholesale beef demand elasticities are estimated in Article 2. The role of the wholesale segment, which consists broadly of the supply chain activities after slaughter and before the retail segment, has evolved in recent decades and is a subject of elevated focus and interest. Thus, industry participants and analysts would also gain from an updated understanding of wholesale beef demand.

Summary of Conclusions

Partial-adjustment supply models were developed to quantify the effect feeder cattle price changes have on beef cow inventory at the national and state levels. A decrease in the feeder cattle price sensitivity for cow-calf producers was expected to be observed over time, reducing the impact a given percentage price change has on herd adjustment decisions. In other words, an increase (decrease) in feeder cattle price was expected to have less impact on a cow-calf producer’s decision to increase (decrease) their herd size than it had in the past. At the national level, a decrease in price sensitivity was observed over 1987 through 2022. A decrease in price sensitivity was also observed for a majority of the states analyzed, with Oklahoma City feeder prices used as the expected feeder cattle prices. At the state level, a decline in price sensitivity to changes in feeder cattle prices occurred in a majority (9 out of 14) of the examined states in this analysis over 1987-2022. Further, when considering only estimates from 2010-2022, a larger majority of states (12 out of 14) are characterized as beef cow inventories being less sensitive to changes in feeder cattle prices, with the remaining two experiencing marginal increasing (close to flat) sensitivity to changes in feeder cattle prices. Overall, this work strengthens available knowledge on cow-calf herd supply response by estimating own-price elasticities of supply for beef cow inventory with respect to feeder cattle prices at both national and state levels.

Wholesale beef demand elasticities were estimated to provide the U.S. beef industry with current wholesale beef demand insights and a better understanding of the impacts of structural changes and supply chain disruptions. Three variations of seemingly unrelated regression (SUR) models were estimated given concerns around data quality. Additionally, a structural break test was used to identify structural breaks in the models. Results from the three variations are compared to each other and to results from previous research to determine if the quality of the chicken data impacts the estimates. Findings suggest that the quality of the chicken data does not significantly impact the own-price elasticity of demand estimates for wholesale beef and pork, but likely impacts estimates for own-price elasticity of demand for wholesale chicken and the cross-price relationships of chicken with beef and pork. Wholesale demand elasticities were estimated for two separate time periods (April 2003-February 2013 and March 2013-April 2022) given the structural breakpoint that was identified, and the findings suggest that the impact of changes in own price on quantity demanded have decreased between the two periods. This further suggests that the relationship between the own price and quantity demanded of protein products is decreasing over time. Stated differently, price sensitivity of wholesale meat buyers has declined.

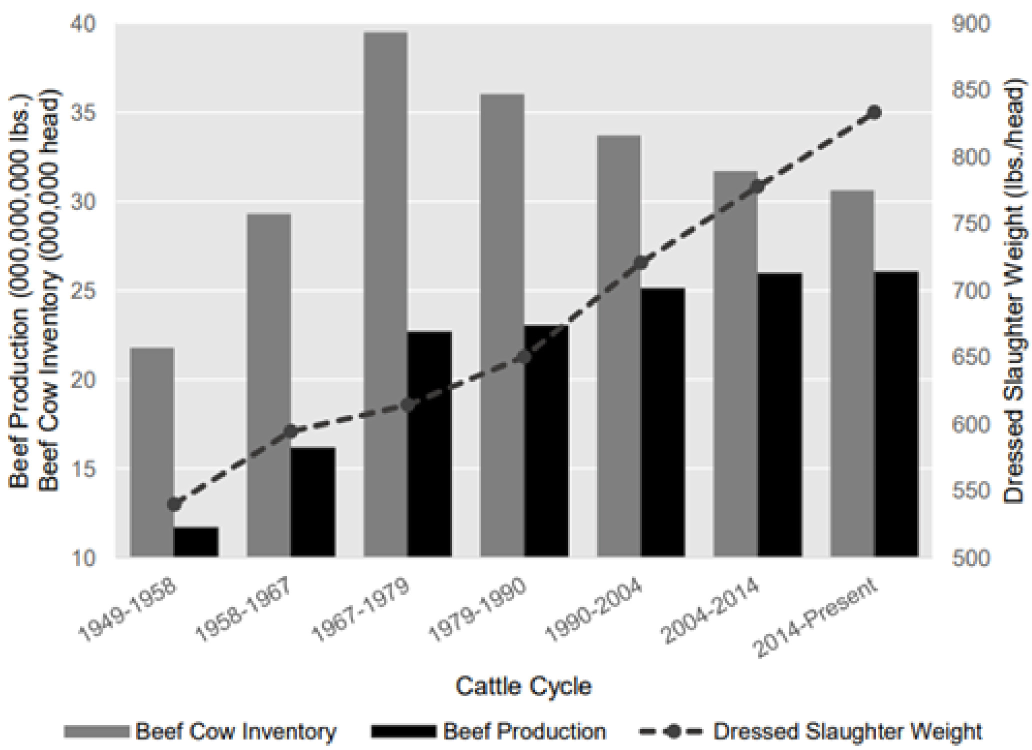
Article 1 - Cow-Calf Level Supply Response: How has the Industry Responded to Changes Over time?

Introduction

The United States is home to approximately 730,000 cow-calf producers who raised about 30.1 million beef cows in 2022 (NASS, 2017; NASS, 2022). Decisions made by producers at the cow-calf level ultimately impact total retail beef supplies, as the number of calves sold determines feedlot inventories, and thus the amount of fed cattle sent to the processing level (Schmitz, 1997). The top ten cow-calf states as of January 2022 were Texas, Oklahoma, Missouri, Nebraska, South Dakota, Kansas, Montana, Kentucky, North Dakota, and Iowa, representing 58 percent of total beef cows in the country (NASS, 2022). A United States map with state beef cow inventories as January 1, 2022 can be found in Figure a.1. Regional differences, such as climate conditions, natural disaster, and land availability, have considerable impacts on the decision-making process of cow-calf producers in these states. Additionally, changes in the beef industry, such as costs, structure, technology, producer and operation demographics, climate events, barriers to entry, and asset fixity, impact cow-calf producer herd expansion and contraction decisions. Therefore, decisions to expand or contract cow-calf herd size may notably differ regionally and year-to-year, based on the different economic, environmental, and social conditions faced by the many cow-calf producers across the country.

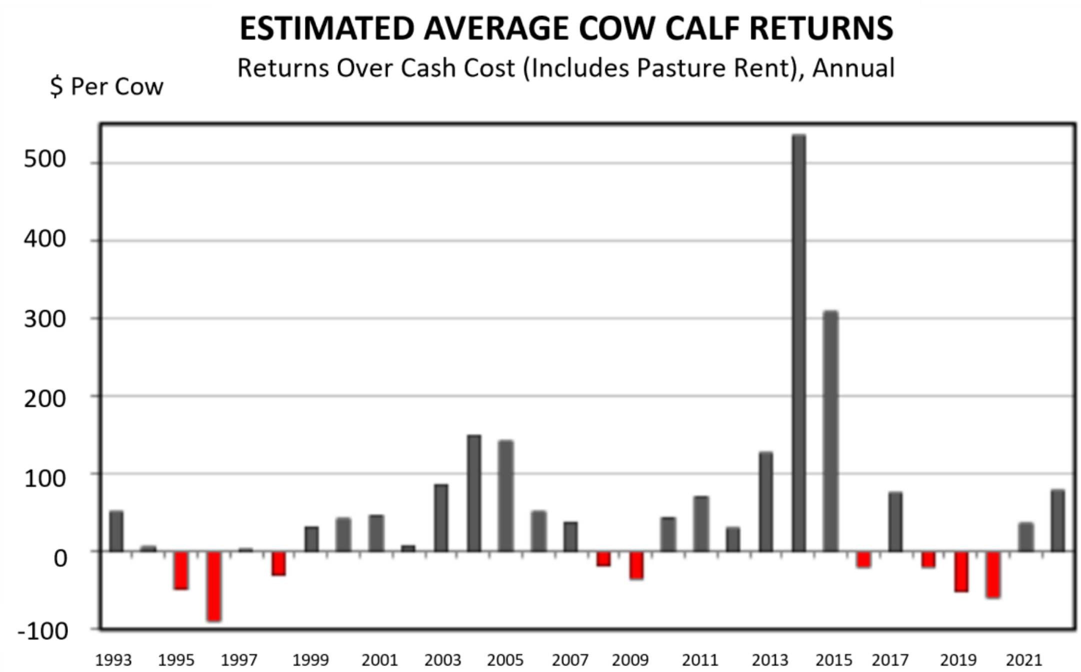
Beef cattle inventory in the United States peaked in 1975, with about 48 million beef cows, and has since been in a state of decline (NASS, 2022). In 1975, the total number of all cattle and calves in the U.S. also peaked, totaling over 132 million head (NASS, 2022). Historic beef cow inventories are known to have a cyclical nature, which is due to cow-calf producers expanding or contracting their herd based on market signals and the biological nature of livestock production (Luke et al., 2022). Additionally, Rosen et al. (1994) note that cattle production follows cyclical patterns because cattle are both capital and consumption goods. These 'cattle cycles' have historically ranged from 9 to 13 years. The current cycle began in 2014 when the last trough in inventory occurred and has been in a state of contraction since 2020 (NASS, 2022). Although the industry has seen a decline in the total number of beef cows since 1976, total beef supplies have increased, as shown in Figure 1.1 (Luke et al., 2022). This is due to efficiency gains in beef production, which has allowed for a decline in beef cow inventory and an increase in beef production.

Figure 1.1. Average inventory, production, and slaughter weight across cattle cycles (Luke et al., 2022)



Tonsor and Mitchell (2017) note that the amplitude of cyclical cow inventories has declined over time. This could occur if cow-calf producers are less sensitive to changes in expected feeder cattle prices (output prices), when making herd adjustment decisions, than they were in the past. As Tonsor and Schulz (2015) point out, less herd expansion investments are expected when a decrease in mean return on investment and/or an increase in investment volatility or uncertainty are experienced. Figure 1.2 shows the estimated average cow-calf returns, compiled by the Livestock Marketing Information Center (LMIC) (LMIC, 2021). This highlights that cow-calf returns are not steady across time and can vary greatly year-to-year. As of August 2021, LMIC projects that cow-calf returns will increase in 2022 and 2023, however with increased uncertainty that is being experienced related to input prices and drought, it is unclear if an increase in returns will increase cow-calf producers' willingness to increase herd size (LMIC, 2021). Understanding the current relationship between feeder cattle prices and cow-calf herd size adjustments would improve forecast accuracy of future cattle cycles, beef cow inventories, and ultimately beef supplies. Such information would provide industry participants more advance notice on upcoming cattle supply changes, which would help in making production and marketing decisions.

Figure 1.2. Estimated average cow-calf returns



Note: The figure was adapted from LMIC (2021)

The objective of this study is to estimate the current relationship between feeder cattle prices and cow-calf herd size in the United States. Additionally, state-level models for 14 of the top 20 beef cow states will also be developed to estimate regional differences in the relationship between feeder cattle prices and cow-calf herd size. Annual own-price elasticities of supply for beef cows with respect to feeder cattle prices will be estimated for the United States and each of the 14 states.

Conceptual Considerations

The objective of this paper is to estimate the current relationship between feeder cattle prices and cow-calf herd size. To do so, one must consider both the expectations of cow-calf producers, who are the primary herd-size decision makers, and the asset fixity faced in the industry. The expectations of cow-calf producers include factors that restrict and support beef herd expansion. Tonsor and Schulz (2015) summarize the restricting factors as land availability, increasing production efficiency, operator demographics, capital requirements, and commodity price volatility, Conversely, they offer the factors that support herd expansion as high cow–calf returns, global beef demand growth, and timing within the current cattle cycle (Tonsor & Schulz, 2015). Additionally, Tonsor and Schulz (2015) also note that there are many individual ranch considerations that impact the overall direction of the beef cattle herd. Without proper consideration of expectations and asset fixity, a supply model will fail to accurately address the important factors that impact supply adjustments in the industry.

One attribute of a successful cowherd supply response model is its ability to accurately reflect cow-calf producers' expectations regarding factors such as output prices, input prices, other costs, and environmental conditions, because it is important to reflect the point in time when the production decision is made relative to the time the output is ready to sell. Although there are many ways a cow-calf producer may increase their herd size, the most common way is to retain heifers they raise. In the cattle industry, it takes roughly two years from the time a cow-calf producers decides to breed a cow to the time they sell the calf or retain the heifer to increase their herd. Therefore, the biological nature of cattle production requires important consideration when choosing the time lag to assign to variables included in the supply model.

Other important conceptional considerations for cowherd supply response models are producer demographics, such as producer age and other income sources. Regarding producer age, Tonsor and Schulz (2015) state, "As an operation manager or owner ages, he or she typically becomes more conservative and may be more likely to use shorter-term horizons in assessing investment opportunities." Regarding other income sources, the authors state, "principal operators having an occupation off-farm may represent operations that lend themselves better to off-farm work and constrain interest in expansion due to time available and/or the financial need to expand" (Tonsor and Schulz, 2015). However, these demographic factors may be more difficult to quantify due to data availability. Therefore, when building a supply model, it is imperative to consider demographic factors, as well as costs, revenue, and environmental expectations.

A second attribute of a successful cowherd supply response model is its ability to account for asset fixity in the industry. The cow-calf sector of the U.S. beef industry is land intensive, as beef cows graze on pasture throughout their life. According to the USDA Natural Resource Conservation Service (NRCS) (n.d.), there are 528 million acres of privately owned grazing lands which accounts for 27 percent of land in the contiguous United States. In addition to privately owned grazing land, there are 155 million acres of public livestock grazing land managed by the Bureau of Land Management (BLM, 2016). Due to the biological nature of cattle production, there are biological lags from the time the initial decision is made to the time the output is sold. Together, the land requirement and biological lags create a cow-calf industry with asset fixity. To account for this asset fixity, a model must consider the number of beef cows in the herd the prior year by including a lagged-dependent variable as an independent variable, creating a dynamic model.

Law of One Price

A final consideration for cowherd supply models is determining what feeder cattle price best represents price expectations for cow-calf producers. Whether naïve or forward-looking expectations are assumed, analysis is limited in data availability for both cash and futures feeder cattle markets. Oklahoma City feeder prices are often used as a proxy for national feeder cattle prices as they reflect prices at the largest cattle auction barn in the country. Further, Oklahoma City is centrally located in relation to many of the top cow-calf states and cattle feeding states.

Moreover, some believe a national feeder cattle price exists in the United States and geographically distinct feeder cattle markets follow the “law of one-price” argument. According to Persson (2008), “The concept “law of one price” relates to the impact of market arbitrage and trade on the prices of identical commodities that are exchanged in two or more markets. In an efficient market there must be, in effect, only one price of such commodities regardless of where they are traded.” If feeder cattle markets are believed to be efficient and the commodities are believed to be interchangeable, then the “law of one price” may hold for feeder cattle markets.

Research has found mixed evidence regarding if the “law of one price” holds for cattle markets, and agricultural commodity markets in general. Specific to cattle prices, Feuz et al. (2008) did not find evidence to support “law of one price” and Grant (2007) found the “law of one price” held in some but not all of the time periods tested. However, as stated in Fuez and Bailey (2008), “Baffes (1990) explained that additional research must be performed in order to fully deny the law of one price. Perhaps, there are variables that are immeasurable or are not considered in this data set.” Therefore, “law of one price” may be challenging to empirically assess given restrictions in data availability.

Given the spatial nature of feeder cattle market, regional differences in feeder cattle prices exist in terms of transportation and transaction costs. However, if the “law of one price” exists for feeder cattle markets, then when regional costs are accounted for, the feeder cattle price in various markets should be equal for a given point in time. Figure 1.3 shows a theoretical example of what the “law of one price” argument would mean for feeder cattle prices in relation to Oklahoma City feeder steer prices. Market A represents a market that has lower regional costs compared to Oklahoma City whereas market B represents a market with higher regional costs than Oklahoma City. However, both market A and B are perfectly correlated with the Oklahoma

City price and follow the same trends in terms of magnitude and direction of price changes, which is key to the argument of the "law of one price".

Figure 1.3. Example of the 'law of one price" for feeder cattle prices in relation to Oklahoma City feeder steer prices. 1973-2021

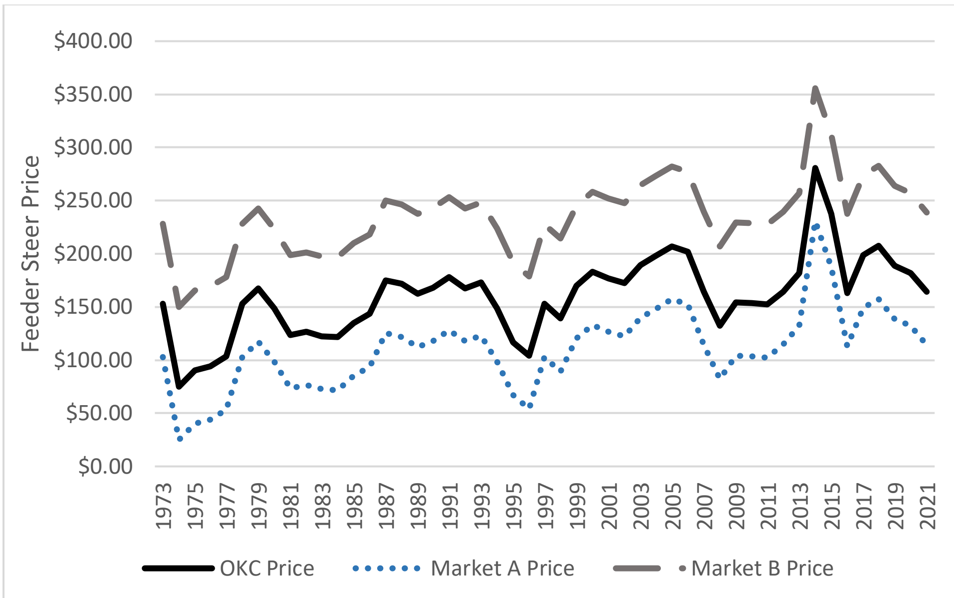


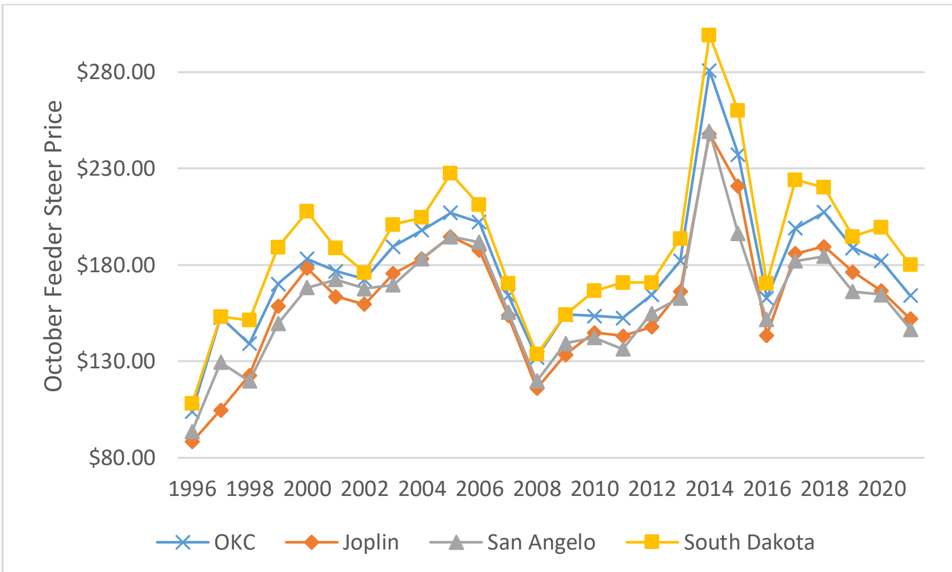
Table 1.1 shows correlations among October feeder cattle prices in various markets from 1996-2021. The Oklahoma City and South Dakota market price refers to 500-600lbs steers, however the Joplin and San Angelo price refers to 550-600lbs steers. Correlation between all prices is above 95 percent, which suggests these prices follow similar trends and are only marginally different in terms of factors that cause price changes. Additionally, Figure 1.4 is a visual representation of these feeder steer prices over time and illustrates how these prices follow similar trends related to the magnitude and direction of price fluctuations. While the "law of one price" for feeder cattle price may fall short in certain examples, high correlation of prices for various feeder cattle markets likely exists. Therefore, in the absence of available feeder cattle price series for different regions and states in the U.S., Oklahoma City prices can serve as a proxy. However, there may be points in time in certain states or regions of the United States

where the "law of one price" argument for feeder cattle prices is less accurate and therefore not a good proxy for feeder prices.

Table 1.1. Correlation of feeder cattle prices in various markets

	OKC	***Joplin***	***San Angelo***	***South Dakota***
OKC	1			
Joplin	0.971	1		
San Angelo	0.977	0.967	1	
South Dakota	0.987	0.978	0.959	1

Figure 1.4. October feeder steer prices in various markets



Literature Review

Research related to the supply changes of the U.S. cow-calf herd is sparse and only periodically updated. Specifically, research concerning the role feeder cattle prices play in cow-calf producers' decision to increase or decrease their herd size is very limited. However, given that feeder cattle price is the price of the direct output (calves) of cow-calf producers and that price sensitivity may be decreasing in the beef industry, it is an area worthy of research. Available research focused on the supply response of the cowherd in the United States is reviewed and discussed to discover the current understanding of cow-herd supply response as well as areas of opportunity and potential limitations.

Jarvis et al. (1974) is an early example of a research article that discussed cowherd supply responses. They found that both negative and positive supply responses are possible in the cattle industry. Aadland and Bailey (2001) is an example of an article that analyzed the response of beef cattle producers to changes in the price of cattle. They built a model that separated the fed and unfed cattle markets and allowed producers to make culling decisions on both the fed and unfed margins. They found price elasticities of -3.59 and -2.18 for fed and unfed cattle, respectively. Further, they note "our results suggest that both positive and negative short-run supply responses have been experienced in the U.S. beef-cattle market" (Aadland and Bailey, 2001). Similarly, Aadland et al, (2000) analyzed supply responses of the cowherd given changes in the cow market and heifer market. They state, "Using annual U.S. time-series data (1930-1997) and a simultaneous-equations econometric approach, we find a positive short-run supply response in the cow market and mixed evidence in the heifer market" (Aadland et al., 2000). While Aadland and Bailey (2001) and Aadland et al, (2000) both analyze supply relationships in the U.S. cattle industry, they do not utilize feeder cattle prices in the same manner as our research. Prevatt and Vansickle (2003) is an example of a study that considers the changes in number of cattle and calves given a change in calf price. However, similar to Aadland and Bailey (2001) and Aadland et al, (2000), their results are outdated by several decades. Due to the outdated nature of these studies, they do not consider changes the beef industry has faced recently. Therefore, a need exists for updated research on supply responses in the U.S. cattle industry.

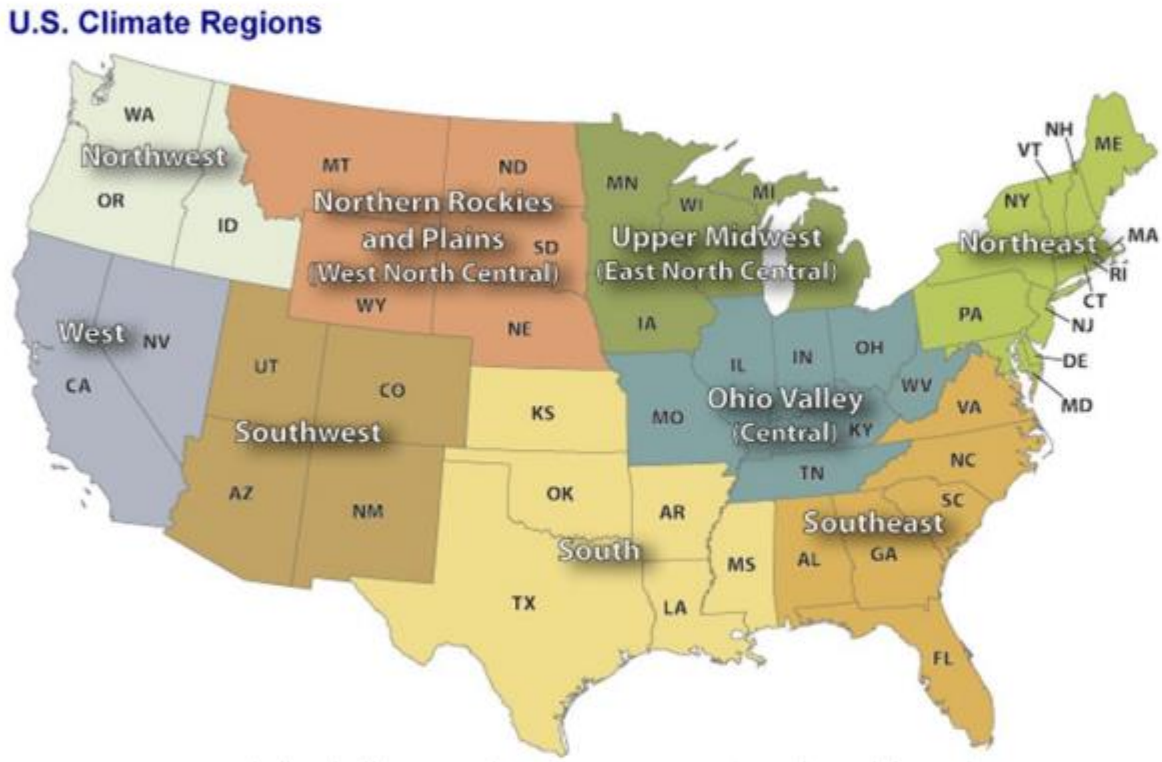
While this literature review is not all encompassing of literature related to the U.S. cowherd and producer supply response, it represents analyses that are commonly cited and are the most relevant to our research to the author's knowledge. Given the limited availability of research related to cow-calf herd size, this study aims to help fill the gap in research on the drivers of cow-herd supply adjustments at national and state levels.

Data

Annual data from 1973-2021 was collected from multiple sources to build farm-level dynamic supply models for cow-calf producers. January 1 national beef cow inventories, denoted Q_{BC}, from the United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) January Cattle Inventory reports and Oklahoma City, OK October 500-600lb feeder steer prices (as a representative proxy for main output prices faces by cow-calf producers), denoted P_{FS}, from USDA Agricultural Marketing Service (AMS) were compiled from Livestock Marketing Information Center (LMIC) (LMIC, 2022).

To account for national drought conditions faced by cow-calf producers, regional data from the Palmer Drought Severity Index (PDSI), denoted PDSI, obtained from the National Oceanic and Atmospheric Administration (NOAA), is used to capture the average drought conditions across the Southern, Northern Rockies and Plains, and Ohio River Valley regions which represent the areas of the country with the top 10 beef cattle states, as previously listed (NOAA, 2022). PDSI values typically range from -4.0 to +4.0, where a -4.0 represents extreme drought conditions and a +4.0 represents extremely moist conditions. However, according to the National Center for Atmospheric Research (NCAR) (2020), more extreme values are possible depending on conditions. A map representing the PDSI climate regions in shown in Figure 1.

Figure 1.5. PDSI climate regions as defined by NOAA (Hartman, 2021)



A national hay price, denoted P_H, measured in dollars per ton, from the USDA NASS QuickStats tool is used as a proxy for a key input cost for cow-calf producers (NASS, 2022). As a proxy for national pasture rental rates, the average pasture rent per acre for the top 10 beef cow states in 2022 was calculated. Historic pasture rent estimates from 1973-1994 were obtained from the "Agricultural Land Values Survey" from USDA NASS (ERS, 2020). Pasture rent estimates from 1995-2020 are from the USDA NASS June Agricultural Survey through the USDA NASS QuickStats tool (NASS, 2022). As a proxy for production efficiency gains in the cow-calf sector, denoted Slt, the national average steer slaughter weight is used from the USDA NASS livestock slaughter monthly report, obtained from LMIC (LMIC, 2022).

All prices are deflated using the producer price index (PPI) commodity data for farm products, with a 2021 base year, from the Bureau of Labor Statistics (BLS) (BLS, 2022).

Variable units are listed in Table 1.2. Descriptive statistics for all variables are shown in Table 1.3. The minimum and maximum of $Q_{BC(t)}$ shows the range of beef cow inventory over the time period. Additionally, time trend charts of each variable can be found in Figures a.2 through a.6.

Table 1.2. Variable descriptions

Variable	Description
$\mathbf{Q_{BC}}$	Beef Cows, (1000 Head)
$\mathbf{P_{FS}}$	Feeder Steer Price, ($/cwt)
PDSI	PDSI Drought Index, (-4.0 = extreme drought, +4.0 = extreme moisture)
$\mathbf{P_{H}}$	Hay Price, ($/ton)
$\mathbf{P_{PR}}$	Pasture Rental Rate, ($/acre)
Slt	Steer Slaughter Weight, (Pounds)

Table 1.3. Variable descriptive statistics: annual observations, 1973-2021. t = year

Descriptive Statistics					
Statistic	**N**	**Mean**	**St. Dev.**	**Minimum**	**Maximum**
$\mathbf{Q_{BC(t)}}$	47	34,038.6	3,579.5	28,956.4	45,711.8
$\mathbf{P_{FS(t-2)}}$	47	159.5	38.1	75.0	280.7
$\mathbf{PDSI_{(t-1)}}$	47	0.7	1.7	-3.1	4.6
$\mathbf{P_{H(t-2)}}$	47	155.9	22.9	112.4	204.3
$\mathbf{P_{PR(t-2)}}$	47	26.2	4.0	19.2	35.7
$\mathbf{Slt_{(t)}}$	47	786.2	69.7	672.5	907.2

State-level data for years 1973-2021 was also collected for Texas, Oklahoma, Missouri, Nebraska, South Dakota, Kansas, Montana, Kentucky, North Dakota, Iowa, Florida, Tennessee, Alabama, and Virginia. These 14 states fall in the top 20 states for beef cow inventory in 2022 and represent 68.41 percent of total beef cows in 2022. Ideally, all of the top 20 states for beef cow inventory would be analyzed, however limitations to various data series restricted the analysis to only 14 states.

January 1 state beef cow inventories from the USDA NASS January Cattle Inventory reports are obtained. State-level feeder cattle prices are less available for the timeseries used in this analysis. Therefore, only data for Texas, Missouri, and South Dakota from 1996-2021 is obtained for state specific feeder cattle prices. For Texas, San Angelo feeder prices from

Producers Livestock Auction Company are used as a proxy for a Texas feeder price. Feeder prices for October medium and large steers from 550-600lbs are obtained from Beef Basis.com. For Missouri, Joplin feeder prices from Joplin Regional Stockyards are used as a proxy for Missouri feeder cattle prices. Joplin feeder prices for October medium and large steers from 550-600lbs are obtained from Beef Basis.com. For South Dakota, LMIC compiled prices from all South Dakota auctions that were attended by AMS reporters. The South Dakota data used reflects feeder prices for medium and large 1, 500-600lb October feeder steers and are obtained from LMIC. The South Dakota specific feeder steer price is referred to as the South Dakota market price. LMIC and BeefBasis.com both compile data from various USDA AMS reports.

Similar to the national data, regional drought data from the PDSI is used to capture the average drought conditions in each of the 14 states analyzed. As shown in Figure 1.5, the South region index is used for Texas, Oklahoma, and Missouri. The Northern Rockies and Plains region index is used for Montana, South Dakota, North Dakota, and Nebraska. The Ohio River Valley region index is used for Missouri, Kentucky, and Tennessee. The Southeast region index is used for Alabama, Florida, and Virginia. Finally, the Upper Midwest region index is used for Iowa. State specific pasture rental rates for the 14 states analyzed are obtained similarly to the national pasture rental rate data. Historic pasture rent estimates for each state from 1973-1994 were obtained from the “Agricultural Land Values Survey” from USDA NASS and pasture rent estimates for each state from 1995-2020 are from the USDA NASS June Agricultural Survey through the USDA NASS QuickStats tool.

Methods

National Model

A partial-adjustment supply model was developed to quantify the effect changes in feeder cattle price have on beef cowherd size in the United States. Nerlove (1956) is credited with developing a dynamic partial-adjustment model for use in agricultural supply research and farmer decision making. The goal of this dynamic model is to provide a better understanding of future cowherd expansion/contraction expectations and update short- and long-run beef cow supply elasticities. Naïve expectations are used to reflect how cow-calf producers respond to conditions they face at the time they are making the production decision. These naïve expectations account for the biological lags in expansion/contraction decisions. The partial-adjustment supply model was selected to account for the asset fixity in the beef industry. Additionally, a partial-adjustment model with a lagged-dependent variable was selected in place of a simpler regression model without the lagged-dependent variable to reduce the variation in the error terms.

Equation (1.1) is the selected regression equation. After considering conceptual considerations and data availability, the independent variables of P_{FS}, PDSI, P_H, P_{PR}, Slt, and Q_{BC} were chosen. β_1 through β_6 are the estimated coefficients. P_{FS} was chosen as a proxy for the expected output price cow-calf producers receive when they sell their calves. β_1 is expected to be positive because an increase in quantity supplied of Q_{BC} is expected to follow an increase in P_{FS}. The drought variable was chosen to reflect expected pasture conditions and the impact weather conditions have on reducing herd size. β_2 is expected to be positive because an increase in supply of Q_{BC} is expected to follow an increase in expected moisture. In other words, as drought conditions worsen, supply of Q_{BC} is expected to decrease, because the PDSI ranges from -4.0

(extreme drought) and +4.0 (extreme moisture). P_H and P_{PR} are proxies for two of the key expected input prices faced by cow-calf producers. β_3 and β_4 are expected to be negative because a decrease in supply of Q_{BC} is expected to follow an increase in the price of an input increases. Slt is used to reflect the efficiency gains in the beef industry, such as increased slaughter weight over time. Ideally, a weaning percentage or other farm-level production efficiency variable would have been chosen, however due to data limitations, Slt was selected as the best proxy available. Further, as the Slt variable captures a slight increasing trend, it serves a similar purpose as a trend variable. β_2 is expected to be negative because as Slt increases, supply of Q_{BC} is expected to decrease. Q_{BC} is included as a lagged-dependent variable to account for asset fixity and should range from 0 to 1. As the number of beef cows in the prior year greatly impacts the number of beef cows in the current, it is expected to be closer to 1 than 0. μ represents the error term.

$$(1.1)\quad Q_{BC(t)} = \beta_0 + \beta_1 P_{FS(t-2)} + \beta_2 PDSI_{(t-1)} + \beta_3 P_{H(t-2)} + \beta_4 P_{PR(t-2)} + \beta_5 Slt_{(t)} + \beta_6 Q_{BC(t-1)} + \mu$$

Variable lags are also included in equation (1.1) to account for expectations and asset fixity in the cow-calf sector. P_{FS}, P_H, and P_{PR} are each lagged two years to represent price expectations and the biological lags in herd expansion/contraction decisions that were previously discussed. PDSI is lagged one year to reflect expectations of the impacts of poor pasture conditions on the ability to expand cowherds. As extreme drought conditions require quick herd contraction relative to decisions to expand, it is only lagged one year. Slt is not lagged because it captures a slight increasing trend in the beef industry and therefore a lag would not drastically impact its effect. Q_{BC} is the lagged-dependent variable as an independent variable. This variable accounts for asset fixity and is important to include as the number of beef cows the prior year has a considerable impact on the number of beef cows in the current year.

Equation (1.1) is estimated 36 times, using rolling time periods of 12 years each, starting with 1975-1986 and ending with 2010-2021. Twelve-year periods were selected as the length of the regressions because the average cattle cycle is 12 years long. Therefore, each model includes periods of high and low herd inventories. The estimates for β_1 in each model are used to calculate the own-price elasticity of supply for beef cows for the United States over years 1987-2022. Own-price elasticity of supply for beef cows for each year are calculated by $\beta_1 * (P_{FS(t-2)}/Q_{BC(i,t)})$, or by multiplying the own-price coefficient estimate by the lagged Oklahoma City feeder steer price for the year being estimated divided by the quantity of beef cows for the year being estimated. Annual own-price elasticity of supply estimates will be analyzed to determine the trend of cow-calf producer sensitivity to changes in feeder cattle prices over time.

Due to periods of increased uncertainty faced in the cow-calf sector, some have questioned if cow-calf producers are becoming less price sensitive to changes in expected feeder cattle prices (output prices), when making herd expansion or contraction decisions, than they were in the past. To understand the current relationship between feeder cattle prices and cow-calf herd size adjustments and to test if the relationship has in fact changed over time, short- and long-run elasticity estimates will be calculated from a regression using equation (1.1) and annual data from 1975-2021. These annual own-price elasticities will be analyzed over time to determine if changes in estimates can be observed.

Out-of-sample regression testing will be conducted to examine if the model accurately predicts beef cowherd size. Equation (1.1) will be estimated a series of 11 times over alternating time periods of 36 years each, from 1975-2020, adding a year and dropping a year each time. Beef cattle herd estimates for years 2011-2021 will be calculated and compared to USDA NASS inventory data. These results will also be compared to similar series results from equation (1.2), which is partial-adjustment supply equation with $Q_{BC(t)}$ as the dependent variable and $Q_{BC(t-1)}$ as the only independent variable. This represents a simple model as compared to equation (1.1) as it only considers the number of beef cows in the prior year and does not consider other factors, such as costs, revenue, drought, and production trends. Moreover, by comparing the accuracy of the estimates from equation (1.1) and equation (1.2), one can assess if using a more complex model such as equation (1.1) improves forecast accuracy.

$$(1.2)\ Q_{BC(t)} = \alpha_0 + \alpha_1 Q_{BC(t-1)} + \mu$$

State-Level Models

While the national model described above aids in understanding changes in the U.S. cowherd as a whole, state-level supply models bring in regional differences cow-calf producers face. Using a similar framework as the national model, partial-adjustment supply models for Texas, Oklahoma, Missouri, Nebraska, South Dakota, Kansas, Montana, Kentucky, North Dakota, Iowa, Florida, Tennessee, Alabama, and Virginia using data from 1975-2021 are developed to estimate state-level annual supply elasticities to quantify the effect changes in feeder cattle price has on state inventories.

Equation (1.1) is altered to incorporate the differences in state-level data used in each state model. Given the lack of state specific feeder cattle prices for many of the states, Oklahoma City feeder prices (P_{FS}) will be used as a proxy for each of the 14 states. Equation (1.3) represents the partial-adjustment supply model that will be estimated for the 14 states. Individual states are represented by i = 1,…,14, with Texas=1, Oklahoma=2, Missouri=3, Nebraska=4, South Dakota=5, Kansas=6, Montana=7, Kentucky=8, North Dakota=9, Iowa=10, Florida=11, Tennessee=12, Alabama=13, and Virginia=14. Similar to the national model, P_H and Slt are used as proxies for hay price and production efficiencies. PDSI, P_{PR}, and Q_{BC} are used for the specific states, as described in the data section.

$$(1.3)\quad Q_{BC(i,t)} = \beta_0 + \beta_1 P_{FS(t-2)} + \beta_2 PDSI_{(i,t-1)} + \beta_3 P_{H(t-2)} + \beta_4 P_{PR(i,t-2)} + \beta_5 Slt_{(t)} + \beta_6 Q_{BC(i,t-1)} + \mu$$

Equation (1.3) is estimated a series of 36 times for states i=1,…,14, using rolling time periods of 12 years each, starting with 1975-1986 and ending with 2010-2021. The estimates for β_1 in each model are used to calculate the own-price elasticity of supply for beef cows for each state over years 1987-2022. Own-price elasticities of supply for beef cows for each year are calculated by $\beta_1 * (P_{FS(t-2)}/Q_{BC(i,t)})$, or by multiplying the own-price coefficient estimate by the lagged Oklahoma City feeder steer price divided by the quantity of beef cows. Annual own-price elasticity of supply estimates for each will be analyzed to determine the trend of price sensitivity over time.

To incorporate state specific feeder cattle prices into the partial adjustment supply models, feeder cattle prices for San Angelo, TX, Joplin, MO and South Dakota market are used in place of Oklahoma City feeder cattle prices for Texas, Missouri, and South Dakota. Similar to equation (1.3) and the methods described above, the partial-adjustment supply models for Texas, Missouri, and South Dakota are altered to use their specific feeder cattle prices (San Angelo, TX, Joplin, MO and South Dakota market) and estimated a series of 13 times, using rolling time periods of 12 years each, starting with 1998-2009 and ending with 2010-2021. These models allow for discussion and comparison of the "law of one price" theory and the Oklahoma City feeder price as a proxy for state-level feeder cattle prices.

While there are various other state specific feeder cattle prices in addition to Oklahoma City, Joplin, San Angelo, and South Dakota market, these are the series that are available as early as 1996. The year 1996 was selected as the latest time period to allow for elasticity estimation over an ample number of years to determine trends, in this case 13 years. The estimates for β_1 in each model are used to calculate the own-price elasticity of supply for beef cows for each state over years 2010-2022 in the same manner described above. Equation (1.4) represents the partial-adjustment supply model form that will be estimated with specific feeder cattle prices for Texas, Missouri, and South Dakota. Like equation (1.3), individual states are represented by i = 1,…,14, therefore in equation (1.4) it still holds that Texas=1, Missouri=3, and South Dakota=5. The only difference between equations (1.3) and (1.4) is the state specific feeder price used in equation (1.4). Annual own-price elasticity of supply estimates for each model with state specific feeder prices will be analyzed to determine the trend of price sensitivity over time and if the "law of one price" holds for feeder cattle prices in this context.

$$(1.4)\quad Q_{BC(i,t)} = \beta_0 + \beta_1 P_{FS(i,t-2)} + \beta_2 PDSI_{(i,t-1)} + \beta_3 P_{H(t-2)} + \beta_4 P_{PR(i,t-2)} + \beta_5 Slt_{(t)} + \beta_6 Q_{BC(i,t-1)} + \mu$$

Results

National Model

Results from the partial-adjustment supply models (equations (1.1) and (1.2)) are shown in Table 1.4. In equation (1.1), β_1 and β_2 are positive and β_3, β_4, and β_5 are negative as expected, as previously discussed. β_6 is within the range of 0 and 1 and is closer to 1 than 0 as expected. Coefficients on $P_{FS(t-2)}$ and $Q_{BC(t-1)}$ are statistically significant ($p<0.01$). Coefficients on PDSI and $P_{PR(t-2)}$ are also statistically significant ($p<0.05$). The coefficient on $P_{H(t-2)}$ is statistically significant ($p<0.1$). The coefficient on Slt is nearly significant with a p-value of 0.1484. In equation (1.2), α_1 is also within the range of 0 and 1 and is closer to 1 than 0 as expected. The coefficient on $Q_{BC(t-1)}$ is statistically significant ($p<0.01$).

Table 1.4. Results from the partial-adjustment supply models estimating annual beef cow inventories in the United States, annual data from 1975-2021

	Dependent variable:	
	$Q_{BC(t)}$	
	Equation (1.1)	Equation (1.2)
$P_{FS(t-2)}$	20.821***	
	(3.956)	
$PDSI_{(t-1)}$	138.215**	
	(61.553)	
$P_{H(t-2)}$	-14.050*	
	(8.091)	
$P_{PR(t-2)}$	-72.155**	
	(30.737)	
$Slt_{(t)}$	-5.969	
	(4.050)	
$Q_{BC(t-1)}$	0.941***	0.914***
	(0.052)	(0.036)
Constant	7,123.062*	2,701.676**
	(4,154.696)	(1,249.443)
Observations	47	47
R^2	0.969	0.934
Adjusted R^2	0.964	0.933
Residual Std. Error	677.911 (df = 40)	929.936 (df = 45)
F Statistic	207.082*** (df = 6; 40)	636.544*** (df = 1; 45)
Note:	*p<0.1; **p<0.05; ***p<0.01	

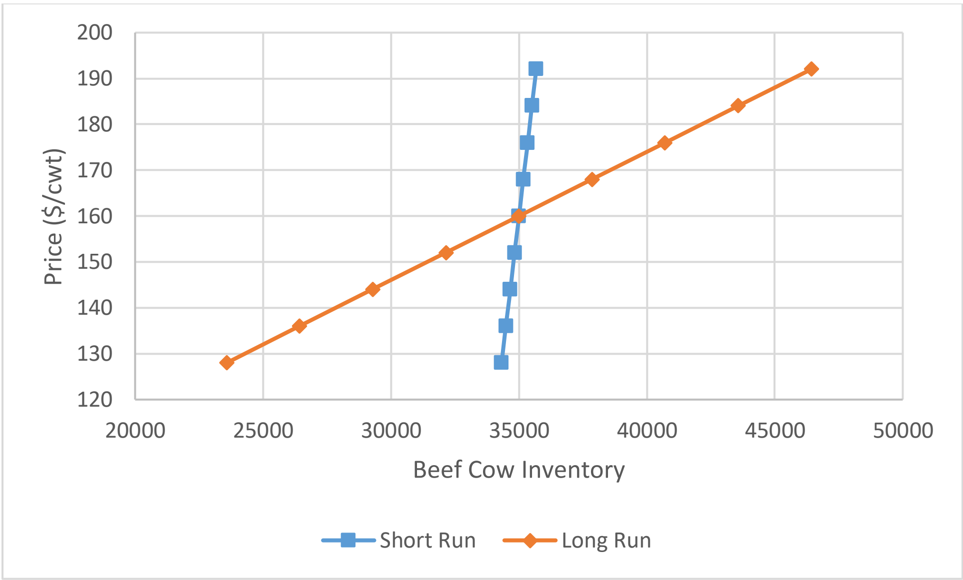
Estimates from equation (1.1) show a 20.821 thousand head increase in quantity supplied of Q_{BC} follows a one dollar/cwt increase in P_{FS} two years lagged. A 138.215 thousand head decrease in Q_{BC} follows a one PDSI point increase in PDSI one year lagged. In other words, as drought worsens by one PDSI point, supply of Q_{BC} decreases by 138.215 thousand head the following year. A 14.050 thousand head decrease in Q_{BC} follows a one dollar/ton increase in P_H two years lagged. A 72.155 thousand head decrease in Q_{BC} follows a one dollar/acre increase in P_{PR} two years lagged. A one-pound increase in Slt decreases supply of Q_{BC} by. As shown in Table 1.4 the R^2 is 0.969, which indicates that the independent variables explain 96.9 percent of the variation in Q_{BC}.

Short- and long-run elasticities are shown in Table 1.5 and were estimated from equation (1.1) using the coefficients from Table 1.4 and the 1975-2021 averages for the dependent and independent variables. All short-run elasticity estimates are inelastic, which is expected, given the nature of the cattle industry. Additionally, the short-run estimates are more inelastic than the long-run estimates as expected, given that cow-calf producers face asset fixity and are less price responsive in the short-term. The P_{FS} own-price elasticity in the short-run is 0.097 percent which indicates a 0.097 percent increase in quantity supplied of Q_{BC} is followed by a one percent increase in P_{FS} two years lagged, in the short run. The P_{FS} own-price elasticity in the long-run is 1.632 percent. A 1.632 percent increase in quantity supplied of Q_{BC} is followed by a one percent increase in P_{FS} two years lagged, in the long run. The short-run estimate is within the range from Prevatt and Vansickle (2003) which found calf price elasticities of cattle and calves inventory in 1949-1999. While the analysis of Prevatt and Vansickle (2003) is outdated and differs in terms of methods from this study, their results consider changes in number of cattle and calves given a change in calf price, which is similar to this analysis. Their results can be found in Figure a.7. Further, most of the existing research on cowherd elasticities are outdated, and given the changes the beef industry has faced, new estimates are needed such as ours are needed. Figure 1.6 is the graph of the implied short- and long-run beef own-price supply curves.

Table 1.5. Short- and long-run beef cowherd supply elasticities for feeder steer price, hay price, and pasture rental rate, calculated from equation (1.1)

	Short-Run	Long-Run
Feeder Steer Price	0.097	1.632
Hay Price	-0.064	-1.077
Pasture Rental Rate	-0.055	-0.929

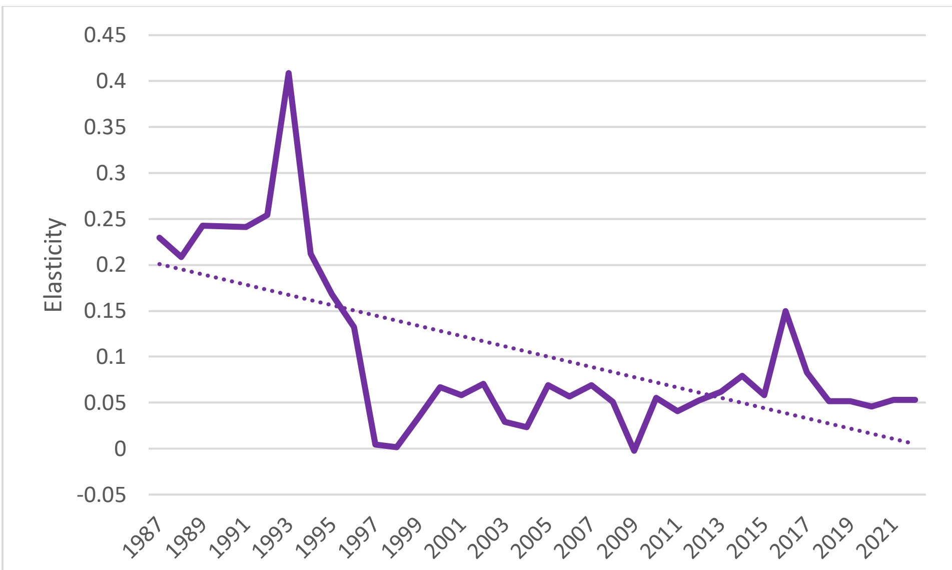
Figure 1.6. Short- and long-run own-price beef cowherd supply elasticity curves calculated from equation (1.1)



Cross-price elasticity of supply estimates for P_H and P_{PR} are also found in Table 1.4. The short-run cross-price elasticity of the input P_H was calculated and is -0.064 percent. A 0.064 percent decrease in supply of Q_{BC} is followed by a one percent increase in P_H two years lagged, in the short run. The long-run cross-price elasticity of the input P_H is -1.077 percent. 1.077 percent decrease in supply of Q_{BC} is followed by a one percent increase two years lagged in the long run. The short-run cross-price elasticity of input P_{PR} is -0.055 percent. A 0.055 percent decrease in supply of Q_{BC} is followed by a one percent increase in P_{PR} two years lagged, in the short run. The long-run cross-price elasticity of input P_{PR} is -0.929 percent. A 0.929 percent decrease in supply of Q_{BC} is followed by a one percent increase in P_{PR} two years lagged, in the long run.

To test the hypothesis that cow-calf producers are becoming less price sensitive to feeder cattle price over time, short- and long-run own-price elasticity estimates for years 1987-2022 were calculated. Figure 1.7 is a graph of these short-run own-price elasticity estimate over time. If the hypothesis was true, a decrease in the elasticities would be expected over time. Results indicate that at the national level, a decrease in price sensitivity to changes in feeder cattle prices has occurred, shown with the decreasing trendline in Figure 1.7.

Figure 1.7. Annual estimates of short-run own-price elasticity of supply for beef cows in the United States with respect to Oklahoma City feeder cattle price, 1987-2022



To test the ability of equation (1.1) to predict beef cowherd size in the United States, a series of out-of-sample regression tests were conducted. Results from these tests were used to calculate the predicted herd size for each year from 2011-2021. These results were compared to results from the same series of tests using equation (1.2) and the annual inventories from USDA NASS (NASS, 2022). Table 1.6 contains results from these analyses. Compared to the annual inventories from USDA NASS, equation (1.1) had a mean error percentage of 2.056 percent whereas equation (1.2) had a higher mean error percentage of 2.145 percent. Further, in eight out of the eleven years, equation (1.1) had lower percent error in absolute value terms. Therefore, even though the difference is marginal, equation (1.1), which included independent variables for annual prices and costs, drought, and slaughter weight, estimated herd size more accurately than equation (1.2), which only considered herd size the prior year.

Table 1.6. Annual beef cowherd estimates from equation (1.1) and equation (1.2) compared to USDA NASS USDA NASS Inventories, 2011-2021 (NASS, 2022)

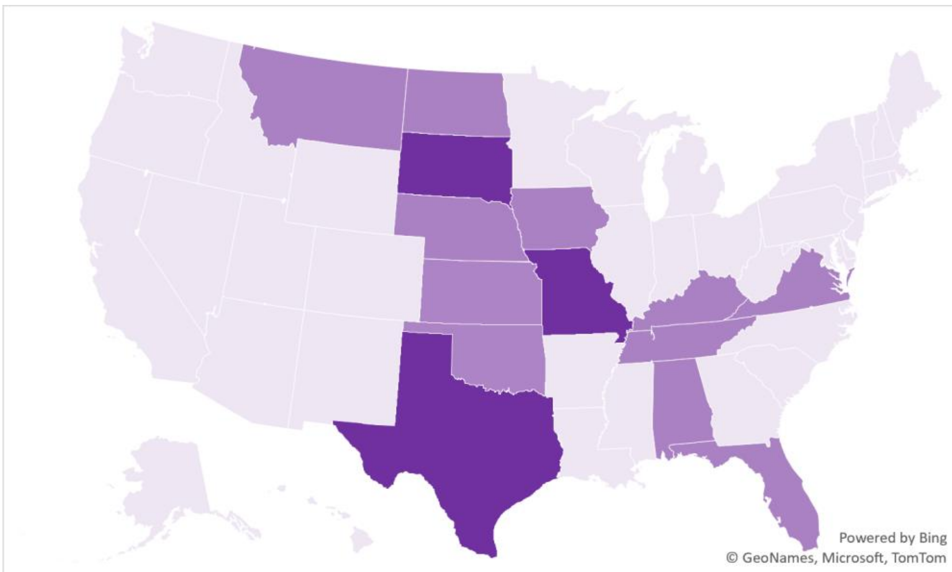
Year	Equation (1.1) Inventory	Equation (1.2) Inventory	USDA NASS Inventory	% Error Equation (1.1)	% Error Equation (1.2)
2011	30,499.939	31,499.544	30,912.600	1.335%	1.899%
2012	30,148.173	31,186.747	30,281.900	0.442%	2.988%
2013	28,684.427	30,627.615	29,631.300	3.196%	3.362%
2014	29,237.125	29,880.291	28,956.400	0.969%	3.191%
2015	28,974.111	28,921.506	29,332.100	1.220%	1.400%
2016	31,980.236	29,236.751	30,163.800	6.022%	3.073%
2017	30,699.388	30,144.615	31,170.700	1.512%	3.292%
2018	30,346.010	31,186.605	31,466.200	3.560%	0.889%
2019	31,645.490	31,494.361	31,690.700	0.143%	0.620%
2020	32,296.179	31,689.001	31,338.700	3.055%	1.118%
2021	31,201.798	31,388.847	30,843.600	1.161%	1.768%
Average				**2.056%**	**2.145%**

Note: Percent errors are in absolute value terms

State-Level Models

Figure 1.8 is a map highlighting the 14 states that supply elasticities are estimated for using equation (1.3). Results from the partial-adjustment supply models (equations (1.3)) that estimated cowherd supply and producer price sensitivity to changes in Oklahoma City feeder cattle prices for each of the 14 respective states over 1975-2021 are shown in Tables a.1 through a.14. Tables a.1 through a.14 also include results a partial-adjustment supply equation, similar to equation (1.2) with $Q_{BC(i,t)}$ as the dependent variable and $Q_{BC(i,t-1)}$ as the only independent variable. Similarly, results from the partial-adjustment supply models (equations (1.4)) that estimated cowherd supply and producer price sensitivity to changes in state specific feeder cattle prices for Texas, Missouri, and South Dakota compared to changes in Oklahoma City prices from 1998-2021 are shown in Tables a.15 through a.20.

Figure 1.8. Map highlighting the 14 states used to estimate cowherd supply elasticities. Darker purple states (Texas, Missouri, and South Dakota) represent the states that were also estimated with a state-specific feeder cattle price



Annual estimates of own-price elasticity of supply for beef cows with respect to Oklahoma City feeder cattle prices from 1987-2022 for each of the 14 states are shown in Table a.21. Additionally, individual state graphs depicting these estimates over time are shown in Figures a.8 through a.21. Similar to the national model, we hypothesize that a decline in price sensitivity to changes in feeder cattle prices is present in these states. Texas, Oklahoma, Nebraska, South Dakota, Kansas, Montana, Iowa, Florida, and Alabama; or nine out of the 14 states have a declining trend in price sensitivity over 1987 through 2022. The remaining five states (Missouri, Kentucky, North Dakota, Tennessee, and Virginia) have an increasing trend over the same time period. However, there are states that only have marginal decreasing or increasing trends over time such as Texas, Kentucky, Alabama, and Virginia.

Annual elasticity graphs for the 2010-2022 time period are not included in the appendix but are created and analyzed in the same manner as those shown in Figures a.8 through a.21. While there are five states with an increasing trend in price sensitivity from 1987-2022, when considering a more recent time period of 2010-2022, 12 of the 14 states have a decreasing trend and only two (South Dakota and Florida) have very marginal increasing trends. These results suggest that a decline in sensitivity to changes in feeder cattle prices has occurred in a majority (9 out of 14) of the states in this analysis over 1987-2022. Further, when considering only estimates from 2010-2022, a larger majority of state (12 out of 14) experiences a decline in sensitivity to changes in feeder cattle prices, with the remaining two experiencing marginal increasing (close to flat) sensitivity to changes in feeder cattle prices. This supports the hypothesis that cow-calf producer price sensitivity is decreasing over time.

Table 1.7 summarizes and compares annual elasticity estimates of supply for beef cows with respect feeder cattle prices for the 14 states over the three time periods of 1987-2022, 2000-2022, and 2010-2022. The average, minimum, maximum, percent of estimates lower than the prior year's estimate, and percent of estimates that have a positive sign are calculated from the 14 states over each period. As a decrease in sensitivity to changes in feeder cattle prices is expected, the average, minimum, and maximum should move closer to zero through each period. The average during the 2000-2022 period is smaller than 2010-2022, which suggests producer's may have been less sensitive in 2000-2010 on average than they were in 2010-2022. However, the average in 2010-2022 (0.078) is smaller than the average and closer to zero in 1987-2022 (0.074), but only slightly (0.004), which matches the expectation of decreased price sensitivity over time. The minimum in 2010-2022 is also smaller and closer to zero than the other two time periods. Similarly, the maximum in 2000-2022 and 2010-2022 are similar but is still lower and closer to zero than the maximum in 1987-2022.

Table 1.7. Elasticity summary (over 14 states) compared over 1987-2022, 2000-2022, and 2010-2022 for annual elasticity estimates for the supply of beef cows with respect to feeder cattle prices

Elasticity Summary (14 States)	1987-2022	2000-2022	2010-2022
Average	0.078	0.061	0.074
Minimum	-0.464	-0.320	-0.158
Maximum	0.837	0.645	0.644
% Lower than Prior Year	0.571	0.578	0.582
% Positive	0.700	0.708	0.731

The percent of estimates lower than the prior year's estimate is expected to increase, as an increase would signal a stronger decreasing trend in price sensitivity. While the increase is only marginal, the percent of estimates lower than the prior year's estimate is higher in 2010-2022 than the other two time periods. As previously stated, own-price elasticities of supply of beef cows with respect to feeder cattle prices are expected to be positive because an increase in quantity supplied of Q_{BC} is expected to follow an increase in P_{FS}. In 2010-2022, 73.077 percent of estimates are positive, which is higher than the other two time periods. This suggests that more recent estimates better match expectations. However, as there are only 12 years of data included in each regression used to estimate each annual elasticity estimate, some variation in signs is expected based on unique events during some periods. Overall, results displayed in Table 1.7 further suggests that cow-calf producer sensitivity to changes in feeder cattle prices has decreased over time in the 14 states analyzed. While only 14 states are analyzed and summarized, these states represent 68.415 percent of total beef cow inventory in 2022 and therefore represent a majority of cow-calf operations in the United States.

Results from equation (1.4), the models using Oklahoma City feeder prices and state specific feeder prices (San Angelo, Joplin, and South Dakota market) with data from 1998-2021 are compared to determine if Oklahoma City is a sufficient proxy for feeder cattle prices across the United States and to consider the "law of one price" for feeder cattle prices in this context. Table 1.8 summarizes and compares annual elasticity of supply estimates for beef cows with respect feeder cattle prices for each of the state specific price models with Oklahoma City price models. Additionally, results from equation (1.4) using Oklahoma City prices and equation (1.4) using these state specific prices can be compared to determine model performance with the price differences.

Table 1.8. Elasticity summary for the state specific models compared to Oklahoma City price models for annual elasticity estimates for the supply of beef cows with respect to feeder cattle prices, 2010-2022

	Texas		Missouri		South Dakota	
	San Angelo Estimate	OKC Estimate	Joplin Estimate	OKC Estimate	SD Market Estimate	OKC Estimate
Average	0.009	0.016	0.085	0.126	-0.012	-0.020
Minimum	-0.084	-0.063	-0.025	0.003	-0.102	-0.110
Maximum	0.077	0.109	0.328	0.396	0.063	0.068
% Lower than Prior Year	0.583	0.500	0.417	0.417	0.750	0.667
% Positive	0.692	0.770	0.769	1.000	0.385	0.231

For Texas, San Angelo feeder prices from Producers Livestock Auction Company are used as a proxy for feeder cattle prices in the state. Results from the equation (1.4) using San Angelo prices to estimate price sensitivity in Texas are shown in Table a.15. Results from the equation (1.4) using Oklahoma City prices to estimate price sensitivity in Texas are shown in Table a.16. The magnitudes of β_1 in the Oklahoma City price model (0.991) and the San Angelo price model (0.979) are similar and neither are statistically significant at a level above $p<0.1$. The adjusted R^2 in the Oklahoma City price model is 0.939 compared to 0.938 in the San Angelo price model. Table a.22 compares the percent error in absolute value terms between the San Angelo price model inventory estimate with the USDA NASS Texas inventory and the Oklahoma City price model inventory with the USDA NASS inventory from 2010-2022. The average percent error for the San Angelo price model inventory estimate is 5.816 percent which is similar to the average percent error for the Oklahoma City price model estimate of 5.890 percent. As the adjusted R^2, the magnitude of $\beta_{1,}$ and the percent error in inventory compared to the USDA NASS Texas inventory in each model are similar, the Oklahoma City price and the San Angelo price do not vastly different in terms of model performance for Texas supply response.

Based on results in Table 1.8, the average and maximum elasticity estimate in the San Angelo price model are lower and closer to zero than the Oklahoma City price model. However, the minimum elasticity estimate is lower and closer to zero in the Oklahoma City price model. Roughly 8 percent more of the estimates are lower than the prior year in the San Angelo price model but a larger percentage of the estimates are positive in the Oklahoma City price model. Overall, these results do not clearly suggest that the Oklahoma City or San Angelo price perform better at estimating Texas beef cow inventory or price sensitivity. However, both the San Angelo price model and the Oklahoma City price model estimate a decreasing trend in cow-calf producer sensitivity to changes in feeder cattle prices, which matches the hypothesis. Figure a.22 is a graph depicting annual own-price elasticity estimates for the supply of beef cows with respect to San Angelo feeder cattle prices in Texas from 2010-2022. A declining trend is shown in Figure a.22, which is similar to the declining trend found when estimating price sensitivity with Oklahoma City prices.

For Missouri, Joplin Regional Stockyard feeder prices are used as a proxy for feeder cattle prices in the state. Results from the equation (1.4) using Joplin prices to estimate price sensitivity in Missouri are shown in Table a.17. Results from the equation (1.3) using Oklahoma City prices to estimate price sensitivity in Missouri are shown in Table a.18. Like the Texas example above, β_1 in the Oklahoma City price model and in the Joplin price model are not statistically significant at a level above $p<0.1$. The magnitude of β_1 in the Oklahoma City price model (0.673) is slightly higher than the Joplin price model (0.503), indicating that there is a larger herd supply response to changes in feeder cattle price when the Oklahoma City price is used. The adjusted R^2 in the Oklahoma City price model is 0.753 compared to 0.737 in the Joplin price model. Table a.23 compares the percent error in absolute value terms between the Joplin price model inventory estimate with the USDA NASS Missouri inventory and the Oklahoma City price model inventory with the USDA NASS inventory from 2010-2022. The average percent error for the Joplin price model inventory estimate is 5.839 percent which is similar to the average percent error for the Oklahoma City price model estimate of 5.804 percent. Based on the similar model fit and the percent error in inventory compared to the USDA NASS Missouri inventory in each model, the performance of the Oklahoma City price and the Joplin price is similar, however the Joplin own-price coefficient better matches the expectation of lower price sensitivity.

Based on results in Table 1.8, the average, minimum, and maximum elasticity estimate in the Joplin price model are closer to zero than the Oklahoma City price model. The same percentage of the estimates are lower than the prior year in both price models, but a larger percentage of the estimates are positive in the Oklahoma City price model. Similar to the Texas models, these results do not clearly suggest that the Oklahoma City or Joplin price perform better at estimating Missouri beef cow inventory or price sensitivity. Although, the Joplin price model and the Oklahoma City price model estimate a decreasing trend in cow-calf producer sensitivity to changes in feeder cattle prices, which matches the hypothesis. Figure a.23 is a graph depicting annual own-price elasticity estimates for the supply of beef cows with respect to Joplin feeder cattle prices in Missouri from 2010-2022. A declining trend is shown in Figure a.23, which is similar to the declining trend found when estimating price sensitivity with Oklahoma City prices.

For South Dakota, South Dakota market feeder prices are used to represent feeder cattle prices in the state. Results from the equation (1.4) using South Dakota market prices to estimate price sensitivity in South Dakota are shown in Table a.19. Results from equation (1.3) using Oklahoma City prices to estimate price sensitivity in South Dakota are shown in Table a.20. β_1 is not statistically significant at a level above $p<0.1$ in either model. Each model has a negative sign for β_1 is which is not expected, and the magnitudes do not differ drastically. The adjusted R^2 in the Oklahoma City price model is 0.441 compared to 0.439 in the South Dakota market price model. Table a.24 compares the percent error in absolute value terms between the South Dakota market price model inventory estimate with the USDA NASS South Dakota inventory and the Oklahoma City price model inventory with the USDA NASS inventory from 2010-2022. The average percent error for the South Dakota market price model inventory estimate is 4.633 percent which is similar to the average percent error for the Oklahoma City price model estimate of 4.734 percent. Based on model fit, own-price statistical significance and magnitude, and the similar percent error in inventory compared to the USDA NASS South Dakota inventory in each model; both prices perform similar but not well in estimating herd supply response in South Dakota. As both the Oklahoma City price and the South Dakota market price do not perform well at estimating inventory in South Dakota and there is mixed evidence of a decline in price sensitivity, it isn't possible to conclude a decrease in sensitivity has occurred in South Dakota. However, the results may be related to poor data fit with the South Dakota beef cattle environment.

Based on results in Table 1.8, the average, minimum, and maximum elasticity estimate in the South Dakota market price model are marginally lower and closer to zero than the Oklahoma City price model. A larger percentage of the estimates are lower than the prior year and a larger percentage of the estimates are positive in the South Dakota market price model. Further, these results do not clearly suggest that the Oklahoma City or South Dakota market price perform better at estimating South Dakota beef cow inventory or price sensitivity. However, both the South Dakota market price and the Oklahoma City price do not have strong performance in estimating South Dakota beef cow inventory or price sensitivity. The South Dakota market price model estimates a decreasing trend in cow-calf producer sensitivity to changes in feeder cattle prices during 2010-2022 (shown in Figure a.24) whereas the Oklahoma City price model estimate a marginal increasing trend over the same time period.

Limitations

The methods and results described allow for beef cow inventories, supply response, and price sensitivity to be estimated at the national and state level. Additionally, the methods and results allow for comparisons to be made between different own-price variables, or feeder cattle prices, used in the models. However, there are a number of limitations to consider. First, cow-calf producer demographic data, such as age and off-farm income, is not available at the scale and time period needed for this analysis. Therefore, it is not included in the analysis. However, these demographic variables can impact producer's price sensitivity and response to industry changes. For examples, as producer ages or as off-farm income grows, their willingness or need to respond to price changes may reduce due to a shorter invest horizon and less dependence on the profit from their cattle operation. Without these demographic variables included in the analysis, their potential impacts are not directly considered.

Another limitation of this analysis is that it does not include state specific cost of production data for cow-calf operations. Due to data limitations related to the availability of cost of production data through the entire time period for specific states, equations (1.3) and (1.4) do not include specific cost of production data besides pasture rental rate. Including state specific cost of production data would likely improve forecasting accuracy and allow for more robust comparisons among state price sensitivity over time. Similarly, state specific feeder cattle prices and pasture rental rate data are limited as well, due to the number of feeder cattle markets and the availability of reports with such data. Therefore, the number of states estimated is restricted to the 14 states in this analysis and the three additional states that include state specific feeder prices.

A third limitation to consider in this model is the type of expected own-price or output price to use in the model. In this analysis, naïve expectations with lagged cash prices, or feeder cattle prices, are used as the expected output prices for cow-calf producers. While feeder cattle cash prices are a sufficient proxy for an expected output price, a futures market price would be an alternative price series to consider as prices in futures markets can impact price expectations for producers. However, due to restrictions in feeder cattle futures prices, such as length of the contract and volume traded, they are not a sufficient proxy for expected output prices in this analysis. An additional consideration for this analysis is that while the “law of one” for feeder cattle prices is assumed and discussed, it is not specifically tested. The primary objective of this study is to analyze cowherd supply responses; however, the model also allows for discussion and analysis of how Oklahoma City feeder cattle prices to estimate and serve as proxies for other states in the country.

An additional limitation of this analysis is that herding decisions are assumed and modeled to be symmetric. In other words, the decision to increase or decrease herd size is forced to be symmetric in this analysis. However, in reality herding decisions are not likely to be symmetric, as a producer likely does not decrease their herd size at the same speed as they increase it. While the symmetric response approach is common in research, it is important to note that it may not perfectly reflect the reality in the industry.

A final limitation to consider when evaluating this research is the length of the timeseries data used in the regressions to estimate annual elasticity estimates. As the regressions only use 12 annual observations, the estimates are likely fragile due to the small number of observations. As a sensitivity check related to this concern, a regression using the national annual data from 1975-2021 was estimated that included interaction terms between the lagged P_{FS} and decade dummy variables for the periods 1975-1984, 1985-1994, 1995-2004, 2005-2014, and 2015-2021 in place of the single lagged P_{FS} as well as all other independent variables and decade dummy shifter variables. A declining trend in the supply elasticities from the decade interaction terms was observed which confirms our result of a decline in price sensitivity at the national level. This approach allows for elasticity estimates to be obtained from different decades while using a longer span of data compared to the 12-year rolling regression approach used above. Therefore, the estimates from the interaction term approach are less fragile. However, the interaction approach only allows the feeder steer price to change with the decades which is a drawback. Overall, both approaches share the result that price sensitivity has decreased at the national level.

Implications and Conclusion

The United States is home to many cow-calf producers who respond to various economic, environmental, and social factors when making herd adjustment decisions. These herd decisions ultimately impact the number of cattle in the country and therefore the amount of beef available. Given calf-calf producer demographic changes, increased efficiencies, increased volatility, and general uncertainty in the cattle industry over the past years, an updated understanding of beef cowherd elasticities is important for industry participants. Additionally, existing research on supply response of the U.S. cow-calf herd to changes in expected feeder cattle prices is sparse and outdated.

National and state-level partial-adjustment supply models were developed to quantify the effect feeder cattle price changes have on beef cow inventory. The national model performed well when estimating out-of-sample regression tests to estimate beef cow inventories for years 2011-2021, with a percentage error of 2.056 percent. A decrease in the feeder cattle price sensitivity for cow-calf producers was expected to be observed over time, reducing the impact a given percentage price change has on herd adjustment decisions. In other words, an increase (decrease) in feeder cattle price was expected to have less impact on a cow-calf producer's decision to increase (decrease) their herd size than it had in the past. At the national level, a decrease in price sensitivity was observed.

Similar to the national results, a decrease in price sensitivity was observed for a majority of the states analyzed with Oklahoma City prices as the expected feeder cattle prices. A decline in cow-calf producer sensitivity to changes in feeder cattle prices has occurred in a majority (9 out of 14) of the states in this analysis over 1987-2022. Further, when considering only estimates from 2010-2022, a larger majority of states (12 out of 14) experience a decline in sensitivity to changes in feeder cattle prices, with the remaining two experiencing marginal increasing (close to flat) sensitivity to changes in feeder cattle prices.

The “law of one price” for feeder cattle prices is assumed and therefore Oklahoma City feeder cattle prices are used as a proxy for national and individual state feeder cattle prices. However, feeder cattle prices from San Angelo, TX; Joplin, MO; and South Dakota are also used to estimate inventory and price sensitivity with state specific feeder prices. These results are compared with similar results from models with Oklahoma City prices as a proxy for state feeder cattle prices. While the models with state specific prices have similar model performance in terms of own-price coefficient magnitude and adjusted R^2 values as the models with Oklahoma City values, the Missouri and Texas models both have decreasing trends in price sensitivity for both state specific prices and the Oklahoma City price. However, for South Dakota, the state specific price model had a decreasing trend, but the Oklahoma City price model was slightly increasing. The inventory estimates from each state specific price model had similar percent errors when compared to the USDA NASS inventory as the Oklahoma City price models. Therefore, none of the state specific prices were more successful at estimating state inventories compared to the Oklahoma City price model estimates.

The goal of comparing results from the state models with different feeder cattle prices is to determine which price performs better at estimating inventory and price sensitivity. While the expectation is that the state-specific prices will perform better than the Oklahoma City prices, due to the size of the cow-calf sectors in Texas and Missouri, a single market price (i.e. San Angelo and Joplin) may not reflect prices throughout the state. However, due to the size and significance of the Oklahoma City market and the “law of one price” theory in feeder cattle prices, results from the Oklahoma City price model should perform similarly to the state specific prices. Our results support the theory that the Oklahoma City feeder cattle prices can be used as a sufficient proxy for feeder cattle prices across the nation and in the three states analyzed (Texas, Missouri, and South Dakota). However, if more robust feeder cattle price series for each state or region were available for a longer time period, results may differ and perform better than the Oklahoma City feeder cattle price series.

Overall, this work strengthens available knowledge on cow-calf herd supply response by estimating own-price elasticities of supply for beef cow inventory with respect to feeder cattle prices at both national and state levels. These estimates can be used to understand changes in cow-calf producer sensitivity to changes in feeder cattle price. Additionally, as much of the work related to cowherd supply is outdated, this work updates elasticity parameter estimates which is important as price sensitivity is likely decreasing over time. Further, we discuss the performance of Oklahoma City feeder cattle prices to serve as a proxy for national and state-level feeder prices.

Article 2 - Demand for Meat at the Wholesale Level

Introduction

Changes in the U.S. beef industry, from the cow-calf level to the packing/processing level, highlight a need for an updated understanding of wholesale beef demand in the country. The beef industry has evolved over time in response to technology changes, consumer preferences, global demand, and production practices at the farm level. Changes in consumer preferences have led to increased product differentiation in terms of type and quality of beef offered at the retail level. Similarly, changes in production practices and increased interest in higher quality beef has led to a larger percent of Prime graded beef. While Choice beef remains the most consumed and produced quality grade, the role of Prime beef has changed dramatically in recent years. Changes in product differentiation and quality grades impact how wholesale producers produce and market their final product. Additionally, the U.S. beef industry has faced a number of supply chain disruptions in recent years. These disruptions may have lasting impacts on how beef moves along the supply chain.

A recent example of supply chain disruptions in the U.S. beef industry is COVID19. Impacts from COVID19 have been far reaching in the U.S. agriculture supply chain, and more specifically the meat-livestock industry. A large shift away from food service (away-from-home consumption) to retail (at-home consumption) purchasing patterns was observed from U.S. consumers during the COVID19 pandemic, and this led to notable impacts on both beef availability and prices for consumers at grocery stores and other retail locations across the country (Malone et at., 2020). Historically, consumption of specific meat products greatly varies across these two domestic market channels. These changes did not go unnoticed by both consumers and the national press, as the price of retail beef products is continually highlighted across the nation.

Wholesalers in the beef market consist of packers and processors engaged in the middle stage of production. They often sell wholesale beef to retailers, food service, and export channels. Peel (2021) explains the impact the pandemic had on the beef supply chain and highlights the complex nature of beef production. Specifically related to the complex nature of the wholesale segment of the supply chain, the article states, “Beef packers provide the animal harvest and the primary fabrication of beef carcasses into wholesale products. Typically, packers fabricate several hundred basic wholesale products, which are marketed as several thousand products representing unique customer specifications. Subsequently, the majority of wholesale beef products move through a diverse and specialized set of further processing activities that further expand the set of products by several thousand additional products into largely separate supply chains” (Peel, 2021, p. 33). As Peel (2021) points out, the beef supply chain is a very complex segment of the U.S. agriculture industry. The role wholesalers play in the industry has evolved over the years as packers and processors are becoming more engaged with retailers and end users.

To provide the U.S. beef industry with current wholesale beef demand and a better understanding of the impacts of structural changes and supply chain disruptions, wholesale beef demand elasticities are estimated. Using past studies and changes in available data and industry operations, new economic parameter estimates are obtained.

Literature Review

While many studies estimate the demand of retail beef and other meat products, research related to demand at the wholesale level is sparse. The wholesale level is a unique segment of the supply chain and reacts differently to shocks and seasonal trends than the farm and retail levels. For example, Lusk et al. (2001) states, “Wholesale meat demand may be subject to even stronger seasonal effects than retail demand due to retailers' attempts to absorb some of the seasonal changes in supply and demand at the retail level (see Capps et al.; Namken, Farris, and Capps).” Additionally, the wholesale level can be faster to react to shocks than the farm and retail levels (Erol and Saghaian, 2022). Further, existing research related to wholesale beef demand is outdated. Due to changes the United States beef and livestock industry has faced in the past 20 years, previous research may not reflect the current demand at the wholesale level. Available research concerning wholesale beef demand is reviewed and discussed to discover potential areas of opportunity and limitations.

The role of wholesalers in the beef supply chain has changed over the past few decades. A 2009 Center on Globalization, Governance, and Competitiveness report analyzed the U.S. beef and dairy value chains. The authors highlight that the relationships between beef retailers, wholesalers, and manufacturers have evolved. This is partly due to increased concentration in the grocery sector. Further, the report states, “Wholesalers are playing a shrinking role in the beef industry because packing companies are often connected to retailers directly, eliminating the need for a middleman. Additionally, wholesale companies are increasingly becoming involved in further processing activities” (Lowe & Gereffi, 2009). As much of the research related to wholesale beef demand is 20 or more years old, the changes in the grocery sector and wholesale beef sector are not reflected. Therefore, a need for an updated understanding of wholesale beef demand is present in meat demand research.

A 2001 study by Lusk, Marsh, Schroeder, and Fox estimated wholesale demand for pork, chicken, and quality differentiated beef. In addition, they estimated own- and cross-price demand elasticities of meat retailers for USDA Choice and Select boxed beef. Using monthly data from July 1987 through December 1999, they found, "meat retailers have more elastic demand for lower quality graded beef. Retail beef price has a strong positive relationship with Choice and Select boxed beef demand, and a strong negative relationship with wholesale pork and chicken demand" (Lusk et al., 2001). They additionally found evidence of seasonality effects on wholesale beef demand. For example, they found that Choice and Select boxed beef becomes very price inelastic during the summer and that the two quality grades are substitutes during winter months. Further, they highlight that "Select beef is not a substitute for Choice beef in the spring and summer" (Lusk et al., 2001). Lusk et al. (2001) is an example of a specific study looking at wholesale meat demand, however it is outdated and does not consider wholesale beef at an aggregate level.

Another example of a specific study focused on wholesale beef demand is Namken, Farris, and Capps (1997). The objective of the study was to estimate the demand of various wholesale beef cuts and analyze changes and trends related to quality, convenience, and season, using monthly data from January 1980 through December 1990. In summary, they found that "The demand for individual wholesale cuts of beef varies mostly by season; however, there has been dramatic trends in demand for all beef as well as unique trends for specific beef cuts" (Namken et al., 1997). The finding that demand of meat demand is seasonal is with consistent historic research findings in the space. Regarding structural changes in meat demand, the authors note, "(Meat consumption) changes apparently have been driven by structural changes in demand. Causes of changes in demand are generally understood but are not easy to document, especially if the change in demand for different segments of each of the red meat and poultry industries is considered" (Namken et al., 1997). As this paper mentions, structural change and seasonality have historically been important considerations when analyzing meat demand at all levels.

Capps et al. (1994) is an early example of a study that recognized the need for meat demand studies at the wholesale level. They highlight the need for research at the wholesale level by stating, “Retailers usually absorb some of the seasonal variation in supply and demand conditions to avoid salient changes in retail meat prices. However, at the wholesale level, prices may fluctuate dramatically over short time periods” (Capps et al., 1994). Therefore, price sensitivity of wholesalers is important for both cattle producers and beef processors as the price reaction of wholesalers impact their businesses. The objective of Capp et al. (1994) was to examine the demand for twelve cuts of wholesale beef. Their data consisted of monthly observations from January 1980 through December 1990. Like other meat demand studies, Capp et al. (1994) found seasonal trends in demand which varied depending on the wholesale cut. Specifically, Capps et al. (1994) found that, “Relative to the price in December, prices at the wholesale level in other months can be as much as 6 percent lower to as much as 21 percent higher.” In addition to seasonality, they summarize the determinants of monthly wholesale prices as quantity of the specific cut, stickiness in prices, marketing costs, and pork and chicken quantities. Similar to Lusk et al. (2001) and Namken et al. (1997), Capps et al. (1994) provides an example of a wholesale beef demand study, however the estimates are outdated and may not reflect the current state in the beef industry.

More recently, meat demand literature has discussed wholesale demand in light of unexpected events which disrupted supply chains. An example is COVID19, which greatly impacted wholesale beef prices because of reduced packing capacity from plant closures. Therefore, livestock and meat economists have analyzed how these disruptions impacted wholesale and retail beef sectors. Peel (2021) explains that wholesale beef prices rose during COVID19 due to supply disruptions in beef packing. Erol and Saghaian (2022) investigated the impact COVID19 had on vertical price transmission in the U.S. beef industry. Their findings state, “in case of the COVID19 shock, wholesale prices adjusted more quickly than both farm (threefold) and retail prices (tenfold). It suggests that wholesale prices were more flexible than retail and farm prices in order to restore to the long run equilibrium with the COVID19 shock” (Erol and Saghaian, 2022). While Peel (2021) and Erol and Saghaian (2022) explain the reason wholesale beef markets were disrupted during the pandemic and the price responses at different supply chain levels, they did not update or analyze wholesale demand elasticities.

These articles are examples of existing research concerning wholesale beef demand. While this literature review is not all encompassing, it represents the existing research concerning wholesale beef demand in the United States. After reviewing the literature, a need for an updating understanding of wholesale beef demand and wholesale beef demand elasticity estimates is present in current research.

Data

Monthly data observations from March 2003 through April 2022 were obtained from multiple sources to build a seemingly unrelated regression model of wholesale beef, pork, and chicken demand. Wholesale price and volume data for the three proteins were collected from the Livestock Marketing Information Center (LMIC). Additionally, price and quantities of the three proteins are transformed into natural logarithms to simplify elasticity interpretation. Choice beef cutout value and total loads are used as representative wholesale beef prices and quantities, as Choice beef is the most consumed quality grade and represents the median grade between Select and Prime. Choice beef cutout value and total loads are published in the USDA Agricultural

Marketing Service (AMS) *National Comprehensive Boxed Beef Cutout – all Fed Steer/Heifer Sales* report (LM_XB463). Observations are aggregated monthly by LMIC. Choice beef cutout value is represented as w_{bc} and Choice beef total loads is represented by Q_{bc}.

Pork and chicken price and quantity data are used to represent two substitutes for beef at the wholesale level. Pork cutout value and total loads from the USDA AMS report, *National Daily Pork FOB Plant – Negotiated Sales – Afternoon* (LM_PK602), are used to represent wholesale pork prices and quantities. Observations are aggregated monthly by LMIC. Pork cutout value is represented as w_{pk} and pork total loads is represented by Q_{pk}.

Wholesale chicken data is not as straight forward as beef and pork as there is not a 'cutout' equivalent in the poultry industry, therefore, limitations exist in terms of obtaining publicly available wholesale level data for chicken. Further, the quality of the chicken data used in this study is not ideal but represents the best available to the author's knowledge. As a proxy for wholesale chicken volume, weekly production of poultry without ducks (1000 lbs) is used and aggregated to monthly observations. This poultry production data is published in the USDA AMS report, *Miscellaneous Poultry Slaughter Under Federal Inspection* (NW_PY017). As a wholesale chicken price proxy, the 12-city composite and the national composite weighted average (whole birds – broilers/fryers) monthly prices are used. The 12-city composite price series was discontinued in December 2013 and the national composite weighted average series began in May 2012. Therefore, the 12-city composite price is used from March 2003 to December 2012 and the national composite is used from January 2013 to April 2022. These data are published in the USDA AMS *Broiler Market News Report*. Wholesale chicken price is represented as w_c and wholesale chicken volume is represented by Q_C.

Per capita gross domestic product (GDP) is calculated for two categories: the United States and the rest of the world. These calculations are used to account for income effects on demand for protein. To calculate per capita GDP for the United States, annual U.S. GDP is divided by annual U.S. population. To calculate per capita GDP for the rest of the world, rest of the world GDP is divided by rest of the world population. Rest of the world GDP is calculated by subtracting annual U.S. GDP from annual world GDP. Similarly, rest of the world population is calculated by subtracting annual world population by annual U.S. population. As both GDP and population are annual series, per capita GDP for the U.S. and the rest of the world is disaggregated to create monthly observations. U.S. and world GDP and population data for 2003 to 2020 was obtained from the World Bank Development Indicators data tool. For 2021 and 2022, GDP and population growth projections from the Organisation for Economic Cooperation and Development (OECD) were used to calculate per capita GDP for the respective categories. Per capita GDP for the United States is represented by GDP_{US} and per capita GDP for the rest of the world is represented by GDP_{RoW}. Variable units and sources are summarized in Table 2.1.

Table 2.1. Variable descriptions and sources

Variable	**Description**	**Source**
w_{BC}	Choice Beef Cutout, $/cwt	USDA AMS
Q_{BC}	Choice Beef Loads (40,000 lbs)	USDA AMS
w_{pk}	Pork Cutout, $/cwt	USDA AMS
Q_{pk}	Pork Loads (40,000 lbs)	USDA AMS
w_c	National Composite Wholesale Broiler, $/cwt	USDA AMS
Qc	Weekly Poultry Production, 1,000 lbs	USDA AMS
GDP_{US}	Per capita GDP for the U.S., $	World Bank and OECD
GDP_{RoW}	Per capita GDP for the Rest of World, $	World Bank and OECD

As demand for protein is influenced by consumer preferences related to quality attributes, production practices, and other factors, oftentimes research at the retail level includes independent variables to capture various consumer preferences related to protein consumption.

However, as this research is concerned with wholesale demand, incorporating variables that capture preferences for the wide range of downstream consumers is a challenge. Specifically, wholesale beef can move through retail (for at-home domestic consumption), food service (for away-from-home domestic consumption), or export channels. Therefore, including preference data for U.S. consumers would not reflect preferences in the many countries where protein is exported to from the United States.

Summary Statistics and Time Series Plots

Table 2.2 shows summary statistics for the data described above. Each variable has 229 observations, spanning from March 2003 through April 2022. The large range between the minimum and maximum observations for Q_{bc} stems from a government shutdown that occurred in October 2013, when USDA AMS reporters were not able to report the total volume for the month. Similarly, the range between the minimum and maximum observations for Q_{pk} is large because prior to 2013, livestock mandatory price reporting was not required for pork. Therefore, before 2013, less volume of pork was included in reports. Statistics for per capita GDP for the rest of the world is much lower than in the United States, which is expected as the U.S. is one of the most developed counties in the world.

Table 2.2. Summary statistics for monthly data observations from March 2003 - April 2022

Descriptive Statistics					
Statistic	**N**	**Mean**	**St. Dev.**	**Minimum**	**Maximum**
$\mathbf{w_{bc}}$	229	189.27	44.26	126.56	396.21
$\mathbf{Q_{bc}}$	229	8,416.23	1,350.02	1,798	12,319
$\mathbf{w_{pk}}$	229	79.74	15.57	54.39	133.58
$\mathbf{Q_{pk}}$	229	4,025.78	2,681.68	1,008.40	10,021.89
$\mathbf{w_{c}}$	229	84.89	15.83	53.52	166.89
$\mathbf{Q_{c}}$	229	4,634,330.00	623,056.20	3,584,491.00	6,192,402.00
$\mathbf{GDP_{US}}$	229	54,144.08	8,039.98	40,050.56	69,446.99
$\mathbf{GDP_{RoW}}$	229	8,193.86	1,216.08	4,910.54	10,109.78

Time series plots for Q_{bc} and Q_{pk} are shown in Figures 2.1 and 2.2, respectively. Figure 2.1 depicts the drop in Q_{bc} in October 2013, when the U.S. government shutdown impacted the quantity of beef reported and published. Figure 2.2 illustrates the impact livestock mandatory price reporting had on the quantity of pork reported. Time series plots for all other variables are shown in Figures b.1 through b.6.

Figure 2.1. Choice beef loads time series plot. March 2003 – April 2022

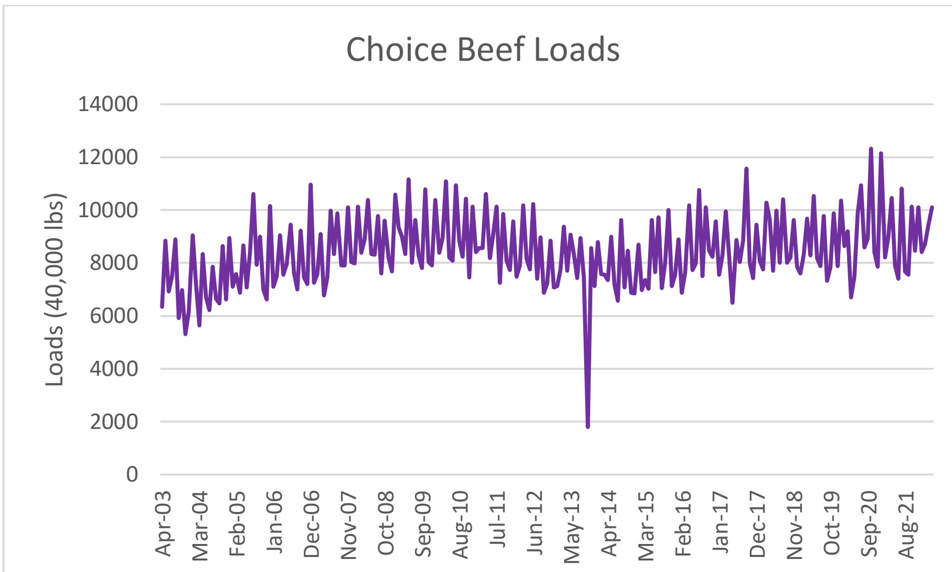
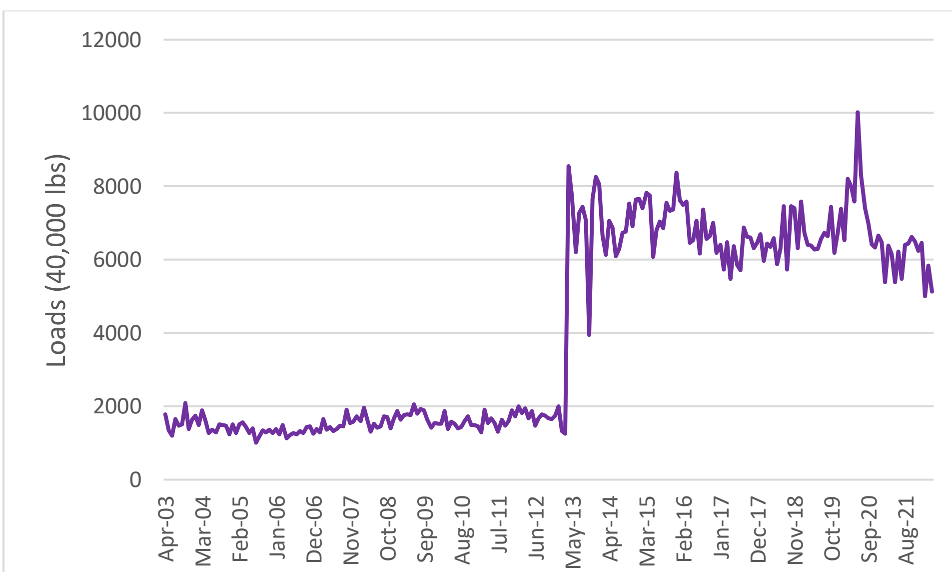


Figure 2.2. Pork loads time series plot. March 2003 – April 2022



Methods

Model Selection

Beef demand is influenced by the price and availability of other proteins, such as pork and chicken. Due to the related nature of demand for beef, pork, and chicken, it is important the selected demand model recognizes the correlation among the three proteins. A seemingly unrelated regression (SUR) model is used because theory suggests that beef, pork, and chicken demand equations have contemporaneous cross-equation error correlation or, in other words, the error terms in the respective equations are correlated (UCLA ARC, 2021). The error terms are believed to be correlated because similar factors can impact demand for beef, pork, and chicken besides those that are captured in independent variables, due to similarities in protein production or demand shocks. Additionally, the SUR method allows symmetry to be imposed on cross-price coefficients which improves the stability of own-price coefficients.

Model Variations

Limitations in obtaining quality wholesale chicken price and quantity data complicate modeling wholesale beef demand in an ideal and complete manner. As the quality of the chicken data available is questionable and less than desirable, three different variations of a SUR model for wholesale beef demand are estimated. The three model variations are referred to as variations (1), (2), and (3), and are shown in Figures 2.3 through 2.5. Variation (1) includes three equations representing wholesale beef, pork, and chicken demand. Own- and cross-price independent variables for the three proteins are included in each equation. Variation (2) includes two equations representing wholesale demand for beef and pork. Own-price independent variables are included as well as cross-prices for beef, pork, and chicken. Finally, variation (3) includes two equations representing wholesale demand for only beef and pork. However, variation (2) does not include chicken cross-prices and only includes own- and cross-price independent variables for beef and pork.

Inclusion of chicken is important in estimation as chicken is the most consumed protein domestically. However, due to concerns with data quality, inclusion of chicken data may poorly impact model performance and the ability to accurately capture wholesale beef demand. Variation (1) represents the reality of protein consumption best, as it includes a chicken demand model and chicken price data in each model. However, the estimates from this variation may be impacted given the concerns with chicken data quality. Variation (2) only includes chicken cross-price data, so will only be impacted by the quality of chicken as a substitutable protein. Variation (3) is the simplest model yet the least representative of protein consumption as it does not include any chicken data in the estimation. Therefore, it is not impacted by the quality of the data. Time subscripts, denoted as $_t$, are omitted from the variations as there are no lagged variables in the estimation.

Figure 2.3. SUR model variation (1)

Variation (1)
$lnQ_{bc} = \alpha_{11} + \beta_{11}lnw_{bc} + \beta_{12}lnw_{pk} + \beta_{13}lnw_c + \theta_{11}GDP_{US} + \theta_{12}GDP_{RoW} + \gamma_1 Oct2013 + \alpha_{12}BP + \zeta_{11}lnw_{bc} * BP + \zeta_{12}lnw_{pk} * BP + \zeta_{13}lnw_c * BP + \theta_{13}GDP_{US} * BP + \theta_{14}GDP_{RoW} * BP + \varepsilon_1$
$lnQ_{pk} = \alpha_{21} + \beta_{21}lnw_{bc} + \beta_{22}lnw_{pk} + \beta_{23}lnw_c + \theta_{21}GDP_{US} + \theta_{22}GDP_{RoW} + \gamma_2 Oct2013 + \alpha_{22}BP + \zeta_{21}lnw_{bc} * BP + \zeta_{22}lnw_{pk} * BP + \zeta_{23}lnw_c * BP + \theta_{23}GDP_{US} * BP + \theta_{24}GDP_{RoW} * BP + \varepsilon_2$
$lnQ_c = \alpha_{31} + \beta_{31}lnw_{bc} + \beta_{32}lnw_{pk} + \beta_{33}lnw_c + \theta_{31}GDP_{US} + \theta_{32}GDP_{RoW} + \gamma_3 Oct2013 + \alpha_{32}BP + \zeta_{31}lnw_{bc} * BP + \zeta_{32}lnw_{pk} * BP + \zeta_{33}lnw_c * BP + \theta_{33}GDP_{US} * BP + \theta_{34}GDP_{RoW} * BP + \varepsilon_3$

Figure 2.4. SUR model variation (2)

Variation (2)
$lnQ_{bc} = \alpha_{11} + \beta_{11}lnw_{bc} + \beta_{12}lnw_{pk} + \beta_{13}lnw_c + \theta_{11}GDP_{US} + \theta_{12}GDP_{RoW} + \gamma_1 Oct2013 + \alpha_{12}BP + \zeta_{11}lnw_{bc} * BP + \zeta_{12}lnw_{pk} * BP + \zeta_{13}lnw_c * BP + \theta_{13}GDP_{US} * BP + \theta_{14}GDP_{RoW} * BP + \varepsilon_1$
$lnQ_{pk} = \alpha_{21} + \beta_{21}lnw_{bc} + \beta_{22}lnw_{pk} + \beta_{23}lnw_c + \theta_{21}GDP_{US} + \theta_{22}GDP_{RoW} + \gamma_2 Oct2013 + \alpha_{22}BP + \zeta_{21}lnw_{bc} * BP + \zeta_{22}lnw_{pk} * BP + \zeta_{23}lnw_c * BP + \theta_{23}GDP_{US} * BP + \theta_{24}GDP_{RoW} * BP + \varepsilon_2$

Figure 2.5. SUR model variation (3)

Variation (3)
$lnQ_{bc} = \alpha_{11} + \beta_{11} lnw_{bc} + \beta_{12} lnw_{pk} + \theta_{11} GDP_{US} + \theta_{12} GDP_{RoW} + \gamma_1 Oct2013 + \alpha_{12} BP + \zeta_{11} lnw_{bc} * BP + \zeta_{12} lnw_{pk} * BP + \theta_{13} GDP_{US} * BP + \theta_{14} GDP_{RoW} * BP + \varepsilon_1$
$lnQ_{pk} = \alpha_{21} + \beta_{21} lnw_{bc} + \beta_{22} lnw_{pk} + \theta_{21} GDP_{US} + \theta_{22} GDP_{RoW} + \gamma_2 Oct2013 + \alpha_{22} BP + \zeta_{21} lnw_{bc} * BP + \zeta_{22} lnw_{pk} * BP + \theta_{23} GDP_{US} * BP + \theta_{24} GDP_{RoW} * BP + \varepsilon_2$

Variation (1) includes three equations representing wholesale demand of beef, pork, and chicken. Own-price and cross-price of each protein are included in each model. Each equation in the SUR model is restricted to impose symmetry on the cross-price elasticities to ensure β_{12} = β_{21}, β_{13} = β_{31}, β_{23} = β_{32}, ζ_{12} = ζ_{21}, ζ_{13} = ζ_{31}, and ζ_{23} = ζ_{32}. This model represents the ideal form as it includes each protein as a separate equation, which best represents meat consumption and production in the United States. However, because the concerns related to the quality of the chicken data, estimates from the model may not represent the reality of protein demand at the wholesale level. Therefore, the variations (1) and (2) attempt to resolve issues related to chicken data quality.

Variation (2) represents a 'middle of the road' attempt between the first and third variation. It includes two equations representing wholesale demand for beef and pork, and also includes their respective own-price independent variables and cross-price independent variables for beef, pork, and chicken in the respective equations. Each equation in the SUR model is restricted to impose symmetry on the cross-price elasticities to ensure β_{12} = β_{21} and ζ_{12} = ζ_{21}. While the quality of chicken cross-price data is not ideal, because chicken is the most consumed protein, it is important to consider in demand equations for beef and pork. Therefore, this variation recognizes the importance of substitutability in protein consumption while also recognizes the data limitations of accurately estimating wholesale chicken demand.

Variation (3) represents the simplest yet least ideal function. Like the variation (2), it includes two equations representing wholesale demand for beef and pork. This variation includes own-prices independent variables and cross-price independent variables for beef and pork in the respective equations. Each equation in the SUR model is restricted to impose symmetry on the cross-price elasticities to ensure $\beta_{12} = \beta_{21}$ and $\zeta_{12} = \zeta_{21}$. The drawback of variation (3) is that it completely excludes chicken demand from the estimation. This is a concern because chicken is the most consumed protein in the United States. On the other hand, the benefit of this variation is concerns of poor data quality from chicken data are removed from estimation.

Each equation in the variations (1) through (3) includes GDP_{US} and GDP_{RoW} to account for income and wealth effects. Changes in income levels both domestically and globally impact demand for protein, especially in low-income countries where an increase in income leads to higher demand for meat protein. In addition, as the United States exports beef, pork, and chicken, it is important to include GDP_{RoW} to capture how income changes in other countries impacts the export demand of wholesale protein. GDP elasticities are then calculated using the GDP_{US} and GDP_{RoW} coefficients. Additionally, Oct2013, which is a dummy variable with a '1' for October 2013 and '0' for all other observations, is included in each model variation to account for the government shutdown in October 2013 which impacted the quantity of beef included in reports where the data was obtained from. An alternative approach to address the quantity discrepancy of October 2013 would have been to conduct linear extrapolation to create an estimate for the actual quantity in the supply chain in October 2013.

Structural Change

An important consideration when modeling time series data, especially with protein demand, is structural changes in the industry. Structural changes can lead to structural breakpoints in the price and volume data and therefore need to be incorporated in demand models. The R package *strucchange* is used to determine breakpoints in the demand functions for beef, pork, and chicken. Specifically, the *breakpoints* command, which implements the algorithm described in Bai and Perron (2003), is used to simultaneously estimate for various breakpoints in each protein demand function. No breakpoints were found in the beef and pork demand functions. One breakpoint was found in the pork demand function at the 120th observation, or March 2013. While the exact cause of the breakpoint is unknown, livestock mandatory pricing reporting was implemented in the pork industry in 2013 which increased the volume of pork loads reported in the data used.

A recent example of a study that identified structural breaks in meat demand data is Erol and Saghaian (2022). Erol and Saghaian (2022) analyzed data from 1970 through 2021 and found four structural breakpoints. Their final breakpoint, which was September 2013, matches closely with the breakpoint found in this study. All other breakpoints found in Erol and Saghaian (2022) are before the possible breakpoints in this study, given the length of the time series data used.

Since a structural breakpoint was found, the SUR model variations are designed to recognize the breakpoint. Incorporating the breakpoint in the models is important to accurately estimate demand elasticities over the time period. A dummy variable for the breakpoint, with ‘0’ from April 2003 to February 2013 and ‘1’ from March 2013 to April 2022, was created. This breakpoint dummy variable is represented as BP. The BP variable is used to create interaction terms between each of the independent variables in respective SUR model variations. By creating these interaction variables, the model can estimate coefficients for the period before and after breakpoint that was found in March 2013. Therefore, own-price and cross-price elasticity estimates can be obtained for each period. Additionally, the inclusion of the interaction variables allows the model to recognize structural change and better estimate wholesale demand.

Post-2013 Model

As an alternative method to implementing the interaction terms to address the structural break, a similar model was estimated using only data from January 2014 – April 2022. This model does not include breakpoint interaction terms as it only contains data after the breakpoint. Additionally, this model does not include data prior to the implementation of livestock mandatory price reporting in the pork industry or data prior to change in the wholesale chicken price series. Further, as this model begins with data in 2014, the October 2013 government shutdown that impacted the quantity of beef reported is also not a concern. Results from this model will be compared with the post-breakpoint results from the breakpoint model to determine if the interaction term method is a sufficient approach.

Seasonality

While effects of seasonality are often cited in meat demand research (see Lusk et al., 2001; Namken et al., 1997), seasonal impacts may be decreasing over time. Potential reasons seasonality in meat demand is decreasing over time are increased exports of protein out of the United States and smoother annual production of protein domestically. To test the seasonality impacts in the SUR model variations, quarterly dummy variables are added to the models and analyzed. The results from the models that included quarterly dummies were not considerably different from the models without them. Additionally, own- and cross-price wholesale demand elasticities did not vary drastically when quarterly dummy variables were considered. Further, quarterly dummy variables were not jointly significant in the different model variations. Therefore, quarterly dummies were not included in the final model variations.

Results

Own- and cross-price wholesale demand elasticity estimates are obtained from the results from SUR model variations (1) through (3). Results from SUR model variations (1) through (3) are shown in Tables 2.3 through 2.5. Table 2.6 summarizes own- and cross-price elasticities before the structural breakpoint that was found in March 2013 and compares the results among SUR model variations (1) through (3). Similarly, Table 2.7 summarizes own- and cross-price elasticities after the structural breakpoint and compares the results among SUR model variations (1) through (3).

Table 2.3. Results from SUR model variation (1)

	Variation (1)		
	$\ln Q_{bc}$	**$\ln Q_{pk}$**	**$\ln Q_c$**
(Intercept)	11.394932***	7.329052***	15.282549***
	(0.813566)	(0.636550)	(0.710366)
$\ln w_{bc}$	-0.798448***	0.285602**	-0.076279
	(0.174058)	(0.095075)	(0.113401)
$\ln w_{pk}$	0.285602**	-0.397054***	0.141988
	(0.095075)	(0.111838)	(0.082187)
$\ln w_c$	-0.076279	0.141988	-0.053850
	(0.113401)	(0.082187)	(0.133076)
GDP_{US}	0.000006	-0.000020	-0.000004
	(0.000012)	(0.000013)	(0.000010)
GDP_{RoW}	0.000061**	0.000075**	0.000028
	(0.000024)	(0.000027)	(0.000021)
Oct2013	-1.486658***	-0.460797**	-0.048358
	(0.139797)	(0.162119)	(0.123694)
(BP intercept)	-1.599744	2.966731***	-0.170923
	(1.021579)	(0.862646)	(0.853193)
$\ln w_{bc}$ * BP	0.402936	-0.228293	0.158001
	(0.211985)	(0.128222)	(0.133084)
$\ln w_{pk}$ * BP	-0.228293	0.318723*	-0.206896
	(0.128222)	(0.158893)	(0.107255)
$\ln w_c$ * BP	0.158001	-0.206896	-0.006378
	(0.133084)	(0.107255)	(0.152710)
GDP_{US} * BP	0.000010	0.000022	0.000012
	(0.000013)	(0.000014)	(0.000011)
GDP_{RoW} * BP	-0.000084	-0.000228***	-0.000033
	(0.000060)	(0.000066)	(0.000051)
R^2	0.473641	0.958487	0.227968
Adj. R^2	0.444399	0.956181	0.185078
Num. obs.	229	229	229

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

Table 2.4. Results from SUR model variation (2)

	Variation (2)	
	$\ln Q_{bc}$	**$\ln Q_{pk}$**
(Intercept)	11.442155***	6.186090***
	(0.833429)	(0.812798)
$\ln w_{bc}$	-0.736611***	0.239740*
	(0.189429)	(0.097373)
$\ln w_{pk}$	0.239740*	-0.419904***
	(0.097373)	(0.110952)
$\ln w_{c}$	-0.112289	0.510508**
	(0.160442)	(0.183978)
GDP_{US}	0.000005	-0.000019
	(0.000012)	(0.000013)
GDP_{RoW}	0.000063**	0.000058*
	(0.000024)	(0.000028)
Oct2013	-1.483012***	-0.502197**
	(0.140276)	(0.160513)
(BP intercept)	-1.569543	4.266523***
	(1.047701)	(0.999319)
$\ln w_{bc}$ * BP	0.255325	-0.071278
	(0.238605)	(0.135419)
$\ln w_{pk}$ * BP	-0.071278	0.345294*
	(0.135419)	(0.157525)
$\ln w_{c}$ * BP	0.187546	-0.813581***
	(0.187310)	(0.212804)
GDP_{US} * BP	0.000013	0.000017
	(0.000013)	(0.000014)
GDP_{RoW} * BP	-0.000115	-0.000142*
	(0.000065)	(0.000070)
R^2	0.477129	0.960055
Adj. R^2	0.448080	0.957836
Num. obs.	229	229

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

Table 2.5. Results from SUR model variation (3)

Variation (3)		
	lnQ_{bc}	**lnQ_{pk}**
(Intercept)	11.076643***	7.902721***
	(0.673789)	(0.559158)
lnw_{bc}	-0.740839***	0.226752*
	(0.188650)	(0.096425)
lnw_{pk}	0.226752*	-0.340212**
	(0.096425)	(0.110789)
GDP_{US}	0.000005	-0.000018
	(0.000012)	(0.000013)
GDP_{RoW}	0.000058*	0.000080**
	(0.000023)	(0.000027)
Oct2013	-1.497581***	-0.453273**
	(0.138980)	(0.164576)
(BP intercept)	-1.215454	2.132195**
	(0.924795)	(0.802775)
lnw_{bc} * BP	0.331019	-0.093349
	(0.232575)	(0.134215)
lnw_{pk} * BP	-0.093349	0.166569
	(0.134215)	(0.155864)
GDP_{US} * BP	0.000011	0.000020
	(0.000013)	(0.000014)
GDP_{RoW} * BP	-0.000078	-0.000225**
	(0.000059)	(0.000068)
R^2	0.475505	0.957078
Adj. R^2	0.451445	0.955109
Num. obs.	229	229

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 2.6. Own- and cross-price wholesale demand elasticity estimates from SUR model variations (1) through (3) before breakpoint (April 2003 - February 2013)

Before Breakpoint (April 2003 - February 2013)							
	Variation (1)			Variation (2)		Variation (3)	
	lnQ_{bc}	lnQ_{pk}	lnQ_{c}	lnQ_{bc}	lnQ_{pk}	lnQ_{bc}	lnQ_{pk}
lnQ_{bc}	-0.7984	0.2856[b]	-0.0763	-0.7366	0.2397[b]	-0.7408	0.2268[b]
lnQ_{pk}	0.2856[b]	-0.3971[a]	0.1420	0.2397[b]	-0.4199[a]	0.2268[b]	-0.3402[a]
lnQ_{c}	-0.0763	0.1420	-0.0539[a]	-0.1123	0.5105[b]		

Note: [a] indicates own-price elasticity is statistically different from -1 ($p<0.05$)
[b] indicates cross-price elasticity is statistically different from 0 ($p<0.05$)

Table 2.7. Own- and cross-price wholesale demand elasticity estimates from SUR model variations (1) through (3) after breakpoint (March 2013 - April 2022)

After Breakpoint (March 2013 - April 2022)							
	Variation (1)			Variation (2)		Variation (3)	
	lnQ_{bc}	lnQ_{pk}	lnQ_{c}	lnQ_{bc}	lnQ_{pk}	lnQ_{bc}	lnQ_{pk}
lnQ_{bc}	-0.3955[a]	0.0573[b]	0.0817	-0.4813[a]	0.1685[b]	-0.4098[a]	0.1334[b]
lnQ_{pk}	0.0573[b]	-0.0783[a]	-0.0649	0.1685[b]	-0.0746[a]	0.1334[b]	-0.1736[a]
lnQ_{c}	0.0817	-0.0649	-0.0602[a]	0.0753	-0.3031		

Note: [a] indicates own-price elasticity is statistically different from -1 ($p<0.05$)
[b] indicates cross-price elasticity is statistically different from 0 ($p<0.05$)

Own-Price Elasticity of Demand Estimates

Own-price elasticity of demand estimates for the time period before the breakpoint can be found directly from the coefficient estimates. Own-price elasticity of demand estimates are expected to be negative as an increase in own-price should lead to a decrease in quantity demanded. To obtain own-price elasticity estimates after the breakpoint, coefficient estimates for the respective proteins can be summed. For example, the own-price wholesale beef demand elasticity can be found by adding the estimates β_{11} and ζ_{11} from the beef regression in each model variation. Own-price elasticity of demand estimates can be found in the diagonals of each variation in Tables 2.6 and 2.7.

The own-price elasticities of demand for wholesale beef are compared among the three SUR model variations to determine if and how the differences in the three variations impact the model performance. In each variation, the own-price elasticity of wholesale beef before the breakpoint can be found from β_{11}. The own-price elasticity of demand for wholesale beef before the breakpoint can be found from β_{11} plus ζ_{11}. Results from variation (1) indicate that a one percent increase in w_{bc} decreases quantity demanded Q_{bc} by 0.798 percent prior to the structural break. After the structural break, a one percent increase in w_{bc} decreases quantity demanded of Q_{bc} by 0.396 percent. Comparatively, results from variation (2) indicate that a one percent increase in w_{bc} decreases quantity demanded of Q_{bc} by 0.737 percent prior to the structural break. After the structural break, a one percent increase in w_{bc} decreases quantity demanded of Q_{bc} by 0.481 percent. Results from variation (3) found that a one percent increase in w_{bc} decreases quantity demanded of Q_{bc} by 0.740 percent prior to the structural break and after the structural break, a one percent increase in w_{bc} decreases quantity demanded of Q_{bc} by 0.410 percent.

Beef own-price elasticities are not statistically different from negative one before the break at a level about $p<0.05$. However, after the break, beef own-price elasticities are statistically different from negative one ($p<0.05$). All own-price elasticities of demand for beef are statistically significant and different from zero ($p<0.001$) before the structural break and all estimates are jointly significant and different from zero ($p<0.001$) after the break. Prior to the structural break, all estimates are relatively similar. However, the inclusion of the chicken equation in variation (1) marginally increases the impact of the elasticity estimate as compared to the estimates in variations (2) and (3). Similarly, after the structural break, estimates do not differ drastically. However, there is variation among them, as the estimate from variation (2) has slighting more impact on quantity demanded than variations (1) and (3).

The estimates for beef own-price wholesale demand are to similar those found in Lusk et al. (2001) and those used in Anderson et al. (2021) and Pendell et al. (2010). Lusk et al. (2001)

found the own-price elasticity of demand for wholesale Choice beef was -0.432. Anderson et al. (2021) quantified the effect of increases in costs at the feeder-packer level has on cattle and beef prices using an equilibrium displacement model. The own-price elasticity of demand of wholesale beef they used was -0.567. Pendell et al. (2010) also used an equilibrium displacement model to examine the impacts of animal identification and tracing systems adoption on the U.S. meat and livestock sectors. The own-price elasticity of demand for wholesale beef they used in their model was -0.58 in the short-run and -0.94 in the long-run. While the results from our study are similar to those previously found, they include data from more recent time periods and therefore provide an updated estimate.

Next, the own-price elasticities of demand for wholesale pork are compared among the three variations to determine if and how the differences impact the model performance. In each variation, the own-price elasticity of demand for wholesale pork before the breakpoint can be found from β_{22}. The own-price elasticity of demand for wholesale beef before the breakpoint can be found from β_{22} plus ζ_{22}. Before the structural break, variation (1) found that a one percent increase in w_{pk} decreases quantity demanded of Q_{pk} by 0.398 percent. After the break, variation (1) found that a one percent increase in w_{pk} decreases quantity demanded of Q_{pk} by 0.078 percent. Results from variation (2) found that a one percent increase in w_{pk} decreases quantity demanded of Q_{pk} by 0.420 percent before the structural break. After the break, variation (2) found that a one percent increase in w_{pk} decreases quantity demanded of Q_{pk} by 0.075 percent. Finally, before the structural break, variation (3) found that a one percent increase in w_{pk} decreases quantity demanded of Q_{pk} by 0.340 percent. After the break, variation (1) found that a one percent increase in w_{pk} decreases quantity demanded of Q_{pk} by 0.174 percent.

Pork own-price elasticities are statistically different from negative one before and after the break ($p<0.05$). All own-price elasticities of demand for wholesale pork are statistically significant and different from zero ($p<0.05$) before the structural break and all estimates are jointly significant and different from zero ($p<0.01$) after the break. Similar to the own-price elasticities of demand for wholesale beef, these estimates only vary marginally. Lusk et al. (2001) found the own-price elasticity of demand for wholesale pork was -0.471. The own-price elasticity of demand for wholesale pork used in Pendell et al. (2010) was -0.71 in the short-run and -1.00 in the long-run.

Finally, the own-price elasticity of demand for wholesale chicken is only estimated in variation (1) and both the estimate before and after the structural break are not statistically significant or different from zero at a level above $p<0.05$. Chicken own-price elasticities are statistically different from negative one before and after the break ($p<0.05$). Given the concerns about the quality of the chicken price and volume data, the own-price elasticities of demand for wholesale chicken likely do not accurately reflect the real demand. Results from variation (1) found that a one percent increase in w_{bc} decreases quantity demanded of Q_{bc} by 0.054 percent prior to the structural break and after the structural break, a one percent increase in w_{bc} decreases quantity demanded of Q_{bc} by 0.060 percent. Lusk et al. (2001) found the own-price demand elasticity for wholesale chicken was -0.020. While the reliability of the own-price elasticity of demand for wholesale chicken found in variation (1) is questionable, the estimates found are similar to what Lusk et al. (2001) found.

The own-price elasticity of demand for each of the wholesale proteins declines after the breakpoint, compared to before the breakpoint, shown in Tables 2. and 2.7. This suggests that price sensitivity has declined for beef, pork, and chicken over the two time periods. In other words, changes in the price of the protein have less impact on quantity demanded than the same price change did in the past. While this analysis does not test why a decrease in price sensitivity has occurred, other factors (besides own price) are impacting quantity demanded. Perhaps non-price factors, such as taste, safety, and convenience, have grown in importance relative to price.

Cross-Price Wholesale Demand Estimates

As mentioned in the methods section, cross-price elasticities between proteins are restricted to impose symmetry on the coefficients in the different SUR model variations. Cross-price elasticity of demand estimates are expected to be positive as an increase in price of a good should lead to a increase in demand for a substitute good. Cross-price elasticity of demand estimates for the time period before the breakpoint can be found directly from the coefficient estimates. To obtain cross-price elasticity of demand estimates after the breakpoint, coefficient estimates for the respective proteins can be summed. For example, the cross-price elasticity of demand for wholesale beef with respect to the price of pork can be found by adding the estimates β_{12} and ζ_{12} from the beef regression in each model variation.

The cross-price elasticity of demand for wholesale beef with respect to the price of pork are restricted to equal the cross-price elasticity of demand for wholesale pork with respect to the price of beef in each SUR model variation. These estimates will be referred to as the cross-price elasticities of demand between beef and pork. In each variation, the cross-price elasticities of demand between beef and pork before the breakpoint can be found from β_{12} and β_{21}. After the breakpoint, these estimates are found from β_{12} plus ζ_{12} and β_{21} plus ζ_{21}. Before the breakpoint in variation (1), a one percent increase in w_{pk} increases the demand for Q_{bc} by 0.286 percent (a one percent increase in w_{bc} increases the demand for Q_{pk} by 0.286 percent). After the breakpoint, results from variation (1) show that a one percent increase in w_{pk} increases the demand for Q_{bc} by

0.057 percent, and vice versa. Variation (2) indicates that a one a one percent increase in w_{pk} increases the demand for Q_{bc} by 0.240 percent before the breakpoint, and vice versa. After the break, a one percent increase in w_{pk} increases the demand for Q_{bc} by 0.169 percent, and vice versa. Finally, variation (2) indicates that a one a one percent increase in w_{pk} increases the demand for Q_{bc} by 0.227 percent before the breakpoint, and vice versa. After the break, a one percent increase in w_{pk} increases the demand for Q_{bc} by 0.133 percent and vice versa.

Similar to the own-price elasticities of demand, the cross-price elasticities of demand between beef and pork before and after the breakpoint only differ marginally. The cross-price elasticities of demand between beef and pork in each variation are statistically significant ($p<0.05$) before the structural break and all estimates are jointly significant ($p<0.05$) after the break. Lusk et al. (2001) found the cross-price elasticity of demand for wholesale Choice beef with respect to the price of pork was 0.096 and the cross-price elasticity of demand for wholesale pork with respect to the price of Choice beef was 0.142. The estimates from Lusk et al. (2001) are similar to our estimates after the structural break.

The cross-price elasticity of demand for wholesale beef with respect to the price of chicken are restricted to equal the cross-price elasticity of demand for wholesale chicken with respect to the price of beef. Similarly, the cross-price elasticity of demand for wholesale pork with respect to the price of chicken are restricted to equal the cross-price elasticity of demand for wholesale chicken with respect to the price of pork. These estimates are only found in variation (1) and (2) and will be referred to as the cross-price elasticities of demand between beef and chicken and the cross-price elasticities of demand between pork and chicken, respectively.

The cross-price elasticity of demand between beef and chicken before the breakpoint can be found from β_{13} and β_{31}. After the breakpoint, these estimates are found from β_{13} plus ζ_{13} and

β_{31} plus ζ_{31}. In variation (1) before the breakpoint, a one percent increase in w_c decreases the demand for Q_{bc} by 0.076 percent (a one percent increase in w_{bc} decreases the demand for Q_c by 0.076 percent). After the breakpoint, a one percent increase in w_c decreases the demand for Q_{bc} by 0.082 percent, and vice versa. In variation (2) before the breakpoint, a one percent increase in w_c decreases the demand for Q_{bc} by 0.112 percent. After the breakpoint, a one percent increase in w_c decreases the demand for Q_{bc} by 0.075 percent. Cross-price elasticity of demand between beef and chicken estimates are not statistically significant at a level above $p<0.05$. While the negative relationship between the cross-price elasticity of demand between beef and chicken found is not consistent with theoretical expectations, it is consistent with the findings of Lusk et al. (2001). Lusk et al. (2001) found the cross-price elasticity of demand for wholesale Choice beef with respect to the price of chicken was -0.030 and the cross-price elasticity of demand for wholesale chicken with respect to the price of Choice beef was -0.031.

The cross-price elasticity of demand between pork and chicken before the breakpoint can be found from β_{23} and β_{32}. After the breakpoint, these estimates are found from β_{23} plus ζ_{23} and β_{32} plus ζ_{32}. In variation (1) before the breakpoint, a one percent increase in w_c increases the demand for Q_{pk} by 0.142 percent (a one percent increase in w_{pk} increases the demand for Q_c by 0.142 percent). After the breakpoint, a one percent increase in w_c decreases the demand for Q_{pk} by 0.065 percent, and vice versa. In variation (2) before the breakpoint, a one percent increase in w_c increases the demand for Q_{pk} by 0.511 percent. After the breakpoint, a one percent decreases in w_c increases the demand for Q_{bc} by 0.303 percent. The cross-price elasticity of demand between pork and chicken estimates in variation (2) are statistically significant ($p<0.01$), however estimates from variation (1) are not statistically significant at a level above $p<0.05$. Lusk et al. (2001) found the cross-price elasticity of demand for wholesale pork with respect to the price of chicken was 0.052 and the cross-price elasticity of demand for wholesale chicken with respect to the price of pork was 0.037. While a negative relationship between the cross-price elasticity of demand between pork and chicken is found in some variations and does not match theoretical expectations, it is likely a result of the quality of data used in the models.

GDP Effects

GDP effects on wholesale protein demand, or the impact of per capita GDP in the U.S. and the rest of the world on protein demand, before and after the breakpoint are summarized in Tables 2.8 and 2.9. At the aggregate level, protein is known to be a normal good, because as income rises, demand for protein is expected to rise. This is especially true for low-income countries, as income increases, protein demand also tends to increase. Additionally, low-income countries tend to be more price responsive to changes in income than middle- and high-income countries (Andreoli et al., 2021). However, in higher-income countries, an increase in income may increase demand for higher value cuts, such as steaks, pork chops, and chicken breasts, compared to lower value cuts, such as ground beef, deli ham, and chicken wings (Lusk & Tonsor, 2016). As this analysis considers protein demand at aggregate levels and not specific cuts, GDP effects and coefficient signs may differ between protein products.

Before the structural breakpoint, the direction of signs for GDP_{US} are mixed between variations and proteins. After the break, direction of signs for GDP_{US} are mostly positive, with the exception of a negative sign for GDP_{US} on pork in variation (2). As GDP_{RoW} is calculated with a large share of low-income countries, GDP_{RoW} effects on protein demand are expected to be positive. Direction of signs on the coefficients before the break for GDP_{RoW} are all positive. After the break, direction of signs for GDP_{RoW} are all negative. This indicates that after the breakpoint, GDP elasticities decreased and shifted towards inferior goods. This is against expectations and is a limitation to these models. In variations (1) through (3), the effect of GDP_{US} on wholesale protein is not statistically significant, both before and after the breakpoint. Conversely, the effect of GDP_{RoW} is statistically significant for most of the proteins and variations, before and after the break, with the exceptions of wholesale chicken before and after the break in Variation (1). As this analysis considers wholesale protein at aggregate levels, demand differences among different value cuts are not reflected.

Table 2.8. Income effects on wholesale protein demand from SUR model variations (1) through (3) before breakpoint (April 2003 – February 2013)

Before Breakpoint (April 2003 - February 2013)							
	Variation (1)			Variation (2)		Variation (3)	
	$\ln Q_{bc}$	$\ln Q_{pk}$	$\ln Q_c$	$\ln Q_{bc}$	$\ln Q_{pk}$	$\ln Q_{bc}$	$\ln Q_{pk}$
GDP_{US}	5.94E-06	-1.96E-05	-4.23E-06	5.41E-06	-1.94E-05	5.31E-06	-1.85E-05
GDP_{RoW}	6.08E-05**	7.46E-05**	2.81E-05	6.32E-05**	5.76E-05*	5.82E-05*	8.00E-05**

Note: ***p< 0.001; **p < 0.01; *p < 0.05

Table 2.9. Income effects on wholesale protein demand from SUR model variations (1) through (3) after breakpoint (March 2013 - April 2022)

After Breakpoint (March 2013 - April 2022)							
	Variation (1)			Variation (2)		Variation (3)	
	$\ln Q_{bc}$	$\ln Q_{pk}$	$\ln Q_c$	$\ln Q_{bc}$	$\ln Q_{pk}$	$\ln Q_{bc}$	$\ln Q_{pk}$
GDP_{US}	1.58E-05	2.85E-06	7.31E-06	1.86E-05	-1.97E-06	1.60E-05	1.26E-06
GDP_{RoW}	-2.35E-05*	-1.53E-04***	-5.11E-06	-5.22E-05*	-8.45E-05*	-2.01E-05*	-1.45E-04***

Note: ***p< 0.001; **p < 0.01; *p < 0.05

Post-2013 Model

To determine if the interaction term approach is a sufficient method to address the structural break and to address data quality concerns, a similar model was estimated with only the subset of data from January 2014 – April 2022. This approach does not include breakpoint interaction terms as it only contains data after the breakpoint. It also does not include data before livestock mandatory price reporting in the pork industry or before the switch in the wholesale chicken price series. Results from this approach are shown in Table 2.10 and can be compared directly to results from Table 2.7. This comparison gives analyst the ability to determine which method they prefer when using the demand elasticities in future analyses. While results from the method with data from January 2014 – April 2022 are similar to the post-breakpoint results, some marginal differences exist.

Table 2.10. Own- and cross-price wholesale demand elasticity estimates from SUR model variations (1) through (3) (January 2014 – April 2022)

	January 2014 – April 2022						
	Variation (1)			Variation (2)		Variation (3)	
	Beef	Pork	Chicken	Beef	Pork	Beef	Pork
Beef	-0.5460[a]	0.1956[b]	0.1239	-0.6109[a]	0.3213[b]	-0.5221[a]	0.2559[b]
Pork	0.1956[b]	-0.2246[a]	-0.0989	0.3213[b]	-0.2818[a]	0.2559[b]	-0.3281[a]
Chicken	0.1239	-0.0989	-0.1112[a]	0.0591	-0.2528[b]		

Note: [a] indicates own-price elasticity is statistically different from -1 ($p<0.05$)
[b] indicates cross-price elasticity is statistically different from 0 ($p<0.05$)

Limitations

These results attempt to update own-price elasticity of demand for wholesale beef, pork, and chicken. Additionally, cross-price elasticity of demand estimates between the different proteins are also calculated. However, due to the quality of chicken data publicly available, the different model variations may struggle to accurately capture protein demand at the wholesale level. While the concerns related to the quality of the chicken data is regularly highlighted in this research, it is important to note that all the wholesale price and quantity variables used in this analysis could be improved. For example, instead of the load variables used as the dependent variables for the beef and pork models, an alternative would be production level variables. Further, Choice cutout and volume are used to represent beef price and volume data. While Choice beef is the most produced and consumed quality grade, Prime is growing in importance in the U.S. beef industry. Therefore, as this analysis only uses Choice grade data, the change in consumption and production of Prime beef may not be reflected in this analysis. Further, due to the complexity of wholesaler interactions with players further down the supply chain, aggregate data variables may struggle to capture the breadth of activities at the wholesale level.

Further, an independent variable that would have been ideal to include in this analysis is a food marketing cost index that incorporated costs to produce and sell protein at the wholesale level. However, due to the availability of cost data at this level, a time-series food marketing cost index is challenging to obtain. Without including a similar data variable, this analysis does not capture changes in operating costs wholesale protein producers face when producing and marketing their products.

Implications

Changes in the beef industry in the United States, such as product differentiation, global protein demand, supply chain disruptions, and the evolving role of wholesale protein producers, have led to a need for an updated understanding of the wholesale relationship among different protein products. Additionally, existing research on wholesale demand elasticities for beef is outdated and therefore does not consider changes the industry has faced in the last few decades. For example, Lusk et al. (2001) found the own-price demand elasticity for wholesale pork was -0.471 whereas this analysis found it to be -0.078 after the structural breakpoint. Our estimate is smaller in magnitude and therefore shows price sensitivity has decreased. Similarly, Lusk et al. (2001) found the own-price demand elasticity for wholesale choice beef was -0.432 whereas this analysis found it to be -0.396 after the structural breakpoint. This research fills that gap by updating own-price elasticity of demand for wholesale beef, pork, and chicken, as well as cross-price elasticity of demand for the different proteins with respect to the price of substitutes.

In addition, this research highlights the challenges of accurately estimating demand elasticity estimates at the wholesale level due to limitations in data availability and quality. Due to these limitations, wholesale chicken own- and cross-price estimates may not reflect the true demand at the wholesale level. Further, food marketing costs are difficult to include for the time period analyzed in this research and therefore the results do not directly consider the cost of producing and marketing protein products at the wholesale level.

Conclusion

Wholesale beef demand elasticities are estimated to provide the U.S. beef industry with current wholesale beef demand and a better understanding of the impacts of structural changes and supply chain disruptions. Previous research, changes in data availability, and differences in industry operations are considered to provide new economic parameter estimates. As beef demand is influenced by both the price and availability of other proteins, such as pork and chicken, seemingly unrelated regression (SUR) models are used to estimate wholesale beef demand and the relationship between pork and chicken. Additionally, Bai and Perron structural break tests are conducted to determine if structural breakpoints are present in the data. One structural breakpoint was found in October 2013 and the models are designed to account for the breakpoint.

Three SUR model variations are estimated given the concerns of chicken data quality. Results from the three variations are compared to each other and to results from previous research to determine if the quality of the chicken data impacts the estimates. Findings suggest that the quality of the chicken data does not significantly impact the own-price elasticity of demand for wholesale beef and pork, but likely impacts the own-price elasticity of demand for wholesale chicken and the cross-price relationships of chicken with beef and pork.

The main result of interest from this research is the own-price elasticity of demand for wholesale beef. Results from SUR model variations (1), (2), and (3) indicate that the own-price elasticity of demand for wholesale beef before the structural breakpoint is -0.798, -0.737, and -0.741, respectively. After the structural breakpoint, variations (1), (2), and (3) indicate that the own-price elasticity of demand for wholesale beef is -0.396, -0.481, and -0.410, respectively. The estimates after the breakpoint are similar to Lusk et al. (2001). Further, results after the break are smaller in magnitude than before the breakpoint. This finding suggests that the impact of changes in own price have decreased over time. This further suggests that the relationship between the own price and quantity demanded of protein products is decreasing over time. Potential reasons a decrease was observed over time is that consumers may be more concerned with attributes such as quality, convenience, production practices, and value-added additions. While price is still an important driver of protein demand, such attributes may be growing in importance to a segment of protein consumers which impacts demand at the aggregate level.

As the beef industry continues to evolve, both globally and domestically, empirical research of the wholesale relationship between various protein products will aid in understanding how consumer demographics, consumer preferences, farm-level production changes, structural changes, supply chain disruptions, and other industry changes impact how protein is marketed and produced.

Future Research

An interesting addition to this analysis would be similar SUR wholesale models utilizing a composite beef price and volume variable made up of shares of Select, Choice, and Prime graded beef over time. As the relationship among the three quality grades has changed over the previous decades, a similar analysis that recognizes those changes would be an interesting comparison for the industry. Additionally, given the concerns of the wholesale price and quantity data used in this analysis, especially related to chicken, improved variables, such as private chicken price and volume data would be interesting to analyze and compare to the results of this analysis.

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a) Appendix – Article 1

Figure a.1. 2022 United States beef cow inventory measured in 1,000 head. Source: USDA NASS January Cattle Inventory Reports (LMIC, 2022)

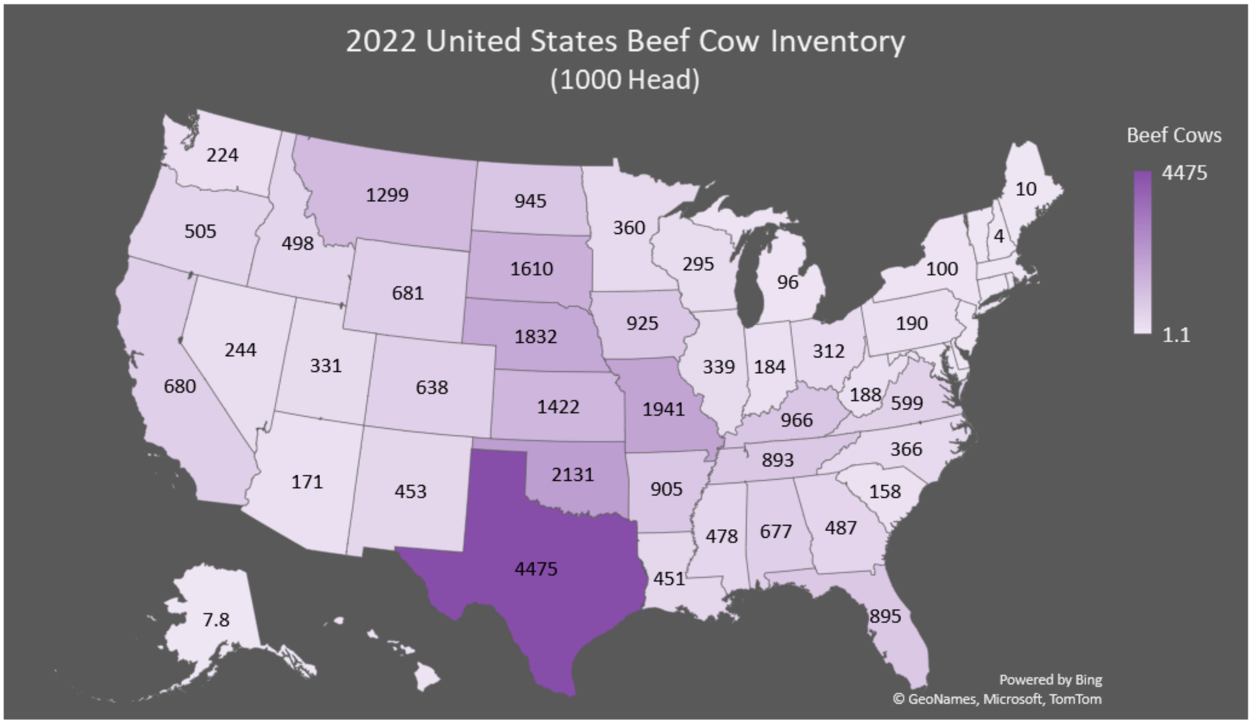


Figure a.2. Beef cow inventory, 1973-2022. Source: USDA NASS January Cattle Inventory Reports (LMIC, 2022)

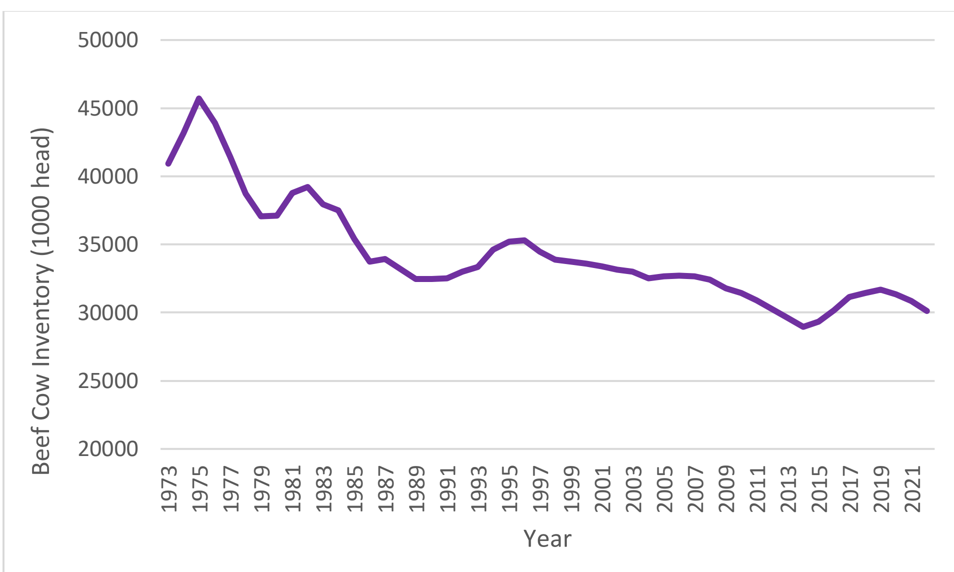


Figure a.3. Oklahoma City October 500-600lb feeder steer real prices, 1973-2021. Base year = 2021. Source: USDA AMS (LMIC, 2022)

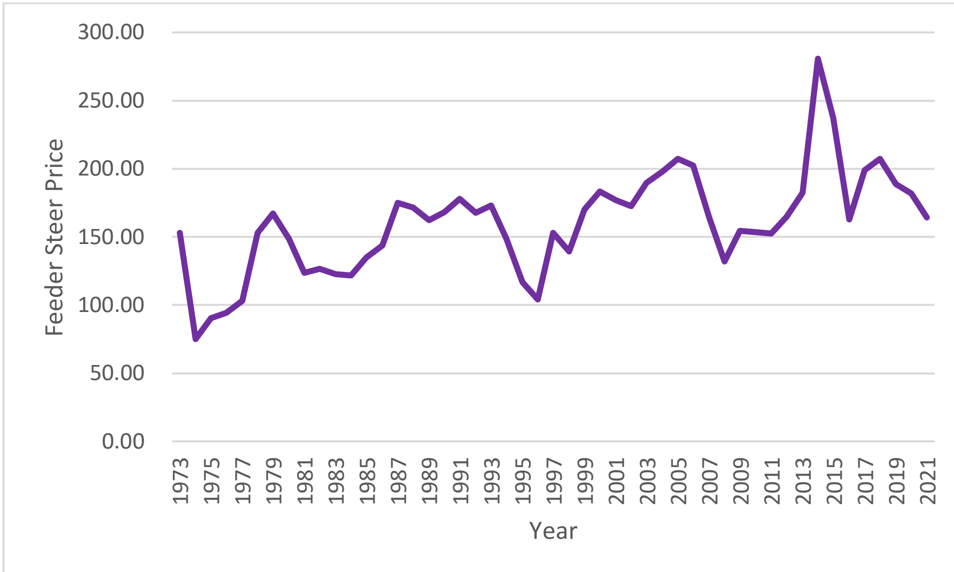


Figure a.4. Real hay price, 1973-2021. Base year = 2021. Source: USDA NASS (NASS, 2022)

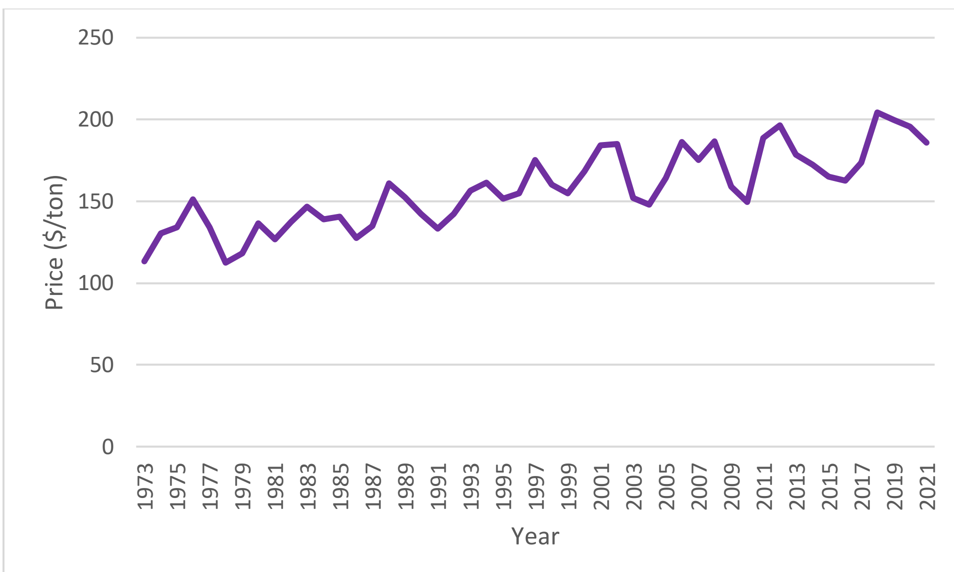
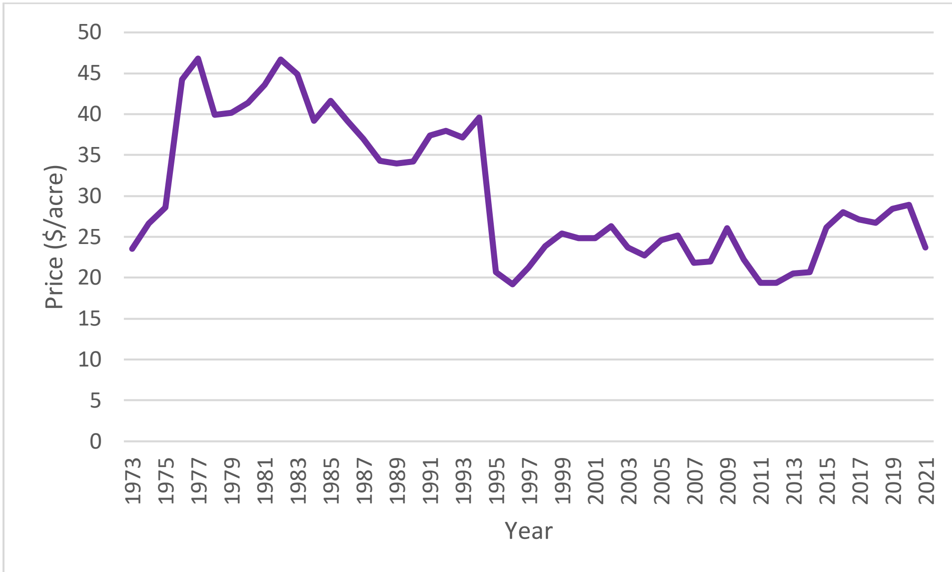
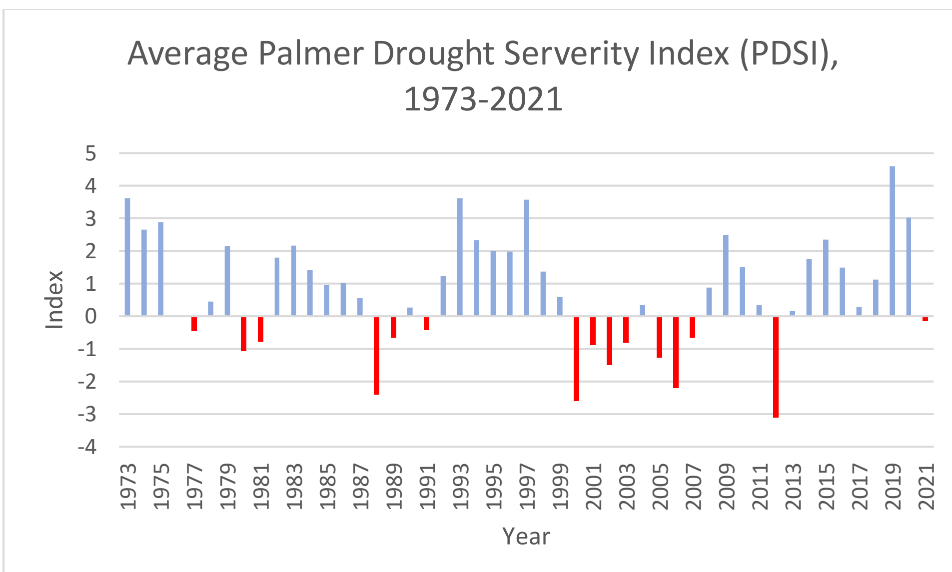


Figure a.5. Average pasture rental rate, real price, 1973-2021. Base year = 2021. Source: USDA ERS and USDA NASS (ERS, 2020; NASS, 2022)



*The average pasture rent per acre for the top 10 beef cow states in 2022 was calculated

Figure a.6. Average Palmer Drought Severity Index (PDSI), 1973-2021. Source: NOAA. (NOAA, 2022)



Note: Average conditions of the Southern, Northern Rockies and Plains, and Ohio River Valley regions which represent the areas of the country with the top 10 beef cattle states

Figure a.7. Calf price elasticity of cattle and calves. 1949-1999 as found in Prevatt and Vansickle (2003)

Item	1949-58	1958-67	1967-79	1979-90	1990-?
Year 1					
Year 2	0.10	0.43	0.11	-0.02	0.24
Year 3	0.26	-0.20	0.04	-0.15	-0.12
Year 4	-0.33	0.44	0.23	-0.14	0.67
Year 5	-0.16	0.47	0.36	-0.12	-0/40
Year 6	-0.84	-0.90	0.14	0.49	-0.10
Year 7	0.53	-0.20	0.13	-0.94	-0.03
Year 8	0.17	0.13	-0.11	2.41	-0.06
Year 9	-0.22	-0.01	-0.13	-0.13	
Year 10			-0.14	-0.19	
Year 11			-0.54	-1.65	
Year 12			-0.12	-0.19	
Year 13			-0.12		

Estimates represent *arc elasticities* [(Q2-Q1)/(Q2+Q1)]/[(P2-P1)/(P2+P1)]

Table 2.11. Results from the partial-adjustment supply model estimating annual beef cow inventories in Texas, annual data from 1975-2021

	Dependent variable:	
	$Q_{BC(i,t)}$	
	Equation (1.1)	Equation (1.2)
$P_{FS(t-2)}$	3.041^{**}	
	(1.157)	
$PDSI_{(i,t-1)}$	30.299^{**}	
	(14.165)	
$P_{H(t-2)}$	-0.850	
	(2.268)	
$P_{PR(i,t-2)}$	-13.337	
	(14.106)	
$Slt_{(t)}$	-1.734	
	(1.318)	
$Q_{BC(i,t-1)}$	0.896^{***}	0.928^{***}
	(0.085)	(0.048)
Constant	1,670.045	350.507
	(1,228.055)	(260.168)
Observations	47	47
R^2	0.927	0.892
Adjusted R^2	0.916	0.890
Residual Std. Error	187.999 (df = 40)	215.153 (df = 45)
F Statistic	84.536^{***} (df = 6; 40)	372.807^{***} (df = 1; 45)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

Table 2.12. Results from the partial-adjustment supply model estimating annual beef cow inventories in Oklahoma, annual data from 1975-2021

	Dependent variable:	
	$Q_{BC(i,t)}$	
	Equation (1.1)	Equation (1.2)
$\mathbf{P_{FS(t-2)}}$	1.470^{**}	
	(0.595)	
$\mathbf{PDSI_{(i,t-1)}}$	13.981^{*}	
	(7.735)	
$\mathbf{P_{H(t-2)}}$	0.025	
	(1.210)	
$\mathbf{P_{PR(i,t-2)}}$	-13.665^{**}	
	(6.372)	
$\mathbf{Slt_{(t)}}$	-0.862	
	(0.536)	
$\mathbf{Q_{BC(i,t-1)}}$	0.844^{***}	0.815^{***}
	(0.085)	(0.079)
Constant	974.499^{**}	370.557^{**}
	(438.747)	(161.440)
Observations	47	47
$\mathbf{R^2}$	0.786	0.701
Adjusted $\mathbf{R^2}$	0.754	0.695
Residual Std. Error	101.258 (df = 40)	112.755 (df = 45)
F Statistic	24.467^{***} (df = 6; 40)	105.652^{***} (df = 1; 45)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

Table 2.13. Results from the partial-adjustment supply model estimating annual beef cow inventories in Missouri, annual data from 1975-2021

	Dependent variable:	
	$\mathbf{Q_{BC(i,t)}}$	
	Equation (1.1)	Equation (1.2)
$\mathbf{P_{FS(t-2)}}$	1.065***	
	(0.345)	
$\mathbf{PDSI_{(i,t-1)}}$	7.151	
	(5.364)	
$\mathbf{P_{H(t-2)}}$	-0.970	
	(0.700)	
$\mathbf{P_{PR(i,t-2)}}$	-1.475	
	(1.736)	
$\mathbf{Slt_{(t)}}$	-0.131	
	(0.327)	
$\mathbf{Q_{BC(i,t-1)}}$	0.909***	0.872***
	(0.053)	(0.042)
Constant	314.097	254.699***
	(266.011)	(89.969)
Observations	47	47
$\mathbf{R^2}$	0.932	0.904
Adjusted $\mathbf{R^2}$	0.922	0.902
Residual Std. Error	58.865 (df = 40)	65.994 (df = 45)
F Statistic	91.356*** (df = 6; 40)	422.926*** (df = 1; 45)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 2.14. Results from the partial-adjustment supply model estimating annual beef cow inventories in Nebraska, annual data from 1975-2021

	Dependent variable:	
	$Q_{BC(i,t)}$	
	Equation (1.1)	Equation (1.2)
$P_{FS(t-2)}$	1.131***	
	(0.364)	
$PDSI_{(i,t-1)}$	4.195	
	(3.195)	
$P_{H(t-2)}$	-1.110	
	(0.704)	
$P_{PR(i,t-2)}$	-3.084	
	(2.421)	
$Slt_{(t)}$	-0.059	
	(0.300)	
$Q_{BC(i,t-1)}$	0.848***	0.789***
	(0.078)	(0.073)
Constant	386.644	398.122***
	(232.897)	(140.614)
Observations	47	47
R^2	0.806	0.722
Adjusted R^2	0.777	0.715
Residual Std. Error	57.177 (df = 40)	64.571 (df = 45)
F Statistic	27.696*** (df = 6; 40)	116.663*** (df = 1; 45)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 2.15. Results from the partial-adjustment supply model estimating annual beef cow inventories in South Dakota, annual data from 1975-2021

	Dependent variable:	
	$Q_{BC(i,t)}$	
	Equation (1.1)	Equation (1.2)
$P_{FS(t-2)}$	0.924*	
	(0.517)	
$PDSI_{(i,t-1)}$	4.368	
	(4.661)	
$P_{H(t-2)}$	-0.242	
	(1.036)	
$P_{PR(i,t-2)}$	0.700	
	(3.580)	
$Slt_{(t)}$	0.051	
	(0.467)	
$Q_{BC(i,t-1)}$	0.684***	0.689***
	(0.091)	(0.091)
Constant	351.092	507.591***
	(229.492)	(151.025)
Observations	47	47
R^2	0.638	0.559
Adjusted R^2	0.583	0.549
Residual Std. Error	84.262 (df = 40)	87.639 (df = 45)
F Statistic	11.738*** (df = 6; 40)	57.083*** (df = 1; 45)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 2.16. Results from the partial-adjustment supply model estimating annual beef cow inventories in Kansas, annual data from 1975-2021

	Dependent variable:	
	$\mathbf{Q_{BC(i,t)}}$	
	Equation (1.1)	Equation (1.2)
$\mathbf{P_{FS(t-2)}}$	0.802*	
	(0.423)	
$\mathbf{PDSI_{(i,t-1)}}$	-2.229	
	(5.624)	
$\mathbf{P_{H(t-2)}}$	-0.864	
	(0.896)	
$\mathbf{P_{PR(i,t-2)}}$	0.586	
	(4.313)	
$\mathbf{Slt_{(t)}}$	-0.147	
	(0.371)	
$\mathbf{Q_{BC(i,t-1)}}$	0.724***	0.734***
	(0.084)	(0.071)
Constant	521.957*	396.431***
	(291.841)	(109.849)
Observations	47	47
$\mathbf{R^2}$	0.744	0.702
Adjusted $\mathbf{R^2}$	0.705	0.696
Residual Std. Error	74.815 (df = 40)	76.005 (df = 45)
F Statistic	19.335*** (df = 6; 40)	106.160*** (df = 1; 45)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 2.17. Results from the partial-adjustment supply model estimating annual beef cow inventories in Montana, annual data from 1975-2021

	Dependent variable:	
	$Q_{BC(i,t)}$	
	Equation (1.1)	Equation (1.2)
$\mathbf{P_{FS(t-2)}}$	0.466	
	(0.353)	
$\mathbf{PDSI_{(i,t-1)}}$	7.021**	
	(3.428)	
$\mathbf{P_{H(t-2)}}$	0.383	
	(0.689)	
$\mathbf{P_{PR(i,t-2)}}$	-3.394	
	(2.698)	
$\mathbf{Slt_{(t)}}$	-0.465	
	(0.320)	
$\mathbf{Q_{BC(i,t-1)}}$	0.577***	0.665***
	(0.114)	(0.093)
Constant	937.167***	490.099***
	(302.018)	(138.330)
Observations	47	47
$\mathbf{R^2}$	0.584	0.532
Adjusted $\mathbf{R^2}$	0.521	0.522
Residual Std. Error	56.060 (df = 40)	56.043 (df = 45)
F Statistic	9.349*** (df = 6; 40)	51.153*** (df = 1; 45)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 2.18. Results from the partial-adjustment supply model estimating annual beef cow inventories in North Dakota, annual data from 1975-2021

	Dependent variable:	
	$Q_{BC(i,t)}$	
	Equation (1.1)	Equation (1.2)
$P_{FS(t-2)}$	0.474^{**}	
	(0.220)	
$PDSI_{(i,t-1)}$	2.013	
	(1.948)	
$P_{H(t-2)}$	0.051	
	(0.437)	
$P_{PR(i,t-2)}$	-1.918	
	(2.741)	
$Slt_{(t)}$	-0.121	
	(0.184)	
$Q_{BC(i,t-1)}$	0.843^{***}	0.790^{***}
	(0.074)	(0.065)
Constant	188.698	195.818^{***}
	(120.913)	(62.562)
Observations	47	47
R^2	0.793	0.764
Adjusted R^2	0.762	0.759
Residual Std. Error	35.374 (df = 40)	35.562 (df = 45)
F Statistic	25.494^{***} (df = 6; 40)	145.925^{***} (df = 1; 45)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

Table 2.19. Results from the partial-adjustment supply model estimating annual beef cow inventories in Iowa, annual data from 1975-2021

	Dependent variable:	
	$\mathbf{Q_{BC(i,t)}}$	
	Equation (1.1)	Equation (1.2)
$\mathbf{P_{FS(t-2)}}$	0.346	
	(0.263)	
$\mathbf{PDSI_{(i,t-1)}}$	-1.380	
	(4.328)	
$\mathbf{P_{H(t-2)}}$	-1.209*	
	(0.602)	
$\mathbf{P_{PR(i,t-2)}}$	-3.342***	
	(0.988)	
$\mathbf{Slt_{(t)}}$	0.254	
	(0.292)	
$\mathbf{Q_{BC(i,t-1)}}$	1.022***	0.959***
	(0.042)	(0.026)
Constant	98.727	29.360
	(217.872)	(32.065)
Observations	47	47
$\mathbf{R^2}$	0.981	0.968
Adjusted $\mathbf{R^2}$	0.978	0.967
Residual Std. Error	48.228 (df = 40)	58.751 (df = 45)
F Statistic	339.130*** (df = 6; 40)	1,353.101*** (df = 1; 45)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 2.20. Results from the partial-adjustment supply model estimating annual beef cow inventories in Kentucky, annual data from 1975-2021

	Dependent variable:	
	$Q_{BC(i,t)}$	
	Equation (1.1)	Equation (1.2)
$P_{FS(t-2)}$	0.790***	
	(0.248)	
$PDSI_{(i,t-1)}$	4.696	
	(3.821)	
$P_{H(t-2)}$	-0.270	
	(0.520)	
$P_{PR(i,t-2)}$	-5.766***	
	(2.055)	
$Slt_{(t)}$	-0.550**	
	(0.233)	
$Q_{BC(i,t-1)}$	0.826***	0.855***
	(0.085)	(0.075)
Constant	681.150***	153.613*
	(219.166)	(83.383)
Observations	47	47
R^2	0.832	0.741
Adjusted R^2	0.807	0.735
Residual Std. Error	43.395 (df = 40)	50.823 (df = 45)
F Statistic	33.077*** (df = 6; 40)	128.856*** (df = 1; 45)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 2.21. Results from the partial-adjustment supply model estimating annual beef cow inventories in Florida, annual data from 1975-2021

	Dependent variable:	
	$Q_{BC(i,t)}$	
	Equation (1.1)	Equation (1.2)
$P_{FS(t-2)}$	0.400	
	(0.301)	
$PDSI_{(i,t-1)}$	3.476	
	(4.139)	
$P_{H(t-2)}$	-1.009	
	(0.607)	
$P_{PR(i,t-2)}$	-0.606	
	(0.876)	
$Slt_{(t)}$	-0.367	
	(0.350)	
$Q_{BC(i,t-1)}$	0.742^{***}	0.913^{***}
	(0.130)	(0.054)
Constant	669.137^{*}	84.572
	(365.246)	(58.247)
Observations	47	47
R^2	0.896	0.863
Adjusted R^2	0.880	0.860
Residual Std. Error	50.945 (df = 40)	55.020 (df = 45)
F Statistic	57.315^{***} (df = 6; 40)	284.128^{***} (df = 1; 45)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

Table 2.22. Results from the partial-adjustment supply model estimating annual beef cow inventories in Tennessee, annual data from 1975-2021

	Dependent variable:	
	$Q_{BC(i,t)}$	
	Equation (1.1)	Equation (1.2)
$P_{FS(t-2)}$	0.549	
	(0.342)	
$PDSI_{(i,t-1)}$	5.628	
	(5.076)	
$P_{H(t-2)}$	-0.307	
	(0.708)	
$P_{PR(i,t-2)}$	-0.425	
	(1.396)	
$Slt_{(t)}$	-0.409	
	(0.374)	
$Q_{BC(i,t-1)}$	0.814***	0.854***
	(0.114)	(0.079)
Constant	480.123	146.057*
	(319.271)	(82.452)
Observations	47	47
R^2	0.767	0.723
Adjusted R^2	0.733	0.717
Residual Std. Error	57.168 (df = 40)	58.781 (df = 45)
F Statistic	22.005*** (df = 6; 40)	117.716*** (df = 1; 45)
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 2.23. Results from the partial-adjustment supply model estimating annual beef cow inventories in Alabama, annual data from 1975-2021

	Dependent variable:	
	$Q_{BC(i,t)}$	
	Equation (1.1)	Equation (1.2)
$P_{FS(t-2)}$	0.344	
	(0.320)	
$PDSI_{(i,t-1)}$	1.207	
	(4.465)	
$P_{H(t-2)}$	-0.517	
	(0.652)	
$P_{PR(i,t-2)}$	-2.261	
	(2.079)	
$Slt_{(t)}$	-0.360	
	(0.358)	
$Q_{BC(i,t-1)}$	0.785^{***}	0.907^{***}
	(0.118)	(0.053)
Constant	544.865	68.203
	(329.324)	(44.670)
Observations	47	47
R^2	0.882	0.865
Adjusted R^2	0.865	0.862
Residual Std. Error	53.367 (df = 40)	53.894 (df = 45)
F Statistic	49.914^{***} (df = 6; 40)	287.880^{***} (df = 1; 45)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

Table 2.24. Results from the partial-adjustment supply model estimating annual beef cow inventories in Virginia, annual data from 1975-2021

	Dependent variable:	
	$\mathbf{Q_{BC(i,t)}}$	
	Equation (1.1)	Equation (1.2)
$\mathbf{P_{FS(t-2)}}$	0.242	
	(0.189)	
$\mathbf{PDSI_{(i,t-1)}}$	1.073	
	(2.751)	
$\mathbf{P_{H(t-2)}}$	-0.083	
	(0.393)	
$\mathbf{P_{PR(i,t-2)}}$	0.605	
	(1.102)	
$\mathbf{Slt_{(t)}}$	-0.054	
	(0.196)	
$\mathbf{Q_{BC(i,t-1)}}$	0.629^{***}	0.638^{***}
	(0.127)	(0.122)
Constant	243.743^{*}	239.939^{***}
	(144.037)	(81.159)
Observations	47	47
$\mathbf{R^2}$	0.427	0.379
Adjusted $\mathbf{R^2}$	0.341	0.365
Residual Std. Error	32.879 (df = 40)	32.257 (df = 45)
F Statistic	4.960^{***} (df = 6; 40)	27.481^{***} (df = 1; 45)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

Table 2.25. Results from the partial-adjustment supply model estimating annual beef cow inventories in Texas using San Angelo prices, annual data from 1998-2021

	Dependent variable:
	$\mathbf{Q_{BC(i,t)}}$
$\mathbf{P_{FS(i,t-2)}}$	0.979
	(1.104)
$\mathbf{PDSI_{(i,t-1)}}$	42.615***
	(12.545)
$\mathbf{P_{H(t-2)}}$	-2.003
	(1.905)
$\mathbf{P_{PR(i,t-2)}}$	10.108
	(19.250)
$\mathbf{Slt_{(t)}}$	-2.051
	(1.830)
$\mathbf{Q_{BC(i,t-1)}}$	0.786***
	(0.126)
Constant	2,849.020
	(1,931.433)
Observations	24
$\mathbf{R^2}$	0.954
Adjusted $\mathbf{R^2}$	0.938
Residual Std. Error	127.599 (df = 17)
F Statistic	59.340*** (df = 6; 17)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 2.26. Results from the partial-adjustment supply model estimating annual beef cow inventories in Texas using Oklahoma City prices, annual data from 1998-2021

	Dependent variable:
	$\mathbf{Q_{BC(i,t)}}$
$\mathbf{P_{FS(t-2)}}$	0.991
	(1.011)
$\mathbf{PDSI_{(i,t-1)}}$	41.237^{***}
	(12.730)
$\mathbf{P_{H(t-2)}}$	-1.816
	(1.924)
$\mathbf{P_{PR(i,t-2)}}$	9.594
	(18.995)
$\mathbf{Slt_{(t)}}$	-2.083
	(1.807)
$\mathbf{Q_{BC(i,t-1)}}$	0.795^{***}
	(0.126)
Constant	2,787.605
	(1,901.644)
Observations	24
$\mathbf{R^2}$	0.955
Adjusted $\mathbf{R^2}$	0.939
Residual Std. Error	126.979 (df = 17)
F Statistic	59.949^{***} (df = 6; 17)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 2.27. Results from the partial-adjustment supply model estimating annual beef cow inventories in Missouri using Joplin prices, annual data from 1998-2021

	Dependent variable:
	$\mathbf{Q_{BC(i,t)}}$
$\mathbf{P_{FS(i,t-2)}}$	0.502
	(0.519)
$\mathbf{PDSI_{(i,t-1)}}$	6.213
	(8.451)
$\mathbf{P_{H(t-2)}}$	-0.343
	(0.900)
$\mathbf{P_{PR(i,t-2)}}$	7.071
	(4.379)
$\mathbf{Slt_{(t)}}$	-0.522
	(0.585)
$\mathbf{Q_{BC(i,t-1)}}$	0.518^{**}
	(0.204)
Constant	1,114.773
	(649.385)
Observations	24
$\mathbf{R^2}$	0.805
Adjusted $\mathbf{R^2}$	0.737
Residual Std. Error	59.797 (df = 17)
F Statistic	11.731^{***} (df = 6; 17)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 2.28. Results from the partial-adjustment supply model estimating annual beef cow inventories in Missouri using Oklahoma City prices, annual data from 1998-2021

	Dependent variable:
	$\mathbf{Q_{BC(i,t)}}$
$\mathbf{P_{FS(t-2)}}$	0.673
	(0.461)
$\mathbf{PDSI_{(i,t-1)}}$	5.995
	(8.154)
$\mathbf{P_{H(t-2)}}$	-0.308
	(0.866)
$\mathbf{P_{PR(i,t-2)}}$	6.547
	(4.050)
$\mathbf{Slt_{(t)}}$	-0.584
	(0.544)
$\mathbf{Q_{BC(i,t-1)}}$	0.539^{**}
	(0.196)
Constant	$1,100.184^{*}$
	(623.890)
Observations	24
$\mathbf{R^2}$	0.818
Adjusted $\mathbf{R^2}$	0.753
Residual Std. Error	57.904 (df = 17)
F Statistic	12.699^{***} (df = 6; 17)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 2.29. Results from the partial-adjustment supply model estimating annual beef cow inventories in South Dakota using South Dakota market prices, annual data from 1998-2021

	Dependent variable:
	$\mathbf{Q_{BC(i,t)}}$
$\mathbf{P_{FS(i,t-2)}}$	-0.013
	(0.371)
$\mathbf{PDSI_{(i,t-1)}}$	-2.228
	(4.258)
$\mathbf{P_{H(t-2)}}$	-0.335
	(0.845)
$\mathbf{P_{PR(i,t-2)}}$	4.746
	(3.549)
$\mathbf{Slt_{(t)}}$	-0.160
	(0.548)
$\mathbf{Q_{BC(i,t-1)}}$	0.603^{**}
	(0.221)
Constant	769.437
	(549.199)
Observations	24
$\mathbf{R^2}$	0.585
Adjusted $\mathbf{R^2}$	0.439
Residual Std. Error	51.562 (df = 17)
F Statistic	3.995^{**} (df = 6; 17)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 2.30. Results from the partial-adjustment supply model estimating annual beef cow inventories in South Dakota using Oklahoma City prices, annual data from 1998-2021

	Dependent variable:
	$Q_{BC(i,t)}$
$P_{FS(t-2)}$	-0.117
	(0.403)
$PDSI_{(t-1)}$	-2.679
	(4.171)
$P_{H(t-2)}$	-0.381
	(0.826)
$P_{PR(t-2)}$	4.846
	(3.548)
$Slt_{(t)}$	-0.097
	(0.535)
$Q_{BC(t-1)}$	0.606**
	(0.219)
Constant	734.935
	(538.939)
Observations	24
R^2	0.587
Adjusted R^2	0.441
Residual Std. Error	51.436 (df = 17)
F Statistic	4.028** (df = 6; 17)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 2.31. Annual elasticity estimates for each state

Year	Texas	Oklahoma	Missouri	Nebraska	South Dakota	Kansas	Montana	Kentucky	North Dakota	Iowa	Florida	Tennessee	Alabama	Virginia
1987	0.0289	0.2548	-0.0328	0.2386	3.9846	0.1843	1.3781	0.5525	-0.2151	-0.5389	1.1021	-0.7071	0.6910	0.6868
1988	-0.0103	0.1792	-0.0386	0.2682	1.5843	0.2297	2.3412	-0.3485	-1.7883	-0.2374	1.5256	-2.8994	-0.3951	0.4197
1989	0.0224	0.4354	-0.0224	0.3393	3.1363	0.5694	2.5690	-0.8320	-0.6934	1.9902	2.0863	-2.7143	1.5599	2.2588
1990	0.0853	0.3174	0.0046	0.3258	2.5847	0.3299	2.9854	0.8216	-0.5747	2.3555	3.0548	-0.7266	0.3278	0.4076
1991	0.1051	0.3171	0.0775	0.1906	3.8814	0.3893	2.1847	1.4482	-0.8799	3.6180	1.4527	-1.4038	-0.0790	0.5558
1992	-0.1335	0.3073	0.1126	0.1926	4.4595	0.4825	0.9766	2.3830	-1.9838	5.5250	0.9304	-1.4470	0.0261	0.2598
1993	0.0530	0.3122	0.1127	0.2435	4.8633	0.4879	3.2914	1.9413	-2.2562	4.8542	1.1312	-0.2827	0.1642	-0.2407
1994	0.1143	0.2571	0.0672	0.2571	2.9551	0.2129	4.0834	1.5925	-0.6147	1.7177	-0.4465	0.6985	-0.2807	0.1781
1995	0.1488	0.0787	0.0886	0.2361	2.8713	-0.2030	2.9159	1.5156	-1.1711	0.6347	-2.3904	0.8425	-1.1230	0.2487
1996	0.1165	0.0737	0.0552	0.1450	2.6934	0.0372	2.9737	1.4289	-0.4585	0.8619	3.5711	1.2502	-1.3634	0.1532
1997	-0.0252	-0.0554	-0.0564	-0.0520	2.1835	-0.0449	1.1530	0.4898	-0.9079	0.0403	3.3715	-0.5129	-1.3226	-0.1078
1998	-0.0168	-0.0868	-0.0421	-0.0648	1.8395	-0.0928	1.6468	0.0434	-0.7134	0.3750	0.2415	0.3989	-1.4222	-0.2194
1999	0.0012	-0.0790	0.0306	-0.0013	1.5024	-0.0918	2.7804	0.1038	1.0551	0.6392	0.8931	0.4975	-1.1129	-1.0296
2000	0.1002	-0.0203	0.0487	-0.0389	1.3613	-0.0533	2.5855	-0.1375	1.0313	0.7197	1.7697	1.0291	0.4029	0.2376
2001	0.1743	-0.0868	0.0215	-0.0608	1.8417	-0.0494	0.9377	-0.5833	0.8930	0.9108	1.3913	0.8925	0.4255	0.1852
2002	0.1996	-0.0818	0.0119	-0.0866	1.8743	-0.0091	0.9640	-0.4956	0.8514	0.5594	1.0553	0.7242	-0.4378	0.2230
2003	0.0886	-0.0937	-0.0183	-0.0922	1.1786	-0.1701	0.2272	-0.3916	0.4535	0.5395	0.7722	-0.0105	-0.5682	0.1850
2004	0.0975	-0.0775	-0.0113	-0.1174	1.5760	-0.1155	0.5578	-0.8806	0.6561	0.3125	0.3559	0.1275	-0.6741	0.2156
2005	0.1405	-0.1031	-0.0011	0.0560	1.4741	-0.1168	0.6119	-0.7788	1.2622	-0.0354	0.2256	-0.1212	-1.2230	0.2589
2006	0.1397	0.1679	0.0430	0.0265	1.4162	0.0915	0.5447	-0.4216	1.0118	-0.3644	0.4963	0.1992	-0.9354	0.5161
2007	0.1751	0.1500	0.0420	0.0305	1.2801	0.1164	0.4038	0.0223	0.3369	0.0275	0.5816	0.2210	-0.8339	0.5353
2008	0.0947	0.2438	0.0863	0.0964	0.2119	0.1134	-0.0685	0.3744	-0.0410	0.0335	0.4233	-0.2943	-0.7901	0.6469
2009	-0.0326	0.1863	0.0811	0.0845	-0.0047	0.1524	0.1417	0.8153	1.5358	0.0720	-0.4858	0.5944	-1.1210	0.7371
2010	0.0002	0.1038	0.0025	0.1098	0.5982	0.0701	0.1878	0.9236	1.3356	0.3764	-0.4464	1.3520	-0.7627	0.8098
2011	0.0105	0.0865	0.0517	0.0933	-0.2849	0.0965	1.4678	1.6087	0.9618	0.4587	-0.4525	2.7010	-0.5752	1.1911
2012	0.0178	0.0794	0.2432	0.0890	-0.5366	0.1046	2.6973	1.7483	0.2000	0.4779	-0.5397	2.6389	-0.3807	0.8313
2013	0.0379	0.1248	0.2738	-0.0179	-0.1354	0.0796	1.3323	1.8567	1.0640	1.3661	-0.2928	3.3800	-0.3893	1.1409
2014	0.0544	0.1393	0.1174	0.0263	-1.0899	0.0397	0.2761	1.5701	-0.4293	2.1316	-0.1569	2.2573	-0.4083	1.3844
2015	0.0397	0.1466	0.2916	0.0583	-0.4343	0.0606	-0.1602	0.9554	0.0926	1.0604	-0.4569	1.1108	-0.3653	2.2554
2016	0.1084	0.2741	0.3961	0.0968	-0.3252	0.0905	-0.3701	1.1962	0.3667	1.3943	-0.4159	1.1202	-0.3783	1.0964
2017	0.0230	0.0560	0.0845	0.0521	0.4748	0.0630	-0.2512	0.6989	0.0790	0.4961	-0.2880	0.6028	0.3028	0.1624
2018	0.0156	0.0381	0.0730	0.0283	0.2443	0.0382	-0.1533	0.8350	0.0022	0.3320	-0.3098	0.6106	0.2331	0.2379
2019	0.0131	0.0302	0.0084	0.0487	-0.1823	0.0546	-0.0882	0.5575	0.0179	0.2027	-0.2685	0.5636	0.0274	0.1447
2020	-0.0631	-0.0689	0.0064	0.0498	-0.3198	0.0686	0.0809	0.1115	-0.0923	0.2034	-0.2505	0.3432	0.0103	0.0147
2021	-0.0134	-0.0056	0.0379	0.0482	-0.1769	0.0789	-0.0315	0.1453	-0.0151	0.1709	-0.2299	0.0490	0.1374	-0.1850
2022	-0.0377	-0.0043	0.0485	0.0541	-0.1371	0.0698	-0.0511	0.2074	0.1024	0.1635	-0.2469	0.1717	0.0884	-0.0634

Figure a.8. Annual estimates of short-run own-price elasticity of supply for beef cows in Texas with respect to Oklahoma City feeder cattle price, 1987-2022

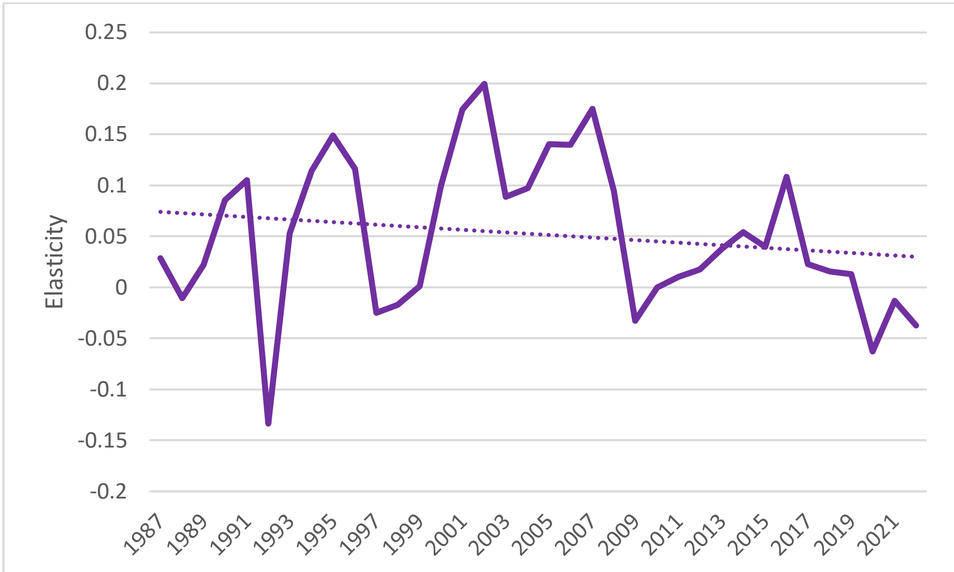


Figure a.9. Annual estimates of short-run own-price elasticity of supply for beef cows in Oklahoma with respect to Oklahoma City feeder cattle price, 1987-2022

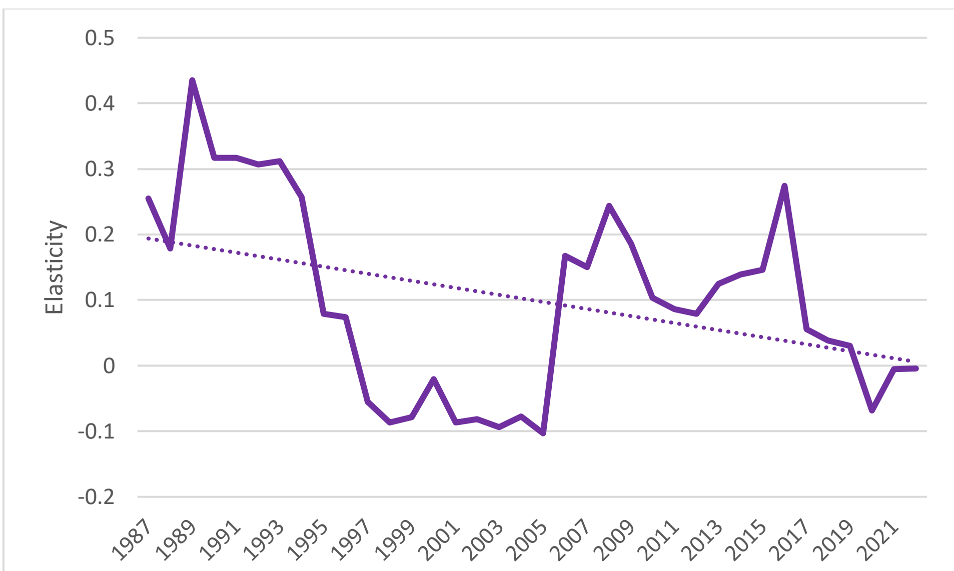


Figure a.10. Annual estimates of short-run own-price elasticity of supply for beef cows in Missouri with respect to Oklahoma City feeder cattle price, 1987-2022

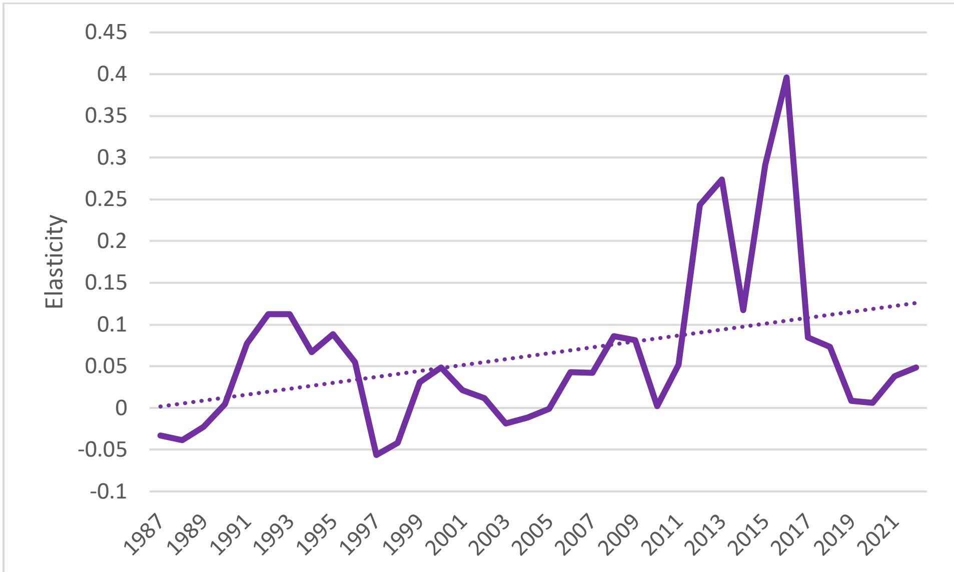


Figure a.11. Annual estimates of short-run own-price elasticity of supply for beef cows in Nebraska with respect to Oklahoma City feeder cattle price, 1987-2022

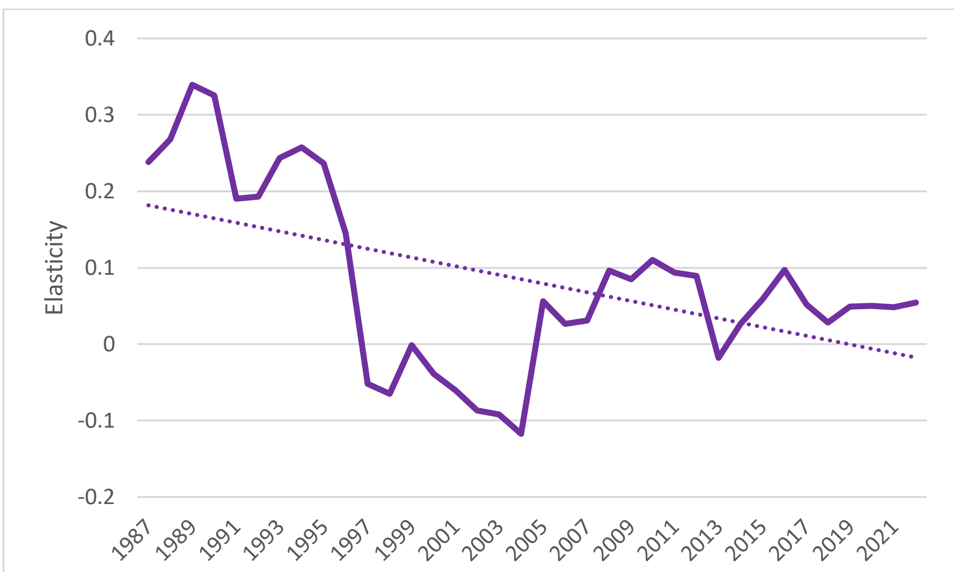


Figure a.12. Annual estimates of short-run own-price elasticity of supply for beef cows in South Dakota with respect to Oklahoma City feeder cattle price, 1987-2022

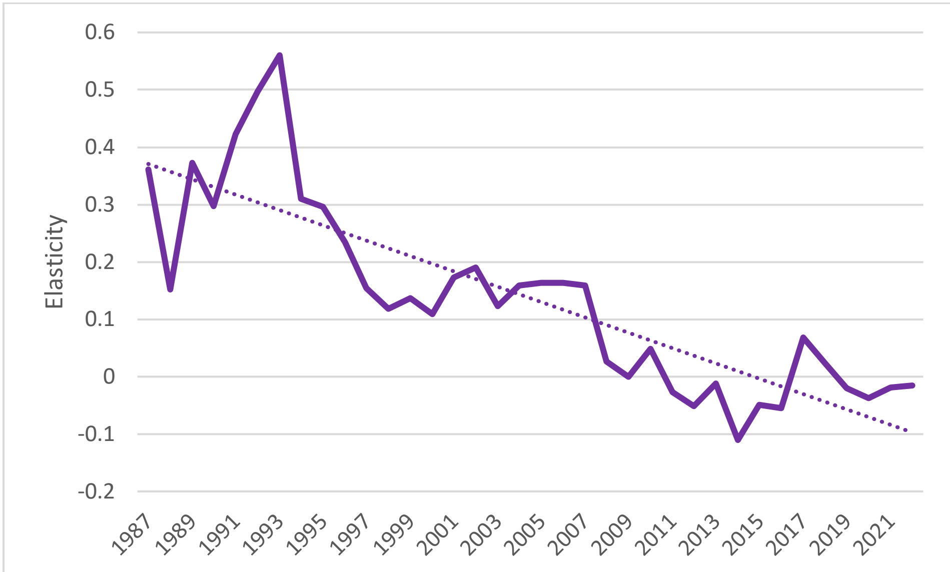


Figure a.13. Annual estimates of short-run own-price elasticity of supply for beef cows in Kansas with respect to Oklahoma City feeder cattle price, 1987-2022

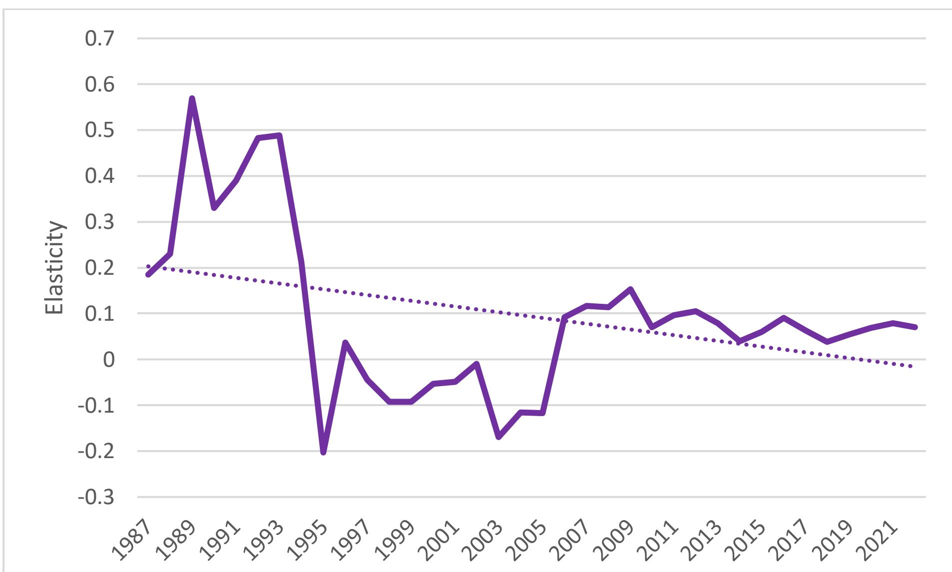


Figure a.14. Annual estimates of short-run own-price elasticity of supply for beef cows in Montana with respect to Oklahoma City feeder cattle price, 1987-2022

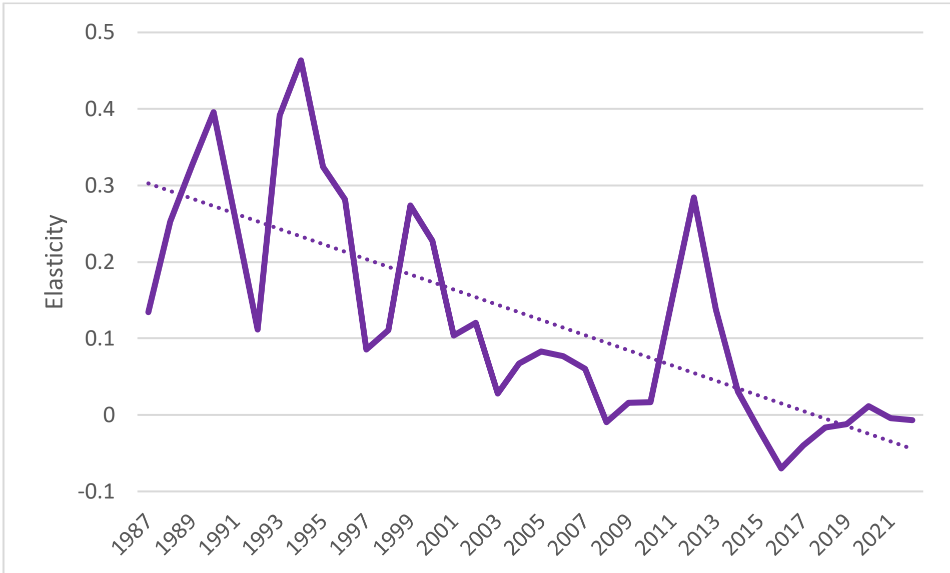


Figure a.15. Annual estimates of short-run own-price elasticity of supply for beef cows in Kentucky with respect to Oklahoma City feeder cattle price, 1987-2022

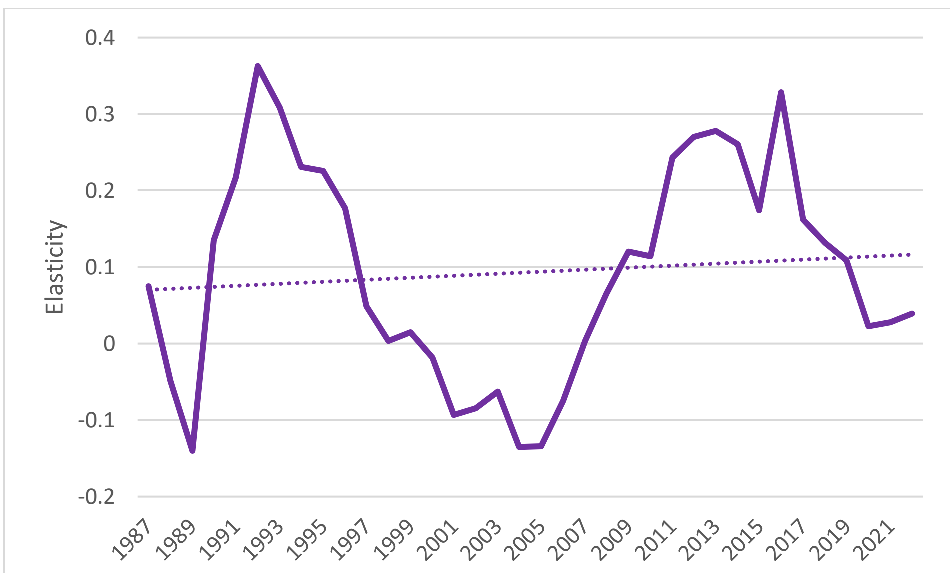


Figure a.16. Annual estimates of short-run own-price elasticity of supply for beef cows in North Dakota with respect to Oklahoma City feeder cattle price, 1987-2022

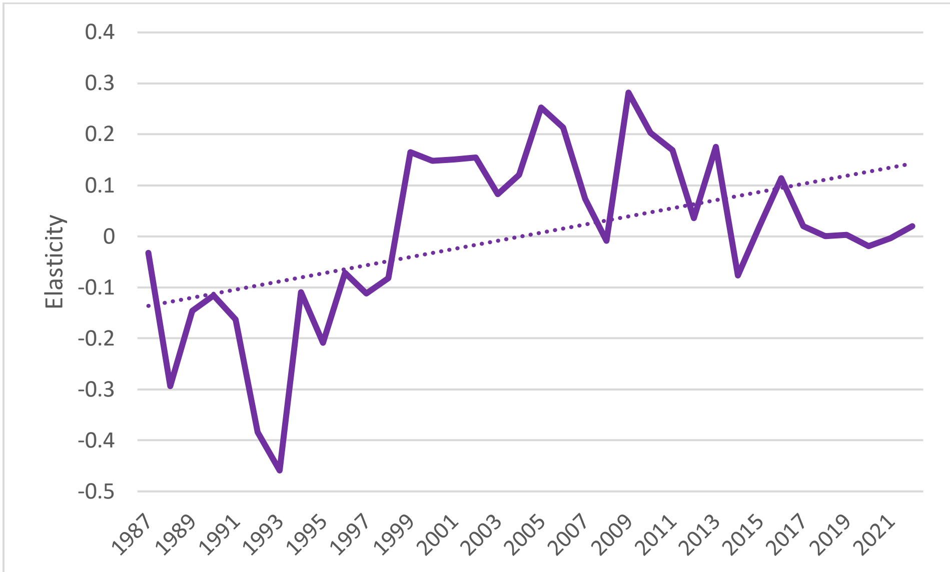


Figure a.17. Annual estimates of short-run own-price elasticity of supply for beef cows in Iowa with respect to Oklahoma City feeder cattle price, 1987-2022

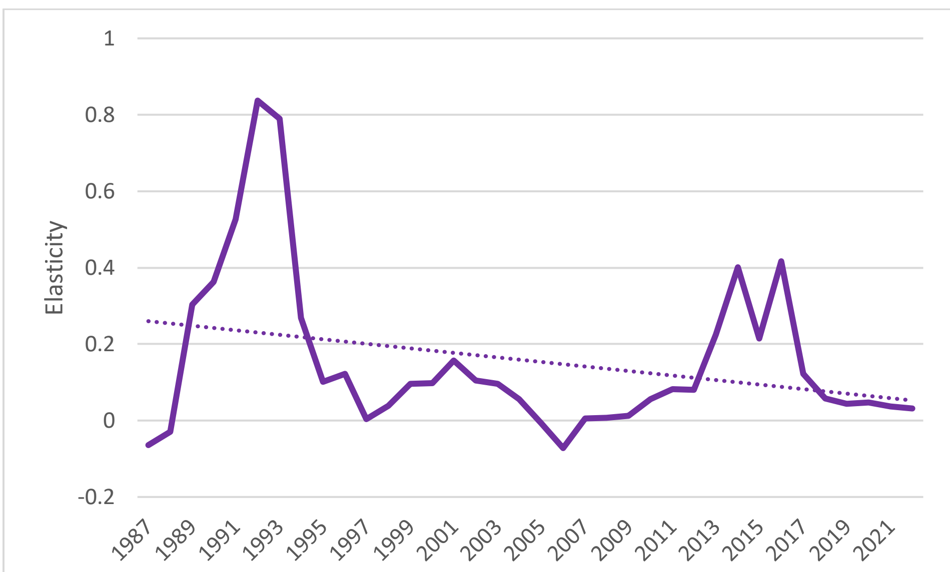


Figure a.18. Annual estimates of short-run own-price elasticity of supply for beef cows in Florida with respect to Oklahoma City feeder cattle price, 1987-2022

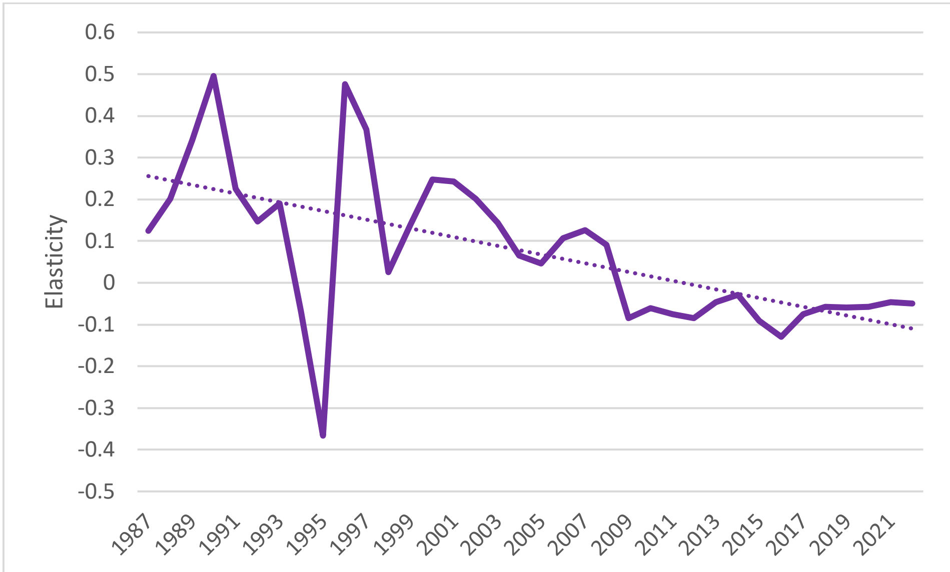


Figure a.19. Annual estimates of short-run own-price elasticity of supply for beef cows in Tennessee with respect to Oklahoma City feeder cattle price, 1987-2022

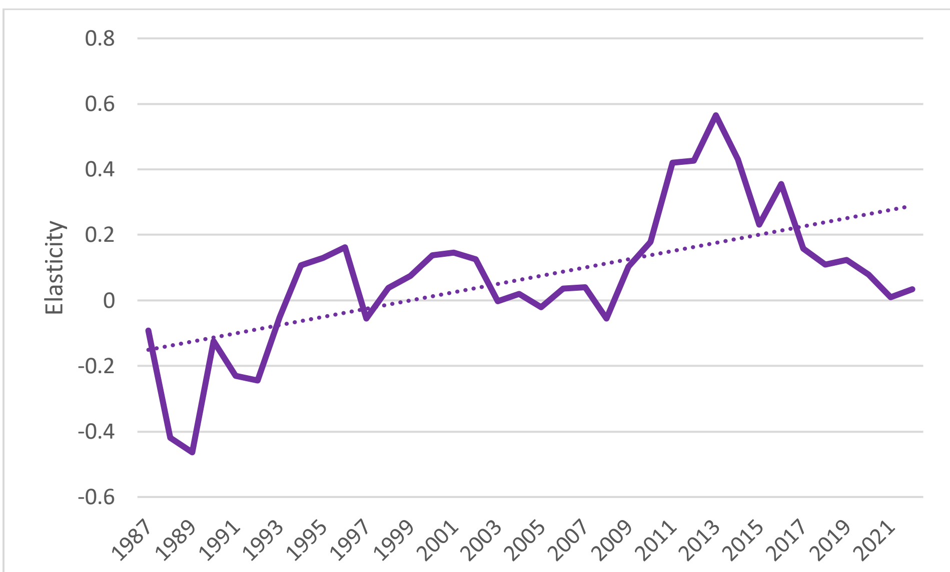


Figure a.20. Annual estimates of short-run own-price elasticity of supply for beef cows in Alabama with respect to Oklahoma City feeder cattle price, 1987-2022

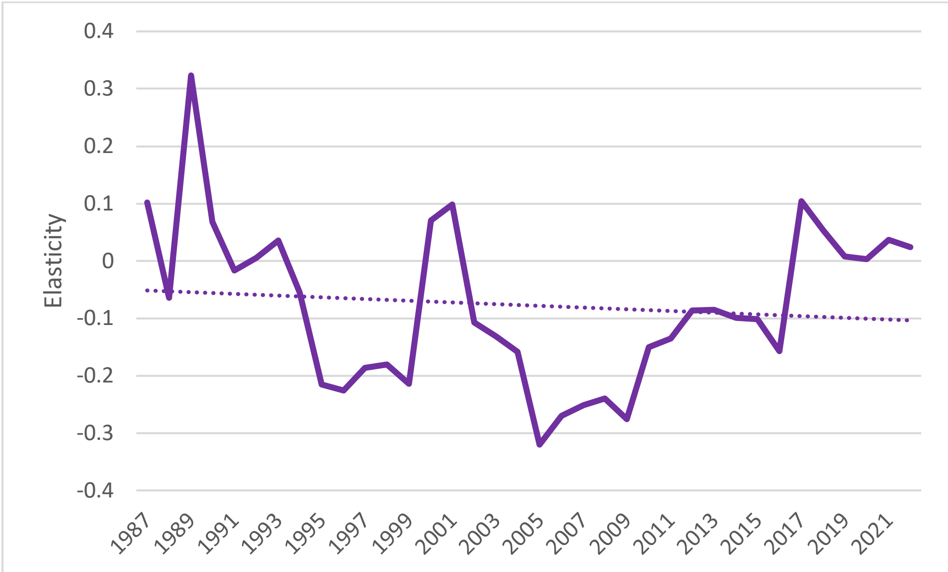


Figure a.21. Annual estimates of short-run own-price elasticity of supply for beef cows in Virginia with respect to Oklahoma City feeder cattle price, 1987-2022

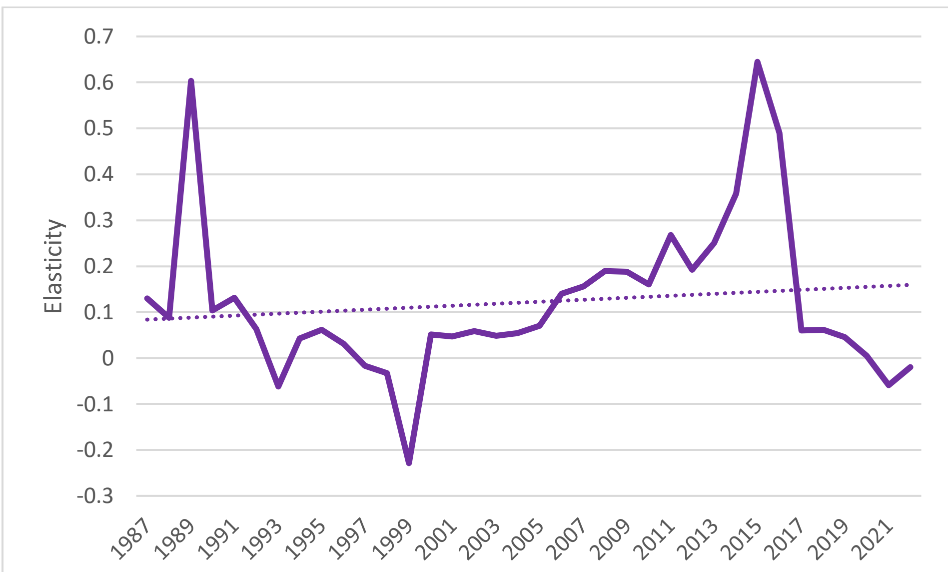


Table 2.32. Annual beef cowherd estimates for Texas using San Angelo and Oklahoma City prices compared to USDA NASS inventories, 2010-2021 (NASS, 2022)

	Texas Inventory				
Year	**San Angelo Price Estimate**	**OKC Price Estimate**	**USDA NASS**	**San Angelo Price % Error**	**OKC Price % Error**
2010	5,184.921	5,181.968	5,140.000	0.867%	0.817%
2011	5,155.607	5,155.209	4,925.000	4.473%	4.674%
2012	4,821.998	4,814.788	4,515.000	6.376%	6.640%
2013	3,928.564	3,951.484	4,215.000	7.249%	6.252%
2014	4,004.558	3,990.349	3,910.000	2.370%	2.055%
2015	3,544.138	3,546.873	4,130.000	16.518%	14.119%
2016	4,440.858	4,489.090	4,290.000	3.361%	4.641%
2017	4,441.343	4,447.280	4,450.000	0.195%	0.061%
2018	4,508.128	4,495.906	4,520.000	0.264%	0.533%
2019	4,580.909	4,581.748	4,655.000	1.617%	1.574%
2020	5,872.761	5,741.902	4,570.000	22.689%	25.643%
2021	4,464.652	4,465.077	4,635.000	3.815%	3.666%
			Average	**5.816%**	**5.890%**

Figure a.22. Annual estimates of short-run own-price elasticity of supply for beef cows in Texas with respect to San Angelo feeder cattle price, 2010-2022

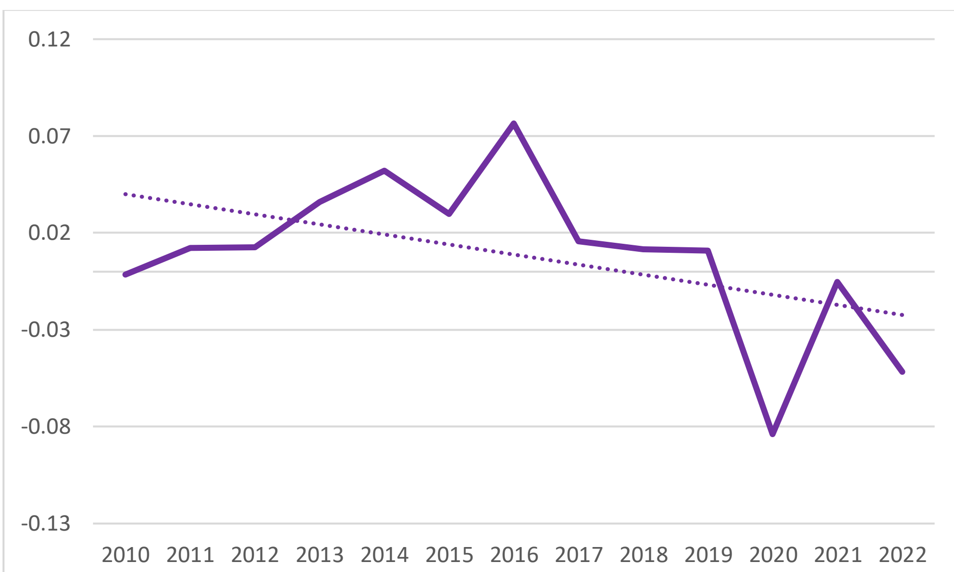


Table 2.33. Annual beef cowherd estimates for Missouri using Joplin and Oklahoma City prices compared to USDA NASS inventories, 2010-2021 (NASS, 2022)

	Missouri Inventory				
Year	**Joplin Price Estimate**	**OKC Price Estimate**	**USDA NASS**	**Joplin Price % Error**	**OKC Price % Error**
2010	2,004.552	1,978.002	1,968.000	1.848%	0.508%
2011	2,172.628	2,078.358	1,865.000	14.802%	11.440%
2012	1,864.491	1,847.364	1,827.000	2.029%	1.115%
2013	1,823.303	1,850.246	1,717.000	5.745%	7.760%
2014	1,567.298	1,586.448	1,820.000	15.929%	12.833%
2015	1,815.866	1,828.512	1,832.000	0.882%	0.190%
2016	2,007.010	2122.533	1,884.000	5.795%	12.661%
2017	1,988.738	1,984.756	2,035.000	2.331%	2.469%
2018	1,936.188	1,966.563	2,086.000	7.618%	5.726%
2019	2,081.907	2,102.449	2,059.000	1.090%	2.110%
2020	2,287.318	2,286.304	2,083.000	8.937%	9.760%
2021	2,099.341	2,097.475	2,035.000	3.068%	3.070%
			Average	**5.839%**	**5.804%**

Figure a.23. Annual estimates of short-run own-price elasticity of supply for beef cows in Missouri with respect to Joplin feeder cattle price, 2010-2022

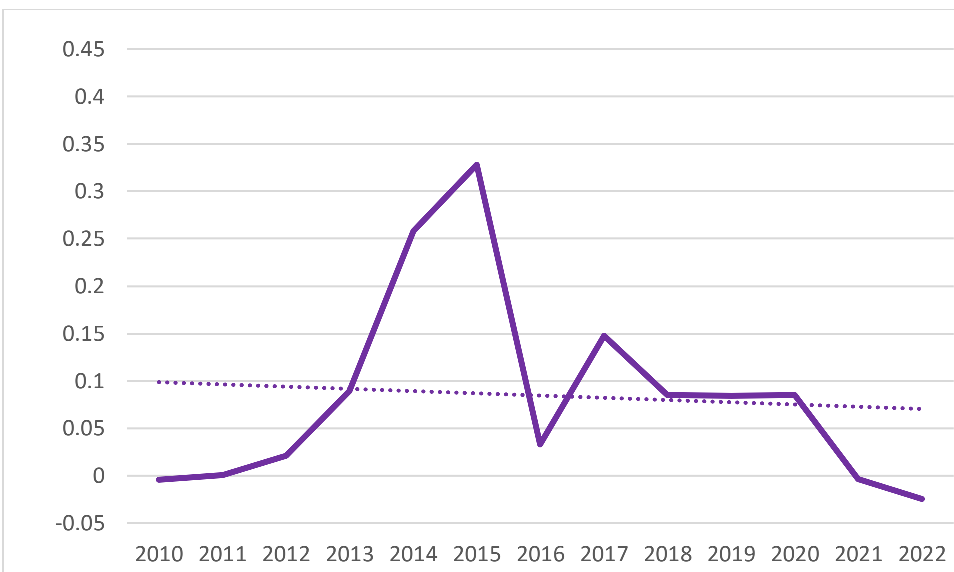
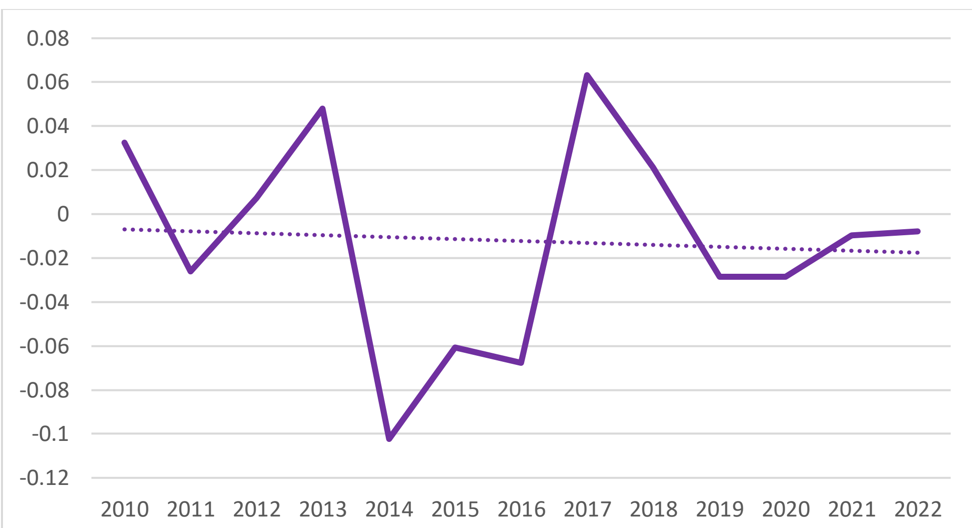


Table 2.34. Annual beef cowherd estimates for South Dakota using South Dakota market and Oklahoma City prices compared to USDA NASS inventories, 2010-2021 (NASS, 2022)

	South Dakota Inventory				
Year	**SD Market Price Estimate**	**OKC Price Estimate**	**USDA NASS**	**SD Market Price % Error**	**OKC Price % Error**
2010	1,624.831	1,622.573	1,637.000	0.750%	0.881%
2011	1,823.835	1,815.278	1,610.000	11.780%	12.750%
2012	1,615.804	1,626.192	1,610.000	0.357%	1.006%
2013	1,532.767	1,567.257	1,698.000	10.543%	7.700%
2014	1,715.633	1,693.096	1,625.000	5.353%	4.191%
2015	1,570.179	1,571.735	1,611.000	2.597%	2.437%
2016	1,568.314	1,574.444	1,670.000	6.459%	5.722%
2017	1,583.658	1,574.584	1,664.000	5.102%	5.374%
2018	1,645.785	1,646.855	1,751.000	6.389%	5.948%
2019	1,752.309	1,665.796	1,818.000	3.944%	8.372%
2020	1,745.434	1,745.504	1,783.000	2.152%	2.103%
2021	1,802.056	1,804.773	1,799.000	0.169%	0.321%
			Average	**4.633%**	**4.734%**

Figure a.24. Annual estimates of short-run own-price elasticity of supply for beef cows in South Dakota with respect to South Dakota market feeder cattle price, 2010-2022



b) Appendix – Article 2

Figure b.1. Choice beef cutout time series plot. March 2003 – April 2022. Source: USDA AMS and LMIC

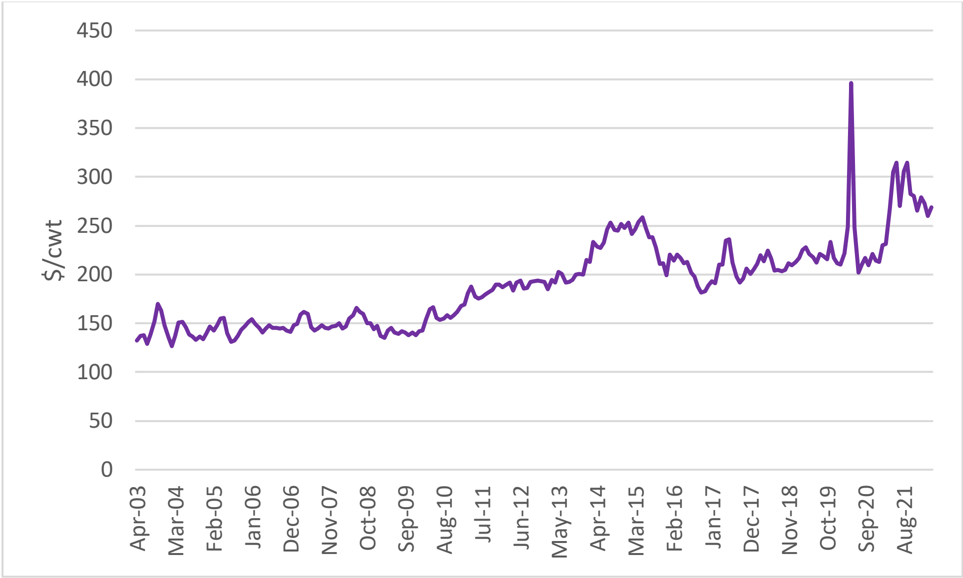


Figure b.2. Pork cutout time series plot. March 2003 – April 2022. Source: USDA AMS and LMIC

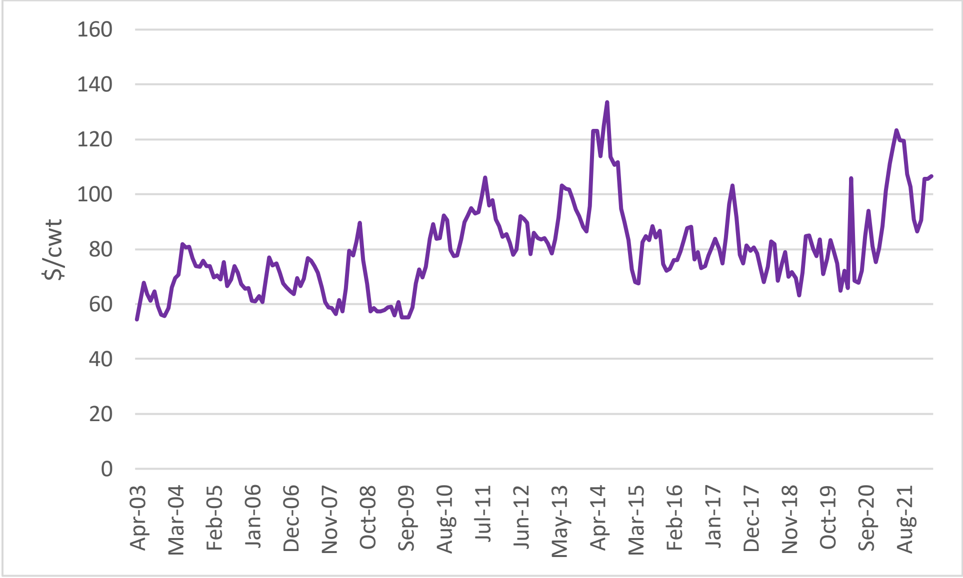


Figure b.3. National composite wholesale broiler price time series plot. March 2003 – April 2022. Source: USDA AMS and LMIC

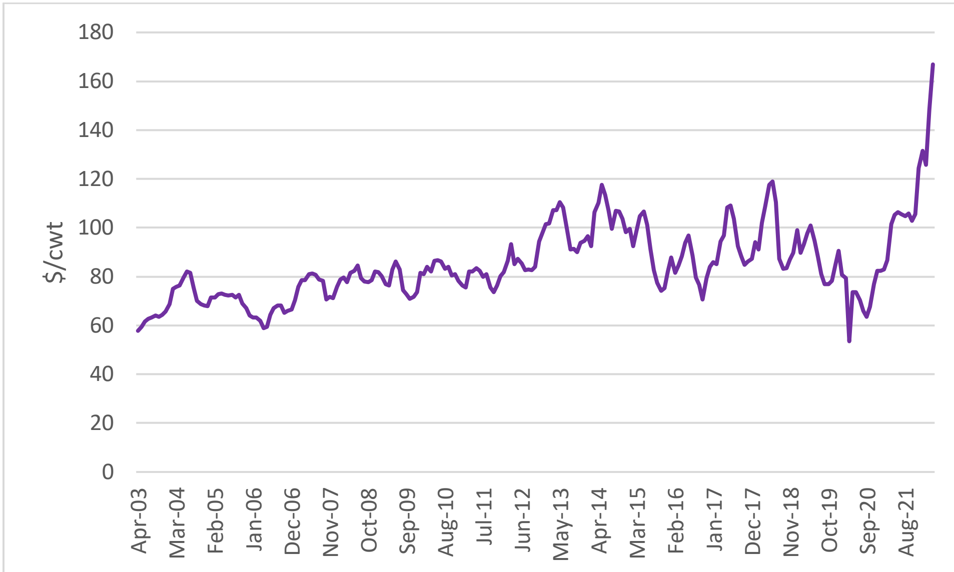


Figure b.4. Poultry production time series plot. March 2003 – April 2022. Source: USDA AMS and LMIC

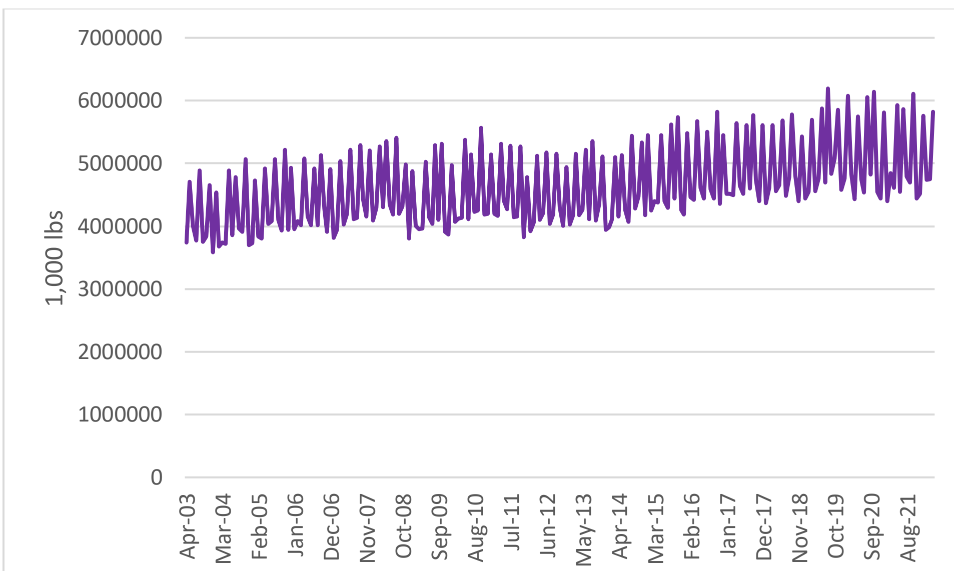


Figure b.5. Per capita U.S. GDP time series plot. March 2003 – April 2022. Source: World Bank and OECD

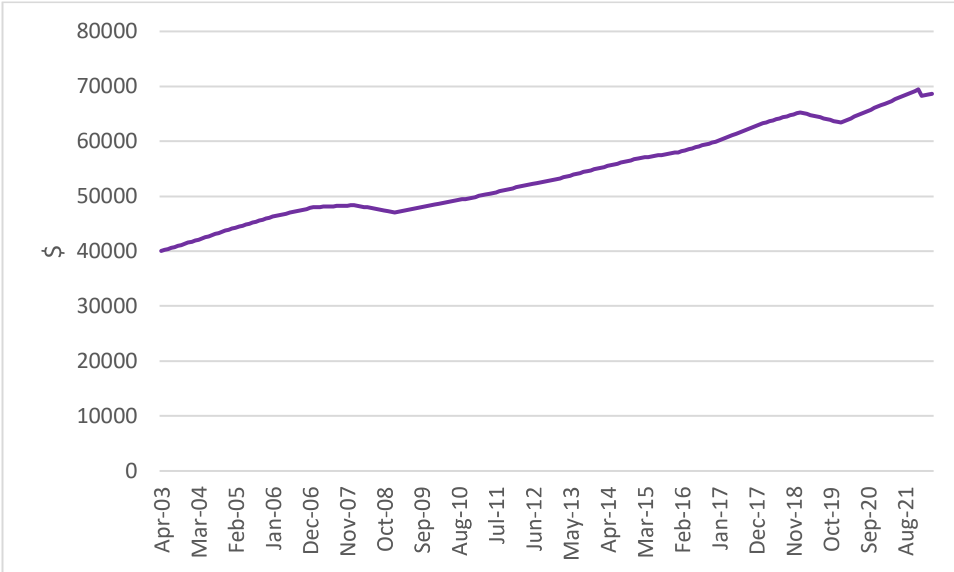


Figure b.6. Per capita rest of the world GDP time series plot. March 2003 – April 2022. Source: World Bank and OECD