

THESIS

FORECASTING FED BEEF PRODUCTION: AN EVALUATION OF SYSTEMS
FORECASTING BY PARTS FOR OPTIMAL SURVEY HISTORY

Submitted by

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ABSTRACT

FORECASTING FED BEEF PRODUCTION: AN EVALUATION OF SYSTEMS FORECASTING BY PARTS FOR OPTIMAL SURVEY HISTORY

The following study examines forecasts of fed beef production through a by-parts estimation framework to provide a more practical alternative to more complex simultaneous systems of equations. A disconnect exists between the academic literature and the methods commonly used in private industry decision making. Practical techniques employed by industry professionals hold promise in strengthening conversations around forecasting research. Recent shifts in cattle production, including elevated contributions of heifers in the slaughter mix and larger than anticipated weights in fed cattle, provide an appropriate case study that underscores the need to revisit past events in the development of new forecasting strategies. By analyzing survey history in the data selection process, examining analog time periods, and considering concerns of autocorrelated errors within Deterministic Trend / Deterministic Seasonality models, this study highlights that practical enhancements to forecast accuracy can be sustained by simple remedial measures. The results of this study demonstrate that (1) historical data selection can significantly impact forecast quality; (2) methods that allow for autocorrelated error corrections can improve model performance; (3) the effectiveness of different forecast estimation methods varies by the selected horizon; and (4) the use of more simplistic assumptions underlying a forecast model can produce competitive and accurate results.

TABLE OF CONTENTS

ABSTRACT.....	ii
LIST OF TABLES	v
LIST OF FIGURES	viii
CHAPTER 1: INTRODUCTION.....	1
1.1 Objective.....	5
1.2 Organization of the Thesis	6
CHAPTER 2: LITERATURE REVIEW	7
2.1 Forecasting in the Cattle Market.....	7
2.2 Interviews with the Private Sector	9
2.3 Forecast Evaluation.....	11
2.4 Contributions to the Literature.....	13
CHAPTER 3: CONCEPTUAL FRAMEWORK.....	15
3.1 The Cattle Supply Chain.....	15
3.2 Candidate Model Development	20
Section 3.2.1: Dependent Variables	20
Section 3.2.2: Independent Variables.....	22
CHAPTER 4: METHODOLOGY	23
4.1 Model Specification.....	23
4.2 Forecast Performance.....	24
4.3 Survey Length.....	27
4.4 Autocorrelated Errors.....	29
CHAPTER 5: DATA.....	31
CHAPTER 6: RESULTS	33
6.1 Fed Cattle Dressed Weights	33
6.2 Steer Slaughter.....	48
6.3 Heifer Slaughter	60
6.4 Fed Beef Production	72
CHAPTER 7: CONCLUSION	75
REFERENCES	81
APPENDIX A.....	85

APPENDIX B	88
APPENDIX C	90
APPENDIX D	91
APPENDIX E	109
APPENDIX F	112

LIST OF TABLES

Table 1: Fed dressed weight survey history summary for 2014 to 2015 optimal window	34
Table 2: Selected fed dress weight model start dates and observations summary.....	39
Table 3: Selected fed dressed weight model error results for the 132-month out horizon	42
Table 4: Selected fed dressed weight model error results summary at the 132-month horizon when corrected for autocorrelated errors	46
Table 5: Steer slaughter survey history summary for 2014 to 2015 optimal window	49
Table 6: Selected steer slaughter model start dates and observations summary.....	53
Table 7: Selected steer slaughter model error results for the 132-month out horizon	55
Table 8: Selected steer slaughter model error results summary at the 132-month horizon when corrected for autocorrelated errors.....	58
Table 9: Heifer slaughter survey history summary for 2014 to 2015 optimal window	61
Table 10: Selected heifer slaughter model start dates and observations summary.....	65
Table 11: Selected heifer slaughter model error results for the 132-month out horizon	67
Table 12: Selected heifer slaughter model error results summary at the 132-month horizon when corrected for autocorrelated errors.....	69
Table 13: 132-month out fed beef production error results summary	74
Table A1: Data sources including reports, history, and explanatory variables	89
Table A2: Fed dressed weight models RMSE summary for all simulated 24-month out forecasts	92
Table A3: Fed dressed weight models MAPE summary for all simulated 24-month out forecasts	93
Table A4: Fed dressed weight models optimal length simulation results for the 24-month horizon of selected models.....	94
Table A5: Selected fed dressed weight model performance summary for 24-month out forecasts	95

Table A6: Selected fed dressed weight models corrected for autocorrelated errors performance summary for the 24-month out horizon	96
Table A7: Steer slaughter models RMSE summary for all simulated 24-month out forecasts.....	97
Table A8 Steer slaughter models MAPE summary for all simulated 24-month out forecasts.....	98
Table A9: Steer slaughter models optimal length simulation results for the 24-month horizon of selected models	99
Table A10: Selected steer slaughter model performance summary for 24-month out forecasts..	100
Table A11: Selected steer slaughter models corrected for autocorrelated errors performance summary for the 24-month out horizon	101
Table A12: Heifer slaughter models RMSE summary for all simulated 24-month out forecasts.	102
Table A13 Heifer slaughter models MAPE summary for all simulated 24-month out forecasts.	103
Table A14: Heifer slaughter models optimal length simulation results for the 24-month horizon of selected models.....	104
Table A15: Selected heifer slaughter model performance summary for 24-month out forecasts.	105
Table A16: Selected heifer slaughter models corrected for autocorrelated errors performance summary for the 24-month out horizon	106
Table A17: 24-month out fed beef production performance summary for forecasts with optimal survey lengths	107
Table A18: 24-month out fed beef production performance summary for forecasts with a January 1990 start date.....	108
Table A19: Recursive fed cattle dressed weight forecast model parameters from each model's optimized start date to December 2013	113
Table A20: Rolling fed cattle dressed weight forecast model parameters from each model's optimized start date to December 2013	114

Table A21: Recursive steer slaughter forecast model parameters from each model’s optimized start date to December 2013	115
Table A22: Rolling steer slaughter forecast model parameters from each model’s optimized start date to December 2013	116
Table A23: Recursive heifer slaughter forecast model parameters from each model’s optimized start date to December 2013	117
Table A24: Rolling heifer slaughter forecast model parameters from each model’s optimized start date to December 2013	118

LIST OF FIGURES

Figure 1: Percent change in cattle inventory and the percentage of heifer slaughter in total federally inspected cattle slaughter, 1980 – 2024	3
Figure 2: Percent change in federally inspected cattle slaughter and the average dressed weight of all cattle, 1990 – 2024.....	4
Figure 3: Simulation and prediction procedural flowchart	30
Figure 4: Fed dressed weight simulation method box and whisker plot RMSE summary.....	36
Figure 5: 24-month out fed dressed weight forecasts	40
Figure 6: 24-month out fed dressed weight forecast RMSE estimates.....	41
Figure 7: 132-month out fed dressed weight forecasts	43
Figure 8: 24-month out fed dressed weight forecasts corrected for autocorrelated errors	44
Figure 9: 24-month out fed dressed weight forecast RMSE percent change when corrected for autocorrelated errors	45
Figure 10: 132-month out fed dressed weight forecasts corrected for autocorrelated errors	47
Figure 11: Steer slaughter simulation method box and whisker plot RMSE summary	50
Figure 12: 24-month out steer slaughter forecast RMSE estimates.....	54
Figure 13: Steer slaughter forecasts.....	56
Figure 14: 24-month out steer slaughter forecast RMSE percent change when corrected for autocorrelated errors	58
Figure 15: Steer slaughter forecasts corrected for autocorrelated errors	59
Figure 16: Heifer slaughter simulation method box and whisker plot RMSE summary.....	62
Figure 17: 24-month out heifer slaughter forecast RMSE estimates.....	66
Figure 18: Heifer slaughter forecasts.....	68
Figure 19: 24-month out heifer slaughter forecast RMSE percent change when corrected for autocorrelated errors	70
Figure 20: Heifer slaughter forecasts corrected for autocorrelated errors	71

Figure 21: Percentage difference in RMSE estimates for forecasts with optimized survey history versus with uniform estimation beginning in 1990 for fed beef production	73
Figure A1: Federally inspected steer slaughter, 1980 – 2024	86
Figure A2: Federally inspected heifer slaughter, 1980 – 2024	86
Figure A3: Steer and heifer (fed) dressed weights, 1980 – 2024.....	87
Figure A4: Fed beef production, 1980 – 2024	87
Figure A5: Fed beef production forecasts with training estimation window from Jan. 1990 to Dec. 2013	110
Figure A6: Fed beef production forecasts with training estimation window from optimized start dates to Dec. 2013.....	111

CHAPTER 1: INTRODUCTION

On January 31, 2024, the U.S. Department of Agriculture's (USDA) National Agricultural Statistics Service (NASS) released their annual Cattle report containing inventory levels for all cattle and calves throughout the United States. In the report, as of the first of the year (Jan. 1st, 2024), all cattle and calves totaled 87.2 million head, the lowest January inventory observed in 73 years when the national herd was an estimated 82.1 million head. This historically low inventory reflects the culmination of challenges faced by the cattle industry, originating from periodic patterns in cattle production exacerbated by external pressures. Traditionally, the U.S. cattle industry operates on a multi-year cycle characterized by phases of expansion and contraction in national herd levels. Fluctuations are influenced by producers' decisions on whether to retain or liquidate portions of their herds. However, recent disruptions have amplified the severity of these fluctuations, creating challenges that exceed what is typically anticipated throughout beef and cattle value chains.

In the aftermath of the COVID-19 pandemic, a surplus of cattle accumulated during the spring and summer months of 2020, resulting in supply chain disruptions for a significant portion of the industry. Decisions across the entire supply network were suspended, as the beef processing sector experienced a reduction of nearly 25 percent in its production capacity (Muth & Read, 2020). To ensure the continued operation of packing plants, an Executive Order was issued to exempt plants from state and local closure orders. However, despite this intervention, COVID-19 outbreaks among the workforce persisted in generating plant closures (Balagtas & Cooper, 2021).

Beyond processing plants, the impact of the pandemic further complicated beef production when meat supply chains encountered difficulties adapting their product lines to changes in retail demand. As a consequence of business closures, the market for food away from home declined significantly, while the demand for food from grocery stores surged (Balagtas & Cooper, 2021). These adjustments necessitated a costly transition in supply chain resources, which contributed to higher wholesale and retail prices. As the supply of backlogged cattle grew, upstream prices for livestock fell. The divergence in prices drove a significant disparity between meat and livestock spreads, which disproportionately impacted profitability across stages of production (Lusk et al., 2021).

As the industry grappled with these challenges, environmental pressures further compounded supply chain disruptions when recursive drought began affecting populous cattle areas in the country. From June 2020 to February 2024, more than 40 percent of the nation's cattle were documented in drought-affected areas, with peaks during summer and fall seasons often remaining at 60 percent or above; November 2023 recorded the highest peak with more than 90 percent of U.S. cattle in drought-affected areas (NDMC, 2024). The ramifications of the drought influenced the entirety of the agricultural industry, but specifically for cattle producers, deterioration in pasture conditions necessitated a greater reliance on hay stocks and feed grains, both of which saw price increases to record levels (Nelson, 2024).

Concurrently, inflation experienced an upward trend, resulting in increased costs for the entire U.S. population. The confluence of backlogged cattle, severe drought, and financial pressure provided incentives for cattle producers to initiate the liquidation of portions of their herds. An aspect of this trend was the divergence of heifers to be marketed for eventual slaughter instead of being held as cow replacements in the herd. As can be seen in Figure 1 and as of the

end of 2024, heifer slaughter constituted 32 percent of total cattle slaughter, the highest it has been since 2004. As heifer slaughter climbed to rival historical highs, dressed weights in cattle also rallied; displayed in Figure 2. From 2023 to 2024, the average dressed weight across all cattle increased by 3.24 percent, despite an overall decline in slaughter of 3 percent. While these reductions in female stock have augmented and at times provided short-term increases in beef production, they continue to exert contractionary pressure on cattle inventories in the long term.

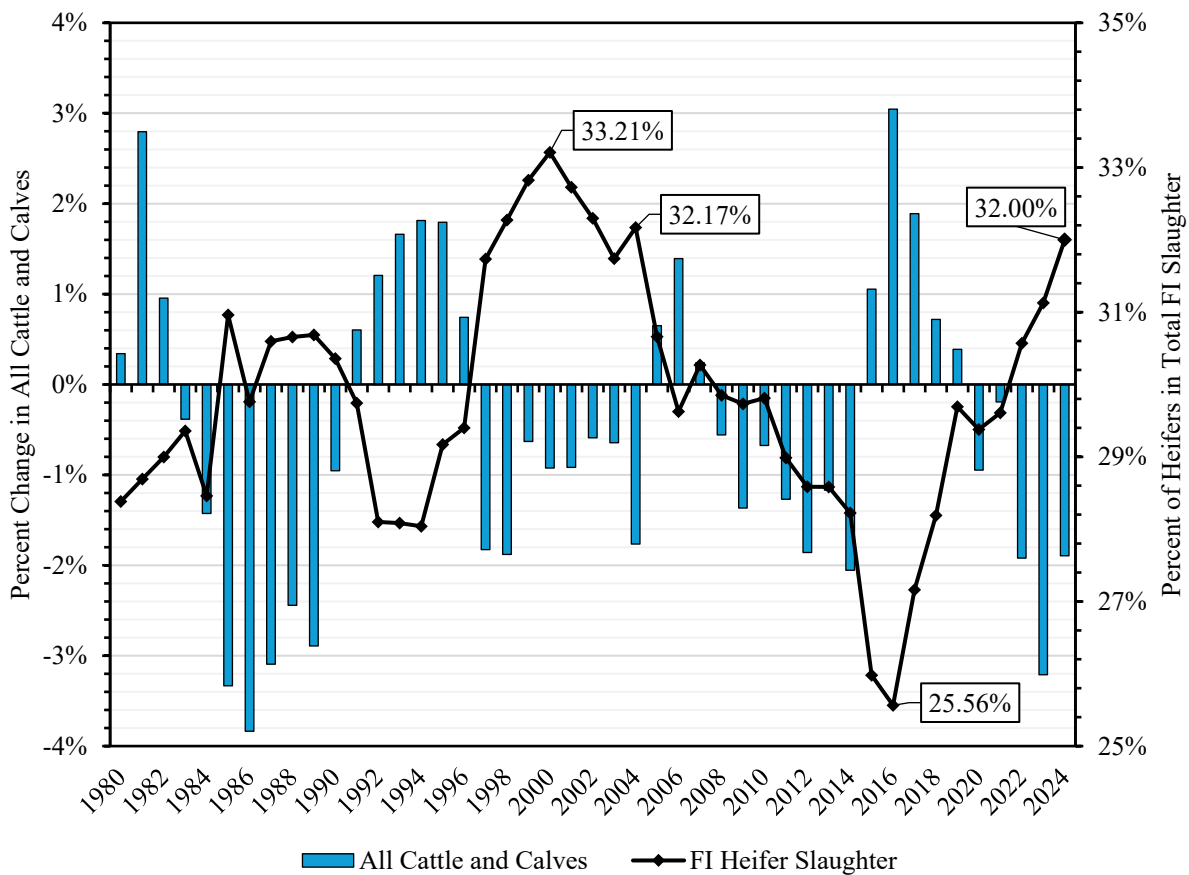


Figure 1: Percent change in cattle inventory and the percentage of heifer slaughter in total federally inspected cattle slaughter, 1980 - 2024

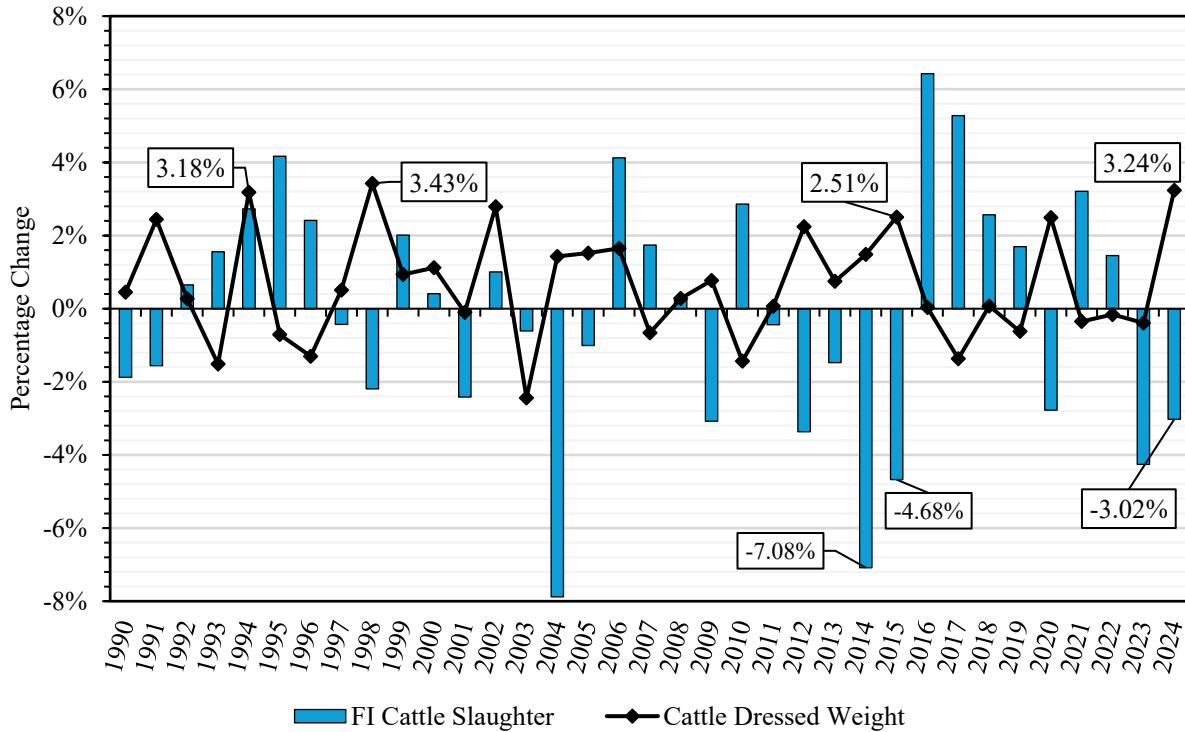


Figure 2: Percent change in federally inspected cattle slaughter and the average dressed weight of all cattle, 1990 – 2024

These circumstances and shifts in market fundamentals have prompted a critical inquiry across the industry regarding the timeline for the expansion of the U.S. cattle herd and the point at which cattle producers will initiate the retention of replacement heifers. Of particular significance in beef production, is the composition of the slaughter mix among marketed cattle and, notably, the substantial influence of heifers in that mix. This study acknowledges that forecasting individual components of the fed slaughter mix could be instrumental in addressing broader questions about the beef and cattle industries. Specifically, the cattle industry in recent years has undergone substantial change that in many aspects has shared similarities with the events that occurred leading into prior troughs of cattle slaughter from 2014 and 2015. However, since that time period heifers contributions to beef production have grown by over 6 percent, generating an added challenge. This analysis considers that the examination of production

specific patterns during previous changes in beef production may aid in elucidating changes in cattle production as well as help extract information from the economic and physical factors that could predict industry movements going forward.

Expanding on recent events, the means by which the literature has approached forecasting production systems, like beef and cattle, appears to show a disconnect with how practitioners, analysts, and risk managers apply their work within the private industry. Literary work often places emphasis on the reduction of concerns such as endogeneity by simultaneously estimating larger systems of equations. However, simultaneous systems often present time consuming and overly complex methods that neglect efficiency and make broad assumptions about what will produce accurate and quality forecasts. Practitioners manage these constraints by estimating systems individually by-parts, or in single-equation pieces that build on one another. The method promotes simplicity, efficiency, and potentially more accurate forecasts. Using fed beef production as the case study, this work seeks to provide an empirical demonstration as to how estimating systems frameworks by-parts, instead of simultaneously, may produce more accurate and quality forecasts. Specifically, because models do not have to be estimated under uniform conditions across all equations, forecasts can further be optimized around their ability to use model tailored explanatory information during the estimation process.

1.1 Objective

The objective of this study is to develop and evaluate the performance of a by-parts forecasting framework, with fed beef production as the case study. Recent dynamics in the composition of cattle slaughter have provided a unique opportunity to identify the indicators at which shifts in supplies of cattle influence beef production. Consequently, this study addresses the research questions of which variables have predicted the mix of slaughtered cattle over recent

history, as well as what variables have predicted dressed weights for cattle within that mix. Furthermore, investigating the relationships between forecast errors and underlying structural changes in market fundamentals may provide insights into possible forecast improvements. As was mentioned, the industry has undergone substantial change over recent years that necessitates the research question of how much historical data should be included within a forecast model to optimize its performance. This study simulates a forecast competition procedure to examine relative optimality in forecasts through error-minimizing survey lengths of time-series. The proposed method shows potential in demonstrating the strengths of by-parts, single-equation systems techniques in place of more complex simultaneous systems of equations.

1.2 Organization of the Thesis

In the preceding chapter, we begin with a review of the literature in which forecasting as a practice is broadly evaluated within academic and business management settings for the cattle industry. Chapter 3 follows with a conceptual framework for understanding and modeling cattle production, where additional relevant literature is discussed as it aids in the analysis of the research question(s). In Chapter 4, the methodology employed for regression analysis, forecast simulation, and forecast performance evaluation is outlined. Chapter 5 details the data used. Chapter 6 discusses the results of the explored methods. Finally, Chapter 7 concludes the paper with takeaways, limitations, implications of the work, and suggestions for further research.

CHAPTER 2: LITERATURE REVIEW

The following literature review explores three key areas for their relevance to cattle production-oriented forecasting. Section 2.1 commences with an overview of the forecasting literature, focusing on its applications in the cattle sector and broader agricultural industry. Section 2.2 follows with a comparative discussion pertaining to the forecasting approach employed by market participants in the private sector. Section 2.3 contains a preliminary assessment of the methodologies and criticisms related to forecast evaluation. Lastly, Section 2.4 highlights the relevance of the work and the contribution to the literature it seeks to make.

2.1 Forecasting in the Cattle Market

Forecasting has long been recognized as a cornerstone within the field of agricultural economics, with its implementation often presenting one of the most challenging tasks faced by academics and practitioners. Initially, work in the field focused on providing producers with prescriptive solutions for increasing financial returns. However, forecasting over time has come to be characterized as the second phase in the progression of agricultural economics research. In practice, forecasting production and price outcomes is valuable for farmers, governments, and agribusiness industries given food production is inherently linked to national security (Allen, 1994). The application of forecasts may be to implement policies for technical and market support within the production sector or to be used as a tool by producers in the development of hedging strategies.

In a comprehensive review of the early literature, Allen (1994) noted that publications within the greater agricultural field placed an emphasis on producing short-term output and

outlook forecasts. Price forecasts were predominantly made using econometric and time-series methods, where the use of single-equation techniques were common. As outlook forecasting increased in prevalence, single-equation models were expanded to encompass multiple sectors and multiple equations. Allen criticized the field for shifts such as this; in part due to an overemphasis on the increasing complexity of forecasting models, a trend he believed reflected a broader tendency among economists to explain rather than predict phenomena.

Specific to the cattle industry, the literature on forecasting has largely been applied to predicting and understanding the factors influencing fed and feeder cattle prices (e.g., Kastens et al., 1998a; Zapata & Garcia, 1990), as well as basis (e.g., Payne & Karali, 2015; Tonsor et al., 2004). The literature in the area of forecasting cattle production has been comparatively less abundant, where work has often focused on simulating and predicting the dynamics of the cattle cycle (e.g., Aadland, 2004; Abidoye & Lawrence, 2009). While studies of this nature place cattle sectoral dynamics as their objective, in a number of observed cases, cattle remain a subsector and integrated component of more elaborate livestock and/or agricultural systems. Of notable significance was the work completed by Stillman (1985), who developed a quarterly model of the livestock sector (i.e., beef, pork, and broiler quantities and prices) that was purported to be an improvement over prior literature in that the model included both behavioral and biological equations that considered cost expectations. In subsequent studies, these systems evolved and estimation techniques changed (e.g., Maples et al., 2022; Weimar & Stillman, 1990); however, the foundation in which they model and understand the cattle industry has remained consistent.

Over time, forecasting production-specific outcomes has garnered some increased attention. A notable study includes that of Bacon et al. (1992), wherein the authors forecasted short-run fed cattle slaughter using information from both proprietary sources and the USDA for

cattle on feed inventories. Another significant contribution comes from Norwood and Schroeder (2000), who evaluated the utility of placement weight data from the updated USDA Cattle on Feed report in forecasting marketings. However, these aforementioned studies represent only two of a limited number of papers that either do not examine sector-level systems and/or do not focus on price as the sole objective. The forecasting literature pertaining to cattle consistently places greater emphasis on the determinants of forecasting prices than on the determinants of forecasting production.

As cited by Campbell et al. (1997), the economics of information are significant in that if prices react to the announcement of information within an efficient market, then the information is deemed valuable by market participants. Previous event studies that have supported this perspective, including those of Falk and Orazem (1985) and Isengildina et al. (2006), have demonstrated the value of USDA-reported information for crop and livestock sectors, respectively. Therefore, in addition to the limitations observed within the forecasting literature, these findings further substantiate the research objective based on the premise that forecasting production-specific outcomes has significant potential for elucidating the factors that determine cattle and subsequently beef prices.

2.2 Interviews with the Private Sector

The difficulty in forecasting anything related to the cattle industry is that there are many exogenous variables that influence the system, while concurrently, there are many interrelated endogenous variables. As such, much of the work conducted in this space has been done by simultaneous and reduced-form systems. However, these modeling structures often result in many insignificant variables, and structural changes can appear unimportant in statistical analyses (Koontz, 2023). The complexity of these issues is being addressed in a fundamentally

different manner in the private sector compared to the approach observed in the literature. During the fall and winter months of the 2023-24 season, interviews were conducted with employees from some of the livestock industry's largest consulting, analytics, and production firms with a goal of understanding the non-academic approach to forecasting. The results of the interviews unanimously revealed that firms did not place immediate stock into concerns such as endogeneity, and rather that they derive estimates through a by-parts modeling structure.

Agribusiness firms are concerned with market information regarding production, prices, trade, and demand. Reports from the USDA are published daily, weekly, monthly, quarterly, biannually, annually, and over multiyear time domains. For firms, this presents a challenging field to navigate regarding the efficiency of intake, dissemination, and application of information. The term by-parts can be defined as being done one piece at a time and/or in fragments. In this context, it signifies that firms execute individual forecasts when information is released on specific components of interest. The benefit of this method is that assessing individual outcomes enhances efficiency and promotes simplicity. By-parts systems structures can also strengthen a model's ability to include outcome specific explanatory information under more flexible conditions. Specifically, the length at which data is used in estimation. This is a superior trait when compared to alternative systems, including VAR, that assume a fixed time period for all included variables (e.g., Linnell, 2017; Zapata & Garcia, 1990).

A complementary trend discussed in the literature and further expressed by firms is that they do not consistently implement and individually forecast outcomes for each topic of interest (e.g., slaughter, dressed weights, cattle on feed, etc.). Instead, firms often have multiple models for one given outcome, which may employ time-series methods, casual and econometric approaches, or more mechanical/additive methods. Depending on the experience of the

practitioner, different models may be used under various scenarios dependent on candidate analog years and/or the time of year. An analog time period can be thought of as a point in past history that has comparable outcomes and/or events to the current period of observation. Analog periods are very common in the analysis of the cattle industry, particularly due to the oscillatory behavior observed in the cattle cycle. However, issues arise within forecasting in the context of analog years, as regression methods make broad assumptions that all events should be weighted equally throughout history. Yet, in practice, the weighting of market information is rarely interpreted equally. A seminal literature exists to explain weighting schemes and the combination of multiple forecasts (e.g., Barrow & Kourentzes, 2016); however, in interviews, this did not appear to be a common practice. Regardless, as stated by Allen (1994) and remains true, routine forecasts are not found in either private business management or the literature. Judgement-based and opinion-oriented forecasting still plays a significant role in short-term outlooks.

2.3 Forecast Evaluation

Allen (1994) posited that every applied economist should consider the following when forecasting: (1) how well the model performs out-of-sample, (2) how the model performs compared to its predecessor/alternative, and (3) the reasons for any discrepancies between competing models. Forecast evaluation focuses on the assessment of errors that occur from a given prediction. Forecast errors are defined as the deviation of the predicted value from the observed or true value, and can be attributed to changes within the underlying relationships that were used to develop a forecast and/or a failure to incorporate all relevant information. According to Nordhaus (1987), efficient forecasts minimize errors based on the information available at the time of prediction, where errors are reflective of random and unexpected market

changes. Nordhaus highlighted that efficient forecasts should adjust to new information through random revisions analogous to a random walk.

The prevalence in increased complexity of forecast models has resulted in the establishment of literature focused on model comparisons. In work by Green and Armstrong (2015), the authors posit that simplicity in forecasting necessitates that the method, representation of cumulative knowledge, and the relationships presented within models be sufficiently uncomplicated and readily comprehensible to decision-makers. In accordance with Allen's (1994) assertion, Green and Armstrong (2015) further contend that complexity in a forecasting model is not invariably a desirable characteristic. They hypothesize that the prevalence of complexity within the forecasting literature may be attributed to (1) the rewards associated with research published in high-ranking journals, (2) forecasters perceiving potential in using complex methods to provide decision support, and (3) the possibility that incomprehensibility may possess reassuring qualities for clients. In their review, they discovered out of 25 papers with quantitative comparisons, that the addition of complexity to a modeling structure increased the average forecasting error by 27 percent.

The level of complexity introduced into a forecasting model is neither a function of the number of variables it includes, nor the amount of effort put into the development of a model. Complexity includes the degree of intricacy and sophistication introduced into the structure, methods, and assumptions underlying the model (Green & Armstrong, 2015). Forecasting with numerous predictors can provide opportunities to exploit a richer information base and provide some robustness against structural instabilities in low-dimensional forecasting. Stock and Watson (2006) emphasize, however, that caution should be exercised as numerous predictors comes with many parameters that can overwhelm the information in the data with estimation error.

Complexity has often been injected into modeling to address the challenge of transforming dimensionality from a curse into a benefit. Although, this often comes at the cost of accessibility. Green and Armstrong (2015) suggest that simplicity can be introduced into a model via decomposition of the time series, the use of premeditated examinations of causal relationships, and the transformation of variables (e.g., taking logarithms).

The length of the time-series data used is also important for the development and evaluation of a forecast model. Between interviews and the literature, a notable pattern was observed in the lack of specificity surrounding the justification for length of time series used for dependent and explanatory variables. While it may be the objective of an analyst or researcher to capture the full duration of a cattle cycle and/or address concerns of prior structural change, economics papers often neglect empirical justification for this component of their model. Data scientists consider this to be a data quality concern and propose simulating a range of different lengths that use the available time series and generate the desired evaluation criteria (Svolba, 2012). To Nordhaus's (1987) point, an efficient forecast should consider the balance of available data and a model's predictive power. Pertinent to economics, this indicates that a change in the optimal length of a given forecast model's history could be indicative of structural change from alterations in the underlying information circulating a market; changes that may have been acknowledged literarily, but have not been explored for their relevance in predicting outcomes.

2.4 Contributions to the Literature

A substantial body of literature exists in the field of agricultural forecasting. However, shortcomings persist in the prediction of production-specific outcomes as a singular practice in the cattle industry. Furthermore, the practicality of forecasting within applied practice has witnessed little attention in the literature. Prior work has not demonstrated the importance of

considering the amount of historical information to include within time series models; and additionally has not explored the importance of promoting simplicity in ones assumptions. Although this research may share similarities with previous studies, it differs in two important aspects: (1) it explicitly models fed beef production and the dynamics surrounding it as a singular and by-parts practice, and (2) it presents a comprehensive evaluation of survey data lengths in the assessment of forecast performance.

CHAPTER 3: CONCEPTUAL FRAMEWORK

The conceptual framework contains two primary elements. Section 3.1 covers the cattle supply chain in which relevant biological and mechanical components of the cattle industry are presented, and Section 3.2 follows with a discussion about candidate model development. The goal of the following chapter is to provide the reader with a working knowledge of cattle sectoral dynamics and how those dynamics are translated into forecasting models.

3.1 The Cattle Supply Chain

The beef cattle industry is best characterized as a dynamic process in which the management of production components (i.e., forage, genetics, feeding systems, and health) intersects with the management of marketing characteristics (i.e., weight, time, location, and marketing strategy). For producers, cattle are considered both capital and consumption goods; animals that progress through the production system for eventual slaughter become consumption goods, while animals that are retained within the production system are considered capital goods (Rosen et al., 1994). Typically, the management of these goods occurs over a yearly budgetary timeframe, where the resulting relationship generates an oscillatory pattern in domestic cattle supplies referred to as the cattle cycle.

The cattle cycle can be defined as the period from the lowest U.S. inventory of cattle and calves to the next lowest inventory. During phases of expansion, inventories increase for approximately six to seven years, during which cow-calf producers cull fewer cows and retain more heifer calves. Expansion in the herd continues until it eventually peaks, and cattle numbers consolidate as fewer heifers are retained. Following a one to two-year consolidation phase, total

U.S. beef cow numbers decline in a liquidation/contraction phase for approximately three to four years, upon which a new cycle commences.

Cattle, like all living organisms, are subject to the constraints of their biological existence. In his work on the USDA quarterly model of the livestock industry, Stillman (1985) posited that the period from the time of conception of a calf until the time when the steak reaches the consumer averages 26 to 28 months. Throughout a calf's stages of growth, various pathways may be pursued before it reaches the packing plant, with the origin being cow-calf producers. The cow-calf stage of the supply chain is the reproductive origin for the entirety of the cattle sector. Producers generate a calf crop using reproductively mature female cattle and create revenue through the sale of those calves. From the time of conception to parturition the gestational period for cows and heifers is 283 days, whereupon birth the calf is anticipated to weigh approximately 65 pounds. After birth, calves remain with their mothers until a weaning weight of approximately 550 pounds. This process can take between 90 and 205 days depending on the breed and genetics of the animal (Maples et al., 2022). Once weaned, calves are directed into various channels contingent on a producer's decision to either increase or decrease their herd size. For heifer calves, cow-calf producers have two options: retain the calf in the herd or market her with the other steer calves.

For those calves that are anticipated to eventually be marketed for slaughter, some cow-calf producers will prepare animals for the feedlot, the final stage of cattle production before harvesting, through pre-conditioning their calves and transitioning them to dry feed. This stage lasts roughly 35 days, after which point producers may send their cattle to graze on pasture before arrival at the feedlot. Once the animal reaches the feedlot, they are fed until they reach a desired slaughter weight and are sent to a processing facility. This stage of feeding cattle can take

up to 230 days, where a given animal has a mean average daily gain (ADG) of roughly 3.66 pounds; 3.81 pounds for steers, and 3.38 pounds for heifers (Stehle et al., 2018).

Another option for weaned calves before they enter the feedlot is to have them backgrounded and/or be fed a mixed ration of dry forages, silage, and grains until they reach approximately 800 pounds. This process can last for roughly 100 days, and once completed, requires a final feeding period of approximately 160 days. Alternatively, weaned calves can be sent to a stocker where they are fed dry forage through the winter and then grazed on summer pastures before being sent to the feedlot. Stocking can last nearly a year, and animals typically spend about 100 days in the feedlot afterward (Maples et al., 2022). Pre-conditioning, backgrounding, and stocking are all voluntary intermediate stages that carry cattle from cow-calf producers to feedlots. Implementation of these practices varies based on geographic area as well as the preferences of both the cow-calf producer selling their calves and the feedlot who later purchases those feeder animals. When cattle exit the feedlot as a fed animal, they are sent to slaughter facilities where their beef is harvested and distributed to wholesalers and retailers.

Optimizing birth, weaning, and slaughter weights is subjective to the goal of a given producer. Important in consideration, however, is that male cattle (i.e., bulls and steers) weigh proportionally more than their female counterparts (i.e., cows and heifers). In 2024, the average live cattle weight across all male and female types was 1,402 pounds per head, where the corresponding average dressed weight was 852 pounds per head. In 2024, the average dressed weight for steers was 931 pounds per head, while it was 848 pounds for heifers.

Stillman (1985) summarized these various stages into a framework that lags cattle entering the beef supply (1) through gestation for 9 to 10 months, (2) has calves with their mothers for 9 months, (3) weaned and outside of the feedlot for 5 months, and (4) fed within a

feedlot for 6 to 7 months. Conversely, in the event a heifer calf is slated to be retained in the herd, Stillman (1985) changes his approach at the birth of the calf to consider (1) a 9-month lag until weaning, (2) the heifer calf bred 4 to 9 months after she has been weaned, (3) calving within another 9 to 10 months, and then (4) with her calf for 9 months.

The biological lags observed in the cattle supply chain are complemented by the decisions producers make when managing their herds. Specifically, due to factors that are beyond the control of the decision maker of a farm or ranch, producers must consider exogenous risk when evaluating their financial outcomes. Notably, and specific to this paper, are the price of inputs (i.e., feed, capital, labor) and the price of outputs (i.e., feeder or fed cattle).

Weather is significant in cattle markets as non-favorable conditions result in the deterioration of optimal plant growth for feed inputs (Patalee & Tonsor, 2021). Cow-calf operations use pasture raising to fulfill roughly two-thirds of their herd's forage requirements (MacDonald & Hoppe, 2018). If temperatures or precipitation deviate from their seasonal averages in a given year, cow-calf producers may be required to reduce grazing days and/or decrease stocking densities to preserve longevity in pasture quality and maintain cattle nutrition. This loss compels producers to increase their reliance on supplemental feeds such as hay, which consequently increases their production costs. In a given livestock producer's annual budget, feed is the single largest expense, accounting for as much as 60 to 70 percent of total enterprise costs (Lawrence et al., 2008). Prior research has demonstrated that changes in the price of corn can contribute up to 22 percent to the variability of feedlot profits (Langemeier et al., 1992), where volatility and seasonality in the cost-of-gain for feeding steers is explained by fluctuations in corn price 63 to 66 percent of the time (Albright et al., 1994). When feed costs increase, the

results pressure cow-calf producers into liquidation phases while also necessitating feedlots to be more mindful in the identification of the profit maximizing length of time to feed cattle.

Future price expectations also determine the movement of cattle. Muth (1961) proposed the rational expectations hypothesis, positing that outcomes in economic phenomena are dependent on the decisions made by economic agents and their expectations of future events. In a producer's decision making process, a producer will observe the present price, supply, and demand for cattle and beef, and form expectations about the price to be received for their cattle in the future. For cow-calf producers, high price expectations on animals lead to the building of inventories through increased heifer retention, while low price expectations lead to reductions in inventories through the sale of suboptimal cows and heifer calf inventories. For feedlots, expectations in future prices manifest in the form of feeder cattle as an input expense and fed cattle sold for slaughter as the revenue-generating output. Higher prices in the future can incentivize producers to keep cattle on feed longer, so long as the cost of gain doesn't deteriorate the potential added profit.

Markets transmit price signals throughout their value chains, driving both the quantity of product demanded and the quantity supplied. In the cattle industry, the supply of calves drives the supply of feeder cattle, feeder cattle supplies drive the supply of fed cattle, fed cattle supplies drive wholesale and retail supplies of beef, and demand for wholesale beef influences the demand for fed cattle (Schultz, 2022). It is important to note that a delicate balance exists between cow-calf producers, feedlots, packers, and wholesale/retailers. Profitability in one stage does not guarantee profitability in another, and each has its respective means for managing price risks. This production stage-dependent balance can present challenges in disaggregating causal factors as motivations across the industry are not homogeneous.

3.2 Candidate Model Development

In the following analysis, multiple candidate forecast models are developed, where only the most accurate are considered for further evaluations of performance. To identify candidate models, combinations of different explanatory variables are examined against dependent variables of interest. Potential complexity is introduced only on the development of candidate composite values such as supply and/or profitability ratios, to ensure that simplicity and comprehensibility are prioritized. Independent variables are identified based on the prior literature as well as through the a priori assumptions outlined in Section 3.1.

Section 3.2.1: Dependent Variables

Ambiguity exists in how one defines the slaughter mix of cattle. A regressand can be a singular component of slaughter, or it can come in an aggregated form. Potential variables are characterized as the inputs of equations 1 through 4; equation 1 specifically defines the foundational makeup of the fed cattle slaughter mix:

$$\text{Fed Cattle Slaughter}_t = \text{Steer Slaughter}_t + \text{Heifer Slaughter}_t \quad (1)$$

Subscript t represents the given time period. Federally inspected fed beef production is derived by multiplying dressed weights with slaughter for each of the animal categories expressed in equation 1. This produces equation 2:

$$\begin{aligned} \text{FI Fed Beef Production}_t & \\ &= (\text{Steer Slaughter}_t \times \text{Steer Dressed Weight}_t) \\ &+ (\text{Heifer Slaughter}_t \times \text{Heifer Dressed Weight}_t) \end{aligned} \quad (2)$$

which can be simplified to the following formula based on the desired level of aggregation:

$$FI\ Beef\ Production_t = FI\ Fed\ Cattle\ Slaughter_t \times Fed\ Cattle\ Dressed\ Weight_t, \quad (3)$$

where *FI Fed Cattle Slaughter_t* is the culmination of steer and heifer slaughter and *Fed Cattle Dressed Weight_t* is a weighted average measure that takes into consideration the proportion of steers and heifers slaughtered. Fed cattle represent those animals that entered the feedlot with the intent of becoming a consumable and are fed specialized rations in order to produce high quality beef products. Nonfed cattle on the other hand, which are not directly assessed in this study, signify those animals that were held as capital for reproductive purposes until they were sold directly for slaughter and did not enter a feedlot. Fed cattle are assessed specifically in this paper due their significant contribution to beef production, and heifers ability to dramatically alter this mix. In 2024 steers and heifers cumulatively accounted for over 80 percent of total slaughter; heifer slaughter was responsible for 32 percent of the total.

For this analysis, slaughter is forecasted for steers and heifers separately, while their corresponding dressed weights are modeled in the aggregated fed cattle form. Aggregation is employed in this case due to similarities observed in overall trends and seasonality; this dimensionality can be visually observed in Appendix A in which graphs of the individual series are provided. For the same reasons, values are left disaggregated and/or in pieces because of differences observed in the series. As such the observed variables of interest are characterized by equation 4:

$$\begin{aligned}
 FI\ Fed\ Beef\ Production_t & \\
 &= (Steer\ Slaughter_t + Heifer\ Slaughter_t) \\
 &\times Fed\ Cattle\ Dressed\ Weight_t,
 \end{aligned} \quad (4)$$

Section 3.2.2: Independent Variables

Industry dynamics have largely been captured and understood within the cattle industry using two intervals of time, annually and monthly. Popularity in modeling annual cattle system dynamics stems from the U.S. cattle inventory report (for all 50 states) only being published once a year. Annual forecasts are common in long-term policy analysis where the goal is to extract trends and cycles. Annual aggregations of production, however, present challenges in identifying the factors that influence the slaughter mix throughout the year. Monthly estimation can more readily address this issue by also considering seasonality. Furthermore, the dynamics and cycles of cattle inventories are attempted to be captured within monthly forecast models.

Candidate subsets of explanatory variables are assessed alongside various dependent variables using scatterplots and correlation analysis to ascertain predictive viability. Suspected lagged explanatory variables are also assessed in this framework. For representative purposes, one can infer that slaughter and dressed weights for any given animal category i in period t will be a function of the following regressor types based on a priori assumptions:

$$\left\{ \begin{array}{l} \text{Slaughter}_{t,i} \\ \text{Dressed Weights}_{t,i} \end{array} \right\} = \left\{ \begin{array}{l} f(\text{Trend}_t, \text{Seasonality}_t, \text{Capacity}_{t-k}, \text{Profitability}_{t-k}, \text{Cattle Supplies}_{t-k}) \\ f(\text{Trend}_t, \text{Seasonality}_t, \text{Profitability}_t, \text{Cattle Supplies}_t) \end{array} \right\},$$

where k represents lag length (including zero), seasonality is representative of the given month, trend is reflective of scientific innovation and changes in consumer preferences, and capacity indicates slaughter capabilities for the given month. Profitability is a function of both revenues and expenses, meaning any variable input could include marginal costs, marginal revenues, anticipated or futures prices, or a derived composite value representing profitability holistically. Lagged cattle supplies along stages of the production process also dictate what is available for slaughter where potential augmentations may be generated due to the trading of live head.

CHAPTER 4: METHODOLOGY

Forecasts for the aforementioned dependent variables are developed using single-equation regression models, where the pre- and post-screening of model information is designed around two contrasting analyses; one in which predictive efficiency is prioritized through simulation, and the other where concerns of autocorrelated errors are attempted to be minimized thereafter. While this paper ignores the presence and potential issues caused by endogeneity and multicollinearity, there exists promise in understanding the influence of serially correlated errors in single-equation models. Previous literature on forecasting in cattle production has often acknowledged the presence of autocorrelated errors; however, papers often ignore correcting for these issues, further motivating question into whether the prioritization of autocorrelated errors coincides with optimality in forecasting. The methods chapter commences with the general framework for model specifications employed. Section 4.2 reviews the criteria used to evaluate forecast performance. Section 4.3 covers the simulation process for optimal survey lengths of time series. Lastly, Section 4.4 covers how models are evaluated and estimated to correct for autocorrelated errors.

4.1 Model Specification

Fed cattle slaughter and dressed weight time series exhibit strong seasonal patterns which can be modeled deterministically using seasonal dummy variables and a time trend. The Deterministic Trend / Deterministic Season (DTDS) model is one of the earliest time series approaches developed to capture both trends and seasonal variation in business and economic data. Its popularity stems from its straightforward estimation using Ordinary Least Squares

(OLS) and its ease of interpretation as a single-equation regression model. Given its simplicity and effectiveness in forecasting, DTDS models serve as the foundational approach for generating initial candidate forecasts. The inclusion or exclusion of series length, explored in Section 4.3, is the newly explored component of leverage within this modeling framework.

For a given dependent variable i in time period t , the general model structure for monthly observations can be defined:

$$Y_{i,t} = \alpha_i + \sum_{n=1}^N \beta_{i,n} x_{i,n,t-k} + \sum_{m=1}^{11} \gamma_{i,m} D_{i,m} + \varepsilon_{i,t} \quad \forall n \in \{1, \dots, N\}, m \in \{1, \dots, 11\}, k \geq 0 \quad (5)$$

where $Y_{i,t}$ is the dependent variable, α_i is a constant, $\beta_{i,n}$ is the coefficient for the n^{th} explanatory variable, $x_{i,n,t-k}$ is explanatory variable n in time period t lagged k time periods (where k can equal zero), D_m is a dummy variable for month m ¹, γ_m is the coefficients for the m^{th} dummy variable, and $\varepsilon_{i,t}$ is the error term. The time trend variable, T , is expressed as one of the n explanatory variables.

4.2 Forecast Performance

The evaluation of forecast performance is facilitated through the segmentation of in- and post-sample periods, where in-sample data is used to produce forecast estimates over the post-sample period. Forecasted estimates are then assessed using various criteria as means to identify relative strengths across models. The maximum in-sample period ranges from January 1980 to December 2013, while the post-sample evaluation period occurs from January 2014 to December 2024. Having an 11-year testing sample allows for the capture of the most recent turning points

¹ Only 11 dummy variables are included where January is omitted for storage in the intercept term to avoid the dummy variable trap.

in both the cattle cycle and total slaughter. Estimation of predicted variables occurs using fixed, recursive, and rolling frameworks due to the desirability in understanding survey data starting lengths as well as more flexible, mobile observation windows.

Initial forecasts are estimated using a fixed window, where parameters are estimated once over the training data and then held constant across the post-sample period. Models are re-estimated in a recursive framework where parameters are iteratively calculated based on in-sample periods and increasing step-ahead windows of data; otherwise meaning recursively estimated models generate expanding surveys of time series, whereas fixed estimation models maintain a fixed sample set. Lastly, models are estimated using rolling estimation, where data is cut off the beginning of the estimation window and expanded onto the end of the included history as step-ahead forecasts are conducted. This estimation method keeps the window of data fixed in length, but not in time as fixed estimation does overall, and recursive estimation does in the starting time period. The goal of alternative estimation procedures is to allow for changes in the parameter values on the premise that changes have been sustained to the underlying market information driving forecast results. Additionally, for practitioners, understanding what methods perform better under various horizons may provide insight into how one prioritizes there time.

After forecasts have been estimated, models are evaluated by comparing the predicted forecast estimates against their respective true, observed values over a 24-month post sample period (from January 2014 to December 2015) and then over the entire 11-year testing sample (January 2014 to December 2024). Evaluation metrics include three criteria: root mean square error (RMSE), mean absolute percentage error (MAPE), and Theil's U for forecast quality (U_2).

RMSE is the standard deviation of prediction errors that are driven by the difference between actual and predicted values. In other words, RMSE measures how spread out the

residuals are around the line of best fit. RMSE is the square root of mean square error (MSE) and retains the beneficial property of penalizing large errors more heavily, but excels over MSE in that its units are the same as the underlying data. RMSE is calculated as follows:

$$RMSE = \sqrt{MSE} = \sqrt{\frac{\sum_{t=1}^n (A_t - F_t)^2}{n}} \quad (6)$$

where n denotes the number of observations, A_t is the actual value of the dependent variable in time t , and F_t is the forecasted value of the dependent variable; the same notation is used in equations 6 through 8. A drawback to RMSE, is that by squaring the errors and calculating their mean, it can be highly sensitive to outliers in the data (Kastens et al., 1998b). Given this may be undesirable, mean absolute percentage error (MAPE) poses as an alternative where added influence from unusually poor predictions won't be heavily weighted. MAPE is beneficial in that it provides an easily interpretable value reflective of the percent in which errors occur on average. MAPE is calculated using equation 7, defined:

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{A_t - F_t}{A_t} \right| \quad (7)$$

MAPE, unlike RMSE, does not measure magnitude or direction (i.e., does not square errors and it measures errors in terms of absolute value), making the two metrics appropriate compliments.

Another forecast evaluation metric considered is Theil's U_2 statistic, also known as Theil's coefficient of inequality for forecast quality, and is calculated:

$$U_2 = \sqrt{\frac{\sum_{t=1}^n ((A_t - A_{t-12}) - (F_t - A_{t-12}))^2}{\sum_{t=1}^n (A_t - A_{t-12})^2}} \quad (8)$$

Equation 8 differs from prior papers, including that of Bliemel (1973), to instead align with work conducted by Stillman (1985) who used the following specification to account for year-over-year changes. In the case of monthly modeling, specifications of Theil's U_2 , such as that reported by Bliemel (1973), are reflective of month-to-month changes that could more heavily be influenced by seasonal change. Given fed cattle slaughter and dressed weights exhibit defined seasonality, calculations of Theil's U_2 in monthly change form would provide estimates that are extremely biased in favor of a given model. Relative to interpretability, in the event U_2 is equal to 0, a forecast method is considered perfect, and if it's less than 1, the forecast method is said to be better than the naïve no-change model. If U_2 is greater than 1, the forecast method should be rejected because it cannot beat the most simple no-change extrapolation (Bliemel, 1973).²

4.3 Survey Length

A component of the forecast model's performance is the survey length of the included time series, and/or the length of history used during estimation. The goal of conducting such analysis is to look at only what market information is deemed important and/or relevant historically for prediction in the post-sample period. The inclusion of irrelevant information could lead to forecast model inefficiencies that reduce predictive quality. Thus, before the review of forecast errors associated with a given a time horizon, for each dependent variable and subsequent model of assessment, different simulation repetitions are executed at various survey lengths where using the aforementioned evaluation criteria, the optimal lengths of the time

² Two Theil's U have been commonly cited in the literature; U_1 measures forecast accuracy and U_2 measures forecast quality. Preference has been shared with the use of U_2 over U_1 due to superiority in properties (e.g., Bliemel, 1973; Granger & Newbold, 1973). Undesirability in U_1 stems from how the function scales down forecast error by variation in the predictions generated, making comparisons between methods complicated and uninformative when identifying superiority in accuracy (Bliemel, 1973). U_1 is neglected in this paper.

history, and/or estimation window size, are presented. Survey length is selected based on RMSE, which is more indicative of the quality of the forecasts history.

Simulation procedures for all models begin with a time history truncated to the length of 36, which is the most current 3 years' worth of data in the in-sample period (i.e., January 2011 to December 2013). Based on the 36-value data observations, forecasts are generated over two test-sample periods and are evaluated against the true, observed data. In the next step, the available time history is extended backward by frequencies of 6 (i.e., six months) and is iterated until a maximum data history is reached. For identification of the best forecasting history, criteria are calculated at each iteration 24-months out to provide a general value of optimality over the suspected analog years. The model lengths that minimize RMSE in the 2 year post sample period are chosen for further comparisons against their next-best alternatives. Lengths are specifically optimizing over a shorter 24-month out sample period because of the desire to understand if the explanatory information that predicted the previous trough in cattle slaughter holds relevance to the most recent time period. An optimal 24-month out forecast should minimize error during the trough of slaughter when herd liquidation came to an end and herd rebuilding was beginning. A similar pattern with weights occurred, in which record high weights attempted to offset the declines in slaughter. These same trends are suspected in 2024 and beyond.

Forecasts are considered using the simulation process under alternative estimation techniques where a single simulation procedure will identify the best survey length for evaluation based on fixed, recursive, and rolling estimation. Fixed and recursive methods are conducted so that optimal starting dates in history can be identified. Rolling estimation is conducted to identify optimal observation lengths that do not hold onto fixed starting points. Specifically, for fixed estimation windows, the optimal length is chosen based on the

minimization of errors from fixed prediction in the post sample period, while for recursive estimation windows, the optimal length is chosen based on the minimization of errors from recursive prediction in the post sample timeframe. However, because differences can occur in how the starting date is identified for the two techniques, the models are also evaluated wherein the two different optimal starting points are used to forecast with fixed and recursive practices. This otherwise means that for a single given variable combination and model specification, four different forecast outputs are produced; two recursive predictions and two fixed predictions, two types of predictions for each of the two identification processes. Under rolling estimation frameworks, because starting dates are not the primary objective, rolling forecast errors are optimized and predicted only under rolling estimation procedures; fixed and recursive prediction methods are not considered here. For enhanced clarity, Figure 3 outlines this process where green boxes coincide with methods that identify starting dates, blue boxes are methods that identify rolling windows, and boxes with a red outline indicate the prediction type used to select the optimal survey length during the simulation process. Combining the total simulation types with the methods of prediction, for one model and/or variable combination, five forecast outputs are produced for evaluation of the forecast competition.

4.4 Autocorrelated Errors

Issues may develop as a byproduct of the simulation process. Notably, is serial correlation within the error terms generated as a consequence of inertia within seasonal time series. While previous papers have often intentionally ignored this, there is cause to concern that lack of correction could be driving errors within the forecasting process. As such, models are assessed over the in- and post-sample period to identify potential remedial measures. To do this, residual plots are examined and use of the partial autocorrelation function (PACF) is employed.

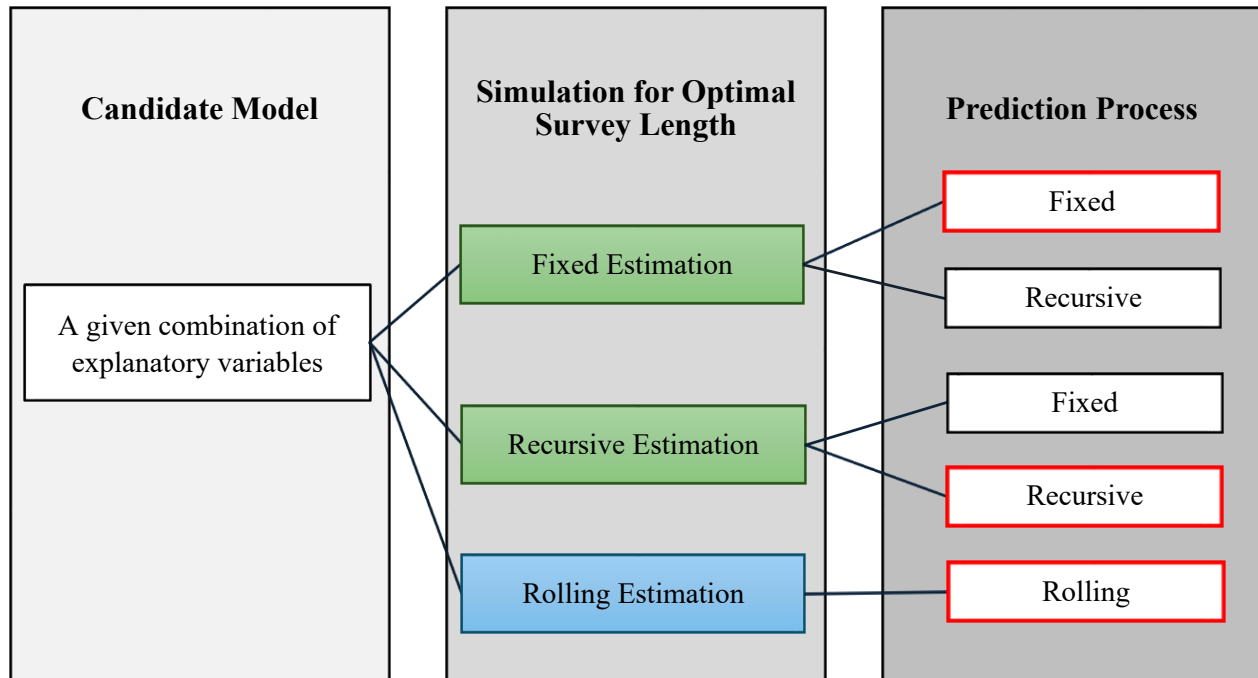


Figure 3: Simulation and prediction procedural flowchart

The PACF aids in the identification of the order of autoregression (AR) within the error terms as it measures the isolated correlation between two points in time and removes the influence of intermediate observations. In the event a model shows signs of significant autocorrelated errors at the 5 percent level, the regression model is re-estimated with the inclusion ARMA (autoregressive moving-average) errors. However, because autocorrelated errors are expected and forecast windows are both expanding and moving in time, models are only modified to the point at which managing issues is deemed appropriate. In short, minor autocorrelation that would require extensive measures will be neglected. For additional details on how models are estimated using ARMA errors, Appendix C contains further information on assumptions and model specification.

CHAPTER 5: DATA

Data used in this analysis are in monthly and annual frequencies spanning from January 1980 to December 2024. The types of data collected pertain to those covered throughout Chapter 3 and encompass factors related to profitability, cattle supplies, and the demand for cattle to slaughter. Data relevant to the operations of the cattle industry, including production, cattle prices, and input prices, are obtained from the Livestock Marketing Information Center (LMIC), which sources data from agencies within the U.S. Department of Agriculture; key agencies include the National Agricultural Statistics Service (NASS) and the Agricultural Marketing Service (AMS). Additionally, data produced by Kansas State University regarding their internal feedlot operations is also collected from LMIC.

As previously mentioned, forecasting and modeling analyses are constrained by the quantity of data available. While this is particularly applicable concerning biological lags and the psychological status of producers, the primary limitations are in the survey history of data and the time-frequency of information. For instance, most cash and futures cattle prices are only available from 1990, while cattle inventory data is only available in annual frequencies. Due to this induced complication, some models assessed do not include time series as far back as January 1980. Instead, models may have shorter observation windows within the training data sample. Additionally, because survey lengths of the included data are of significant interest, the assumption is made that increased histories of given variables may not present any inherent benefit. Instead, exploitation of the available data should be prioritized and forecasts should be evaluated based solely on their ability to accurately predict phenomena rather than statistically

explain them. Table A1 within Appendix B provides an outline of the data sources of reviewed variables, including information on the frequency of observations and their earliest availability.

Data transformations performed include the extrapolation of annual data into monthly and the division of inventory and price values to derive measures of relative supplies and profitability. Given the objective is to focus on monthly forecasts, annual data is extrapolated in a stairstep manner. This approach assumes that yearly values are consistent for every month within that year. For example, the national all cattle and calves number for 2024 was 87.2 million head. Extrapolation extends this value from January 2024 to December 2024, where each month assumes the value of 87.2 million. Using this information provides the model with a rough estimation of where cattle supplies are for the year without making assumptions about intra-year behavior. With respect to price data, prices collected on cattle and feed inputs are left in nominal terms. When producing forecasts, to use real prices would also necessitate a practitioner to forecast inflation. Nominal prices are used to prevent what those issues would produce within a management setting.

CHAPTER 6: RESULTS

The overall results of analysis show there is evidence to support that models of alternative outcomes should be tailored to the explanatory power of their given history to enhance forecast performance. Forcing uniform history into an endogenous system, like those of VAR models, can greatly reduce a model's ability to use its included information within the prediction process. In the preceding sections, in depth overviews are provided for each of the three outcome variables. Within each section, model specifications for a given regressand are provided along with simulation results for optimal survey lengths. At the end of the chapter, a holistic summary of slaughter and weight model outcomes are presented as they relate to forecasting total fed beef production.

6.2 Fed Cattle Dressed Weights

Dressed weights in fed cattle showed defined upward patterns through time that were easily predictable using a deterministic time trend and seasonal dummy variables. The inclusion of information outside key structural parameters generally boosted forecast performance regardless of explanatory type (e.g., feed prices, revenue incentives, price ratios, and/or measures of relative supplies). Factors that showed promise in predicting weights were defined by two mechanisms: (1) feeders' willingness to retain cattle on feed and (2) supplies of cattle on feed for greater than 150 days. Supply variables related to head slaughtered or the percentage by which heifers or steers made up the slaughter mix, did not enhance the explanatory power of models. During simulation, forecasts responded best to recursive and rolling forecast estimation methods when compared to fixed estimation. The inclusion of autoregressive errors, in necessary circumstances, yielded improvement to model's forecasting ability.

The analysis emphasizing the minimization of errors associated with a 2-year out forecast between 2014 and 2015, included 30 model simulations that produced 150 alternative forecast outputs. In the mix, each of the 30 models were simulated using fixed and recursive estimation to identify optimal starting points in history, and using rolling estimation to identify the optimal rolling window in time. To summarize the findings of the total simulation, Table 1 contains summary statistics for optimized survey lengths by simulation method. Considering start dates that were identified by both fixed and recursive estimation, the methods reflected similar median and minimum lengths beginning within 2010 and 2011, respectively. On average, fixed estimation gravitated towards longer observation windows and/or older starting points for parameter estimation when compared to recursive methods. Considering the optimal size of rolling window, observation counts on average required more history than recursive methods, but less than fixed estimation. Overall, between the three methods, the estimation techniques that adapted to new information as they were made available in the testing window, required less information to produce error minimizing forecasts (i.e., recursive and rolling). On the other hand, methods that relied on a fixed sets of observations within the training data sample, required more data to produce error minimizing forecasts.

Table 1: Fed dressed weight survey history summary for 2014 to 2015 optimal window

Simulation Design	Starting Date			
	<i>Oldest</i>	<i>Most Common</i>	<i>Average Start</i>	<i>Most Recent</i>
Fixed	Jul-96	Jan-10	Apr-08	Jan-11
Recursive	Jul-03	Jul-10	Feb-10	Jan-11
<i>Rolling</i>	<i>Jan-02</i>	<i>Jan-10</i>	<i>Jul-09</i>	<i>Jan-11</i>
Simulation Design	Observations (N)			
	<i>Longest</i>	<i>Median Length</i>	<i>Average Length</i>	<i>Shortest</i>
Fixed	210	48	68	36
Recursive	126	42	46	36
Rolling	144	48	53	36

Note: Observations range from the specified start date to Dec-13, the end of the training window. Rolling estimation start dates are italicized to reflect the non-fixed nature of the method.

Taking into account the error performance for each respective method, estimation techniques were further broken down by their ability to perform in the 2014 to 2015 testing window; Figure 4 illustrates these key findings. By method, out of the 150 forecast outputs, each forecasting estimation type contains 30 observations; one model and/or variable combination per method. In the box and whiskey plot, 2 key findings are derived as they relate to the identification of fixed starting points in history. First, by the 24-month forecast horizon model start dates identified using recursive estimation and further forecasted using recursive estimation (i.e., recursive-recursive) reduced estimates of RMSE the best on average. The method that identified start dates using fixed estimation and then recursively forecasts thereafter (i.e., fixed-recursive) followed in rankings. Secondly, out of those models that possessed a fixed starting point in history, estimation methods produced ambiguity within the 6- and 12-month out forecast horizons. Model performance at these horizons is comparable on average and by median, but recursively identified start dates (i.e., recursive-fixed and recursive-recursive) performed marginally better. By the 18- and 24-month out forecast horizon, methods that relied on fixed estimation in the prediction process (i.e., fixed-fixed and recursive-fixed) drove larger relative increases in RMSE.

Across the five different simulation and prediction methods, two additional findings emerged. First and notably, the method employed that identified the optimal rolling window (i.e., rolling-rolling) reduced estimates of RMSE the best on average for all 6-month increment forecast horizons. However, in comparison to the four methods that identified optimal starting dates, at the 12-, 18-, and 24-month horizons, rolling-rolling models produced the largest box, indicating that as forecasts roll forward, rolling-rolling models generated greater relative variability in expectations for RMSE. Secondly, methods that adapted with history did a better

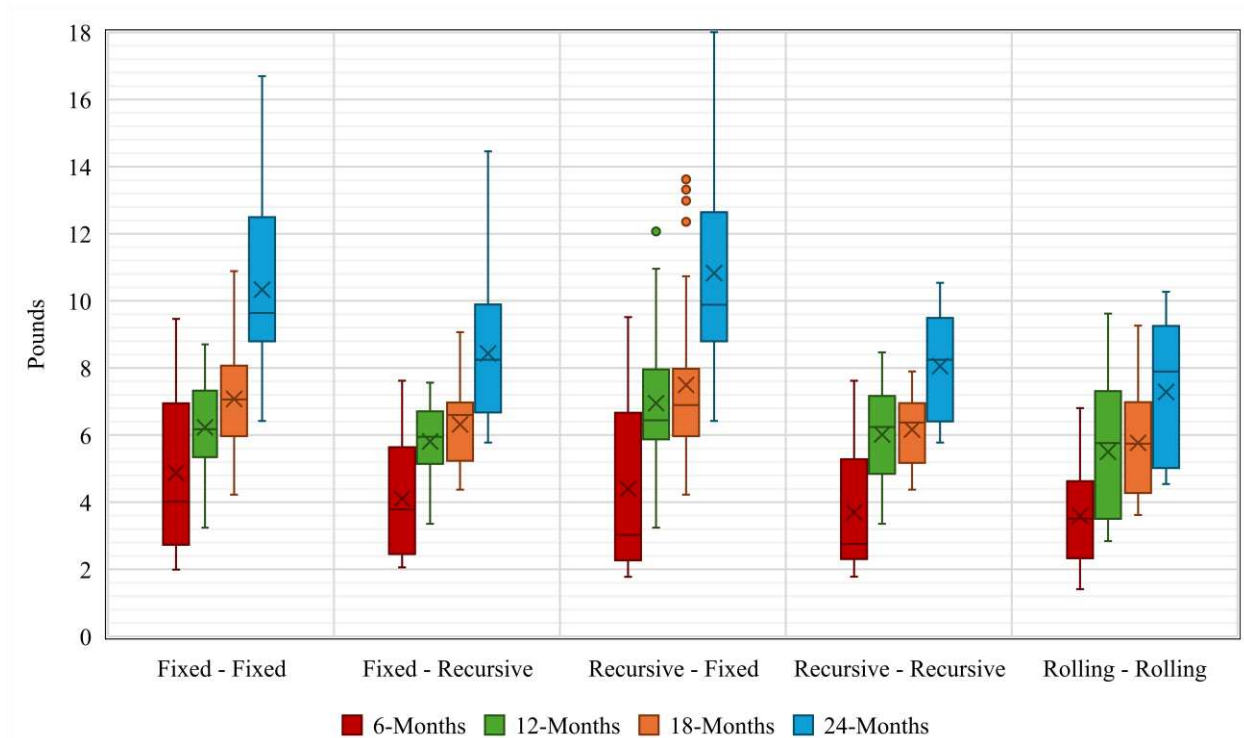


Figure 4: Fed dressed weight simulation method box and whisker plot RMSE summary

job overall in reducing RMSE. Fixed prediction methods lost ability to capture changes the further they were required to forecast. Given methods recursive-recursive and rolling-rolling performed relatively the most optimal and provide contrast in models that select optimal starting dates versus optimal rolling windows. The two methods are further considered in the identification process for optimal models of fed cattle dressed weights and are put in competition with one another for overall performance. Tables A2 and A3 in Appendix D, contain total sample and individual method error summary statistics for further reference.

During the prior trough in slaughter during 2015, weights in cattle climbed to record highs as the cost of feed inputs had succeeded to lower levels, cattle prices were at an all-time high, and supplies of cattle available to be placed on feed were dwindling. Reflective of these influences were 3 models that contained the explanatory variable cattle on feed over 150 days (denoted COF150 and COF >150 Days). COF150 reflects the net culmination of cattle placed on

feed in the prior 5 months and subtracts that value from the total number of cattle on feed within the current month, demonstrated in equation 9. The result measures the number of cattle that are perceived to still be within the feedlot, gaining weight, and not being marketed for slaughter.

$$COF150 = CattleonFeed_t - \sum_{i=1}^5 NetPlcmt_{t-i} \quad (9)$$

COF150 showed strong ability in predicting dressed weights as their value reflects more days on feed equates to more pounds added to carcass weights. To further supplement COF150, the models selected from the recursive-recursive and rolling-rolling estimation forecasts were chosen for their ability to leverage combinations of major feed input prices and perceived returns.

Out of 30 variable combinations, RMSE and MAPE reported the rolling-rolling model containing COF150 and cash corn price as the most accurate model over the 2 year time span. This model is defined by equation 10.

$$FedDress_t = \alpha + \beta_1 Trend_t + \beta_2 COF150_t + \beta_3 CornPrice_t + \sum_{m=1}^{11} \gamma_m D_m + \varepsilon_t \quad (10)$$

Based again on both criteria, the model chosen as the most optimal by recursive-recursive in the 2 year timeframe, contains COF150 and a futures premium, or conversely discount, that can be generated by cattle feeders if they hold cattle on feed, defined by equation 11.

$$FedDress_t = \alpha + \beta_1 Trend_t + \beta_2 COF150_t + \beta_3 FuturesPremium_t + \sum_{m=1}^{11} \gamma_m D_m + \varepsilon_t \quad (11)$$

The futures premium is calculated by finding the difference between the nearby live cattle futures contract approaching expiration and the next closest/nearby contract. The inclusion of

this premium/discount is added to capture potential incentive amongst transaction participants to either immediately market or defer marketing of cattle for slaughter.

An additional competing model that ranked highly among evaluation criteria is defined by equation 12, in which equations 10 and 11 are extended to include both the cash corn price and the futures premium. Including both variables accounts for the tradeoff that occurs during the marketing of fed cattle for slaughter. When the value of corn weakens relative to the perceived profitability gain captured by the futures premium, cattle will gain more weight as there is incentive to hold cattle on feed. Conversely, if corn prices strengthen relative to perceived future revenue, cattle will be marketed for slaughter at a lighter weight.

$$\begin{aligned}
 FedDress_t = & \alpha + \beta_1 Trend_t + \beta_2 COF150_t + \beta_3 CornPrice_t + \beta_4 FuturesPremium_t \\
 & + \sum_{m=1}^{11} \gamma_m D_m + \varepsilon_t
 \end{aligned} \tag{12}$$

Variable combinations that took this tradeoff into consideration were integrated into the simulation procedures. Some examples included the ratio of the two values and the ratio of steer cash and nearby futures prices relative to corn and other feed input prices. None of these variable combinations performed as optimally as the three models chosen and drove greater relative forecast error. Estimates of feedlot returns were neglected during simulations due to feedlots decisions regarding the profitability of placing cattle already being a sunk cost to production.

Of the three models, each share notable similarities in the number of observations required to minimize errors. All recursive-recursive model simulations chose January 2011 as the most optimal starting point, and rolling-rolling models in majority chose the same number of observations with the exception of one. The model containing COF150 and the futures premium chose to include one extra year, using a rolling window of 48 months as opposed to 36. When

considering each of the models selection process, not one of the six appeared to show preference in the selection of full or partial seasons (i.e., 12- or 6-month increments) to reduce error estimates. Summary information regarding models identified start dates and observations are displayed in Table 2. More comprehensive information is provided in Table A4 of Appendix D, which includes the top 5 starting dates for each model along with estimates of RMSE and MAPE for the 24-month out period.

Table 2: Selected fed dress weight model start dates and observations summary

Model	Method	Start Date	Observations (N)
COF >150 Days & Corn	Recursive-Recursive	Jan-11	36
	Rolling-Rolling	<i>Jan-11</i>	36
COF >150 Days & Futures Premium	Recursive-Recursive	Jan-11	36
	Rolling-Rolling	<i>Jan-10</i>	48
COF >150 Days, Corn, & Futures Premium	Recursive-Recursive	Jan-11	36
	Rolling-Rolling	<i>Jan-11</i>	36

Note: Methods begin with the simulation method for optimal length and are followed by the prediction method. Rolling-Rolling model start dates are italicized to reflect the non-fixed nature of the method.

Each respective forecast can be observed in Figure 5 along with the actual dressed weights recorded for 2014 and 2015. Overall, rolling models visually appear to follow seasonal flows in dressed weights the most accurately compared to recursive methods. Rolling models extend into peaks more precisely, just as they stay tighter to the observed data through troughs. Regardless of estimation method, for models that include corn price as a variable, forecasts follow weights better going into 2015 peaks compared to models that exclude corn price. In every case, models had trouble predicting the contra seasonal behavior that occurred from January 2015 to May 2015, when weights did not depress to typical seasonal lows. Even the use of alternative explanatory information, including average days on feed reported by Kansas State University, failed to pick up on the contra seasonal behavior that occurred during the time period.

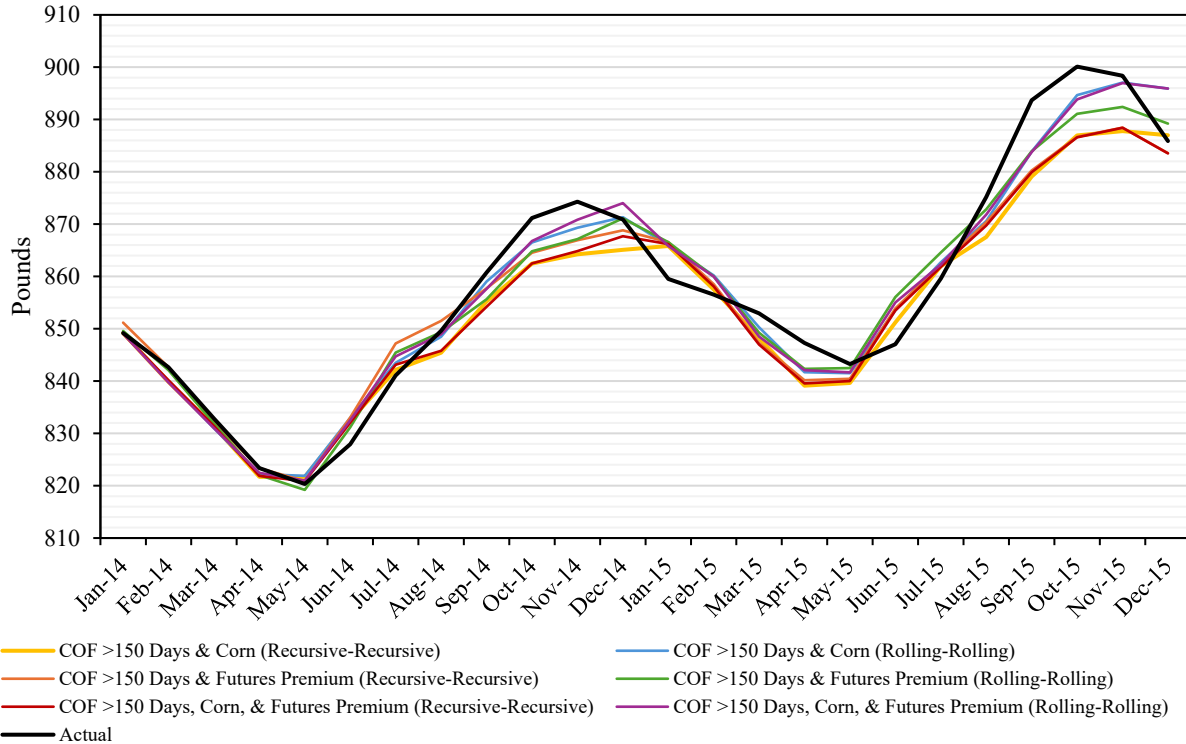


Figure 5: 24-month out fed dressed weight forecasts

To compliment Figure 5, Figure 6 displays the RMSE documented for each model leading up to a 24 month forecast horizon. Comprehensive criteria estimates, including Theil's U_2 , are available in Table A5 of Appendix D. Empirically, all forecasts are considered highly accurate and contain ending MAPEs of less than one percent. Theil's U_2 also report values less than one suggesting performance quality is preferred over the naïve no-change form. For RMSE, the average magnitude of prediction error climbs more dramatically for recursive methods as opposed to rolling. Models inclusive of corn price drove both the most and least amount of error over the sample for recursive and rolling estimation, respectively. The models containing only the futures premium and COF150 performed within the middle range of the forecasts. However, when we add corn price with the futures premium, we again see corn prices driving both larger and lower errors for recursive and rolling estimation, respectively.

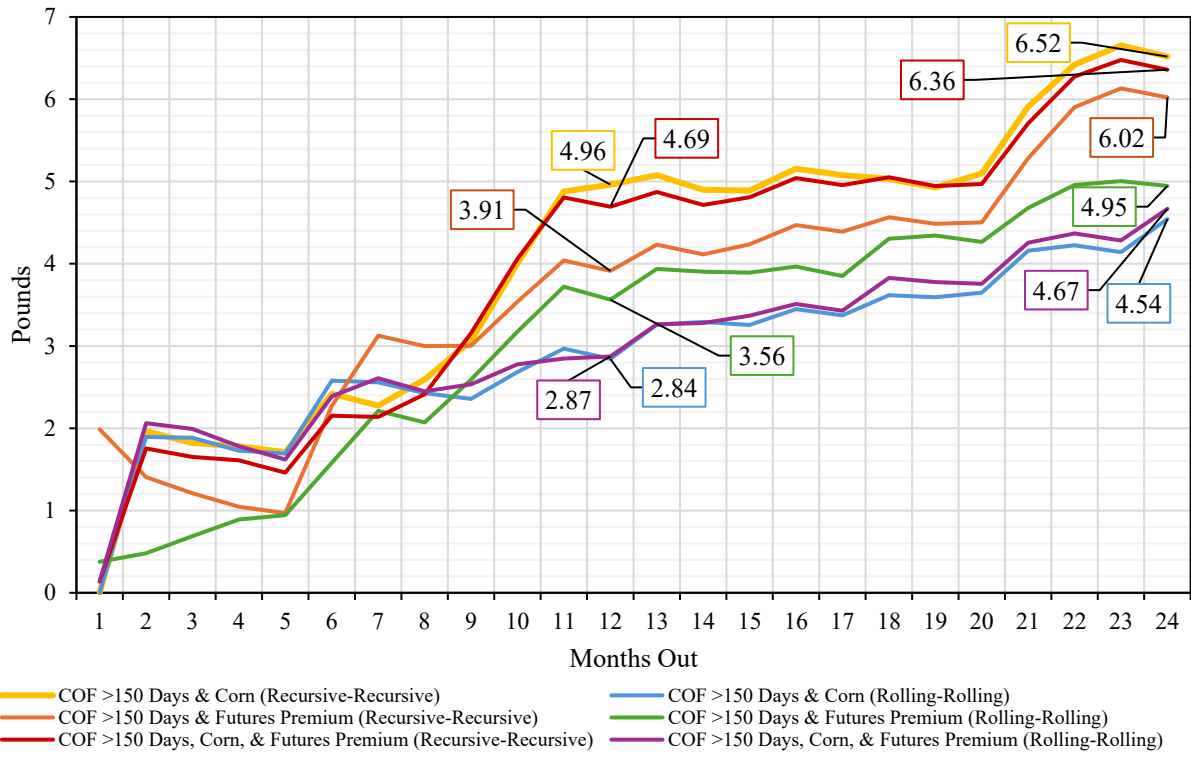


Figure 6: 24-month out fed dressed weight forecast RMSE estimates

When the window of the forecasts are extended over the full testing sample of 11 years, spanning from January 2014 to December 2024, error estimates remain low and possess the same rankings as can be seen in Table 3; rolling models have slightly more optimal results than recursive. However, if we visually inspect forecasts ability to follow the actual observations over the 11-year window in Figure 7, model performance deteriorates. Models often over or underestimate seasonal highs and lows and some years appear to have elongated or reduced seasonal patterns. Notably, the rolling-rolling COF150 and futures premium model, depicted by the green line, severely underestimates the contra-seasonal trough in 2020 and likewise with 2024. Of additional significance, are recursive-recursive models visually predicting more optimally during spikes in 2024; however, this performance came at the cost of severe overestimation during 2023. By method, recursive methods possessed smoother changes with

time, indicative of increased history in the estimation window, while rolling methods became more choppy and inconsistent the further out they were estimated into the testing sample.

Table 3: Selected fed dressed weight model error results for the 132-month out horizon

Model	Method	RMSE	MAPE	U_2
COF >150 Days & Corn	Recursive-Recursive	12.141	1.144	0.783
	Rolling-Rolling	9.321	0.800	0.601
COF >150 Days & Futures Premium	Recursive-Recursive	13.245	1.248	0.854
	Rolling-Rolling	11.575	0.969	0.747
COF >150 Days, Corn, & Futures Premium	Recursive-Recursive	12.207	1.139	0.787
	Rolling-Rolling	9.646	0.825	0.622

Note: Methods begin with the simulation method for optimal length and are followed by the prediction method.

If autocorrelated errors are considered as potential suspect in why models saw performance deterioration, through examinations of the PACF it was observed that models frequently possessed first order autocorrelated (AR(1)) errors; and if they did not initially, they developed them over the 24-month out horizon. To manage this concern, models were re-estimated with the inclusion of AR(1) errors and forecasts graphed again over the 24-month out horizon. In Figure 8, it's possible to ascertain that models achieved notable gains in performance. Before, models struggled to estimate values into seasonal troughs and peaks. However, following correction they appear to follow highs and lows with more accuracy. Although, overall models visually look better by the end of sample, early months in the forecasts appear to have gotten worse. Models also continue to exhibit a lagged behavior throughout the testing window, where contra seasonal patterns are instead managed by the reduction of errors on average, instead of by exact accuracy.

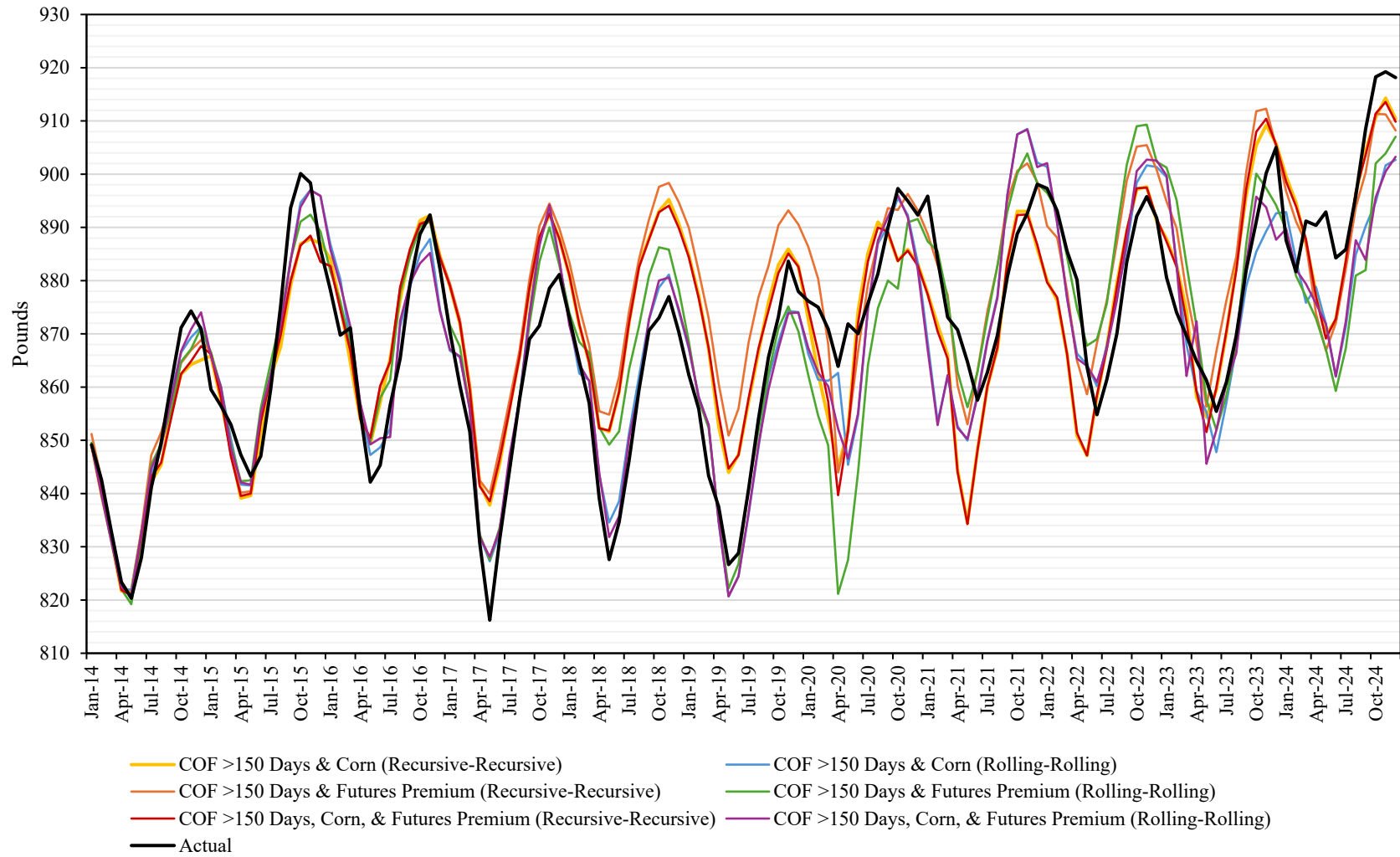


Figure 7: 132-month out fed dressed weight forecasts

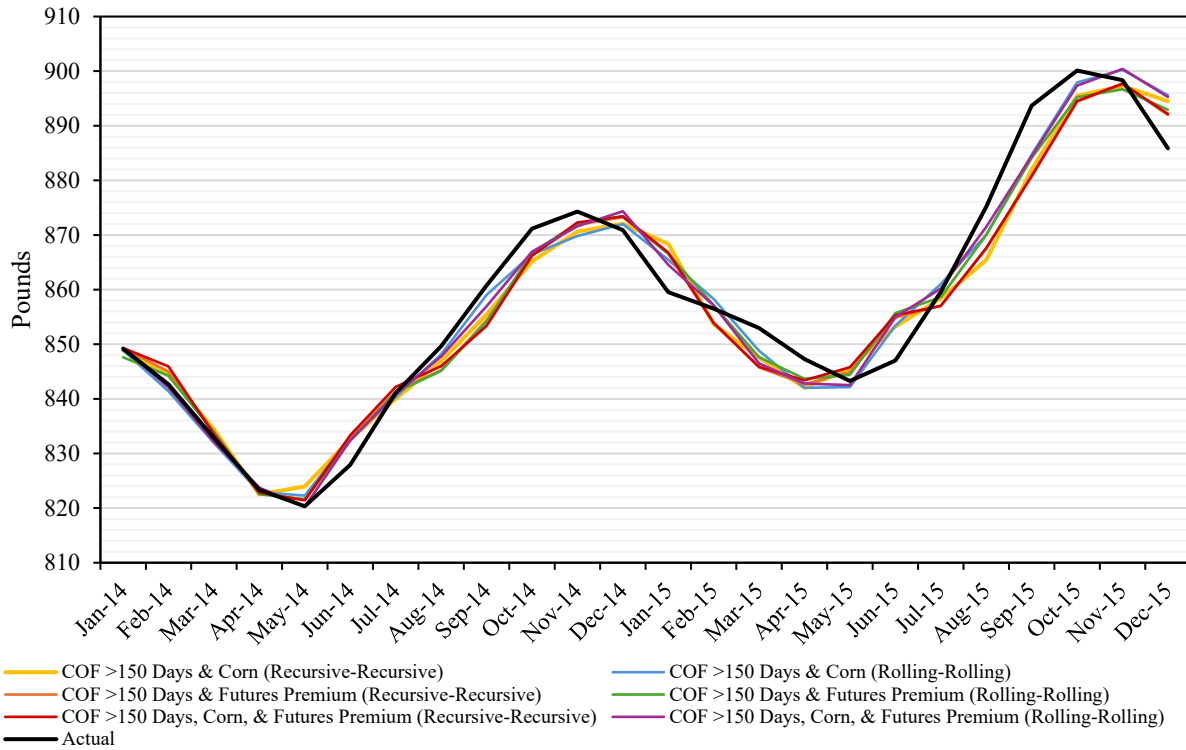


Figure 8: 24-month out fed dressed weight forecasts corrected for autocorrelated errors

Gains achieved in RMSE when considering first order autocorrelated errors are graphically displayed in Figure 9 which shows the percentage by which errors were reduced from the original errors, but in terms of percentage gains; Table A6 contains comprehensive error statistics at each horizon for the adjusted models. Overall, by the 24-month horizon, RMSE was reduced anywhere from 9 to 26 percent dependent on the given model and its estimation method. However, discrepancies developed within the 1- to 10-month out forecast horizons as almost all models witnessed increases to RMSE. Only the model containing both corn price and the futures premium using rolling estimation observed overall gains across every horizon. Coming in close second was the model containing COF150 and corn price, also in a rolling framework, which only lost predictive quality at the 1-month horizon. By method, across horizons recursive models showed the most improvement with rolling models posting more modest gains.

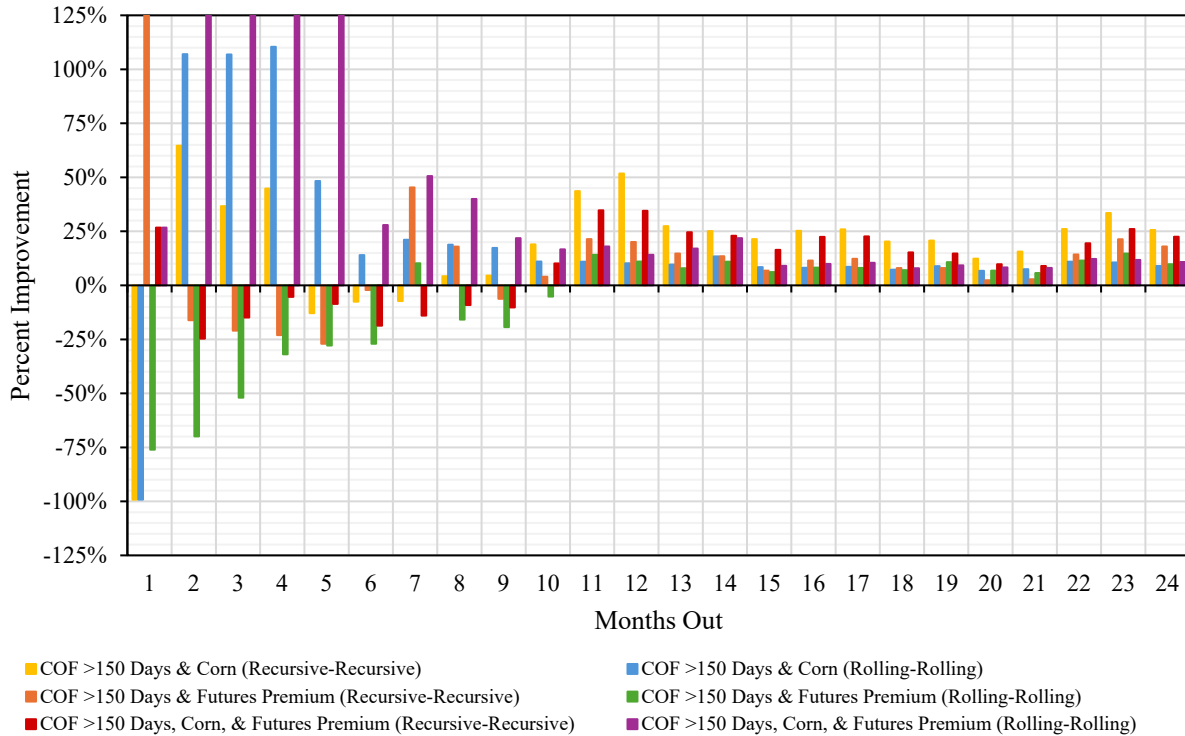


Figure 9: 24-month out fed dressed weight forecast RMSE percent change when corrected for autocorrelated errors

When inspections for autocorrelated errors were executed over the 11-year testing window, it was observed that recursive models developed more complex issues. Examinations of the PACF prompted the inclusion of a first order autoregressive error as well as a first order moving average term (MA(1)) and seasonal autoregressive error (SAR(1)). Rolling models were also tested at the final window and issues did not stem beyond the requirement of AR(1) errors to reduce autocorrelated errors. Table 4 provides a summary of the models, methods, autoregressive error requirements, and error performance measures. Overall, errors measured in MAPE terms were reduced by roughly half, with similar results for RMSE and Theil’s U_2 . Due to the broader issues observed among recursive models, their reductions were more pronounced and proved more useful compared to rolling models. Regardless, over the entire 11-year testing window, errors were reduced substantially by accounting for autocorrelated errors.

Table 4: Selected fed dressed weight model error results summary at the 132-month horizon when corrected for autocorrelated errors

Model	Method	ARMA Order	RMSE	MAPE	U_2
COF >150 Days & Corn	Recursive-Recursive	ARMA(1,1) & SAR(1)	5.642	0.518	0.364
	Rolling-Rolling	AR(1)	6.112	0.529	0.394
COF >150 Days & Futures Premium	Recursive-Recursive	ARMA(1,1) & SAR(1)	5.531	0.513	0.357
	Rolling-Rolling	AR(1)	6.175	0.526	0.398
COF >150 Days, Corn, & Futures Premium	Recursive-Recursive	ARMA(1,1) & SAR(1)	5.564	0.515	0.359
	Rolling-Rolling	AR(1)	6.190	0.540	0.399

Note: Methods begin with the simulation method for optimal length and are followed by the prediction method.

If we compare forecasts depicted in Figure 7 to corrected forecasts in Figure 10, we again observe substantial improvements to the overall fit of the forecasts. Of particular note are models more adequately using estimates of COF150 to accommodate for backlogged supplies produced during 2020 and the contra seasonal behavior observed during 2024. Model's also fitted to seasonal patterns more accurately compared to previous uncorrected forecasts. If we compare the corrected models performance optimized around 2014 and 2015, our analog years, to what occurred in 2024, we see models having no issue forecasting the sharp peak, despite models struggling earlier in the year.

The following review of fed dressed weight forecasts was the simplest of the models to theoretically develop due to fundamental patterns in the data. However, compared to models in the preceding sections on slaughter, dressed weights possessed the most apparent and systemic issues with autocorrelated errors. Simulation patterns also largely remained consistent across different outcome variables. To reduce redundancy, the following sections focus on new and emerging information observed only as they relate to the given outcome variable. Contrast is sought as it is deemed relevant for discussion, but overall trends are preserved for the conclusion.

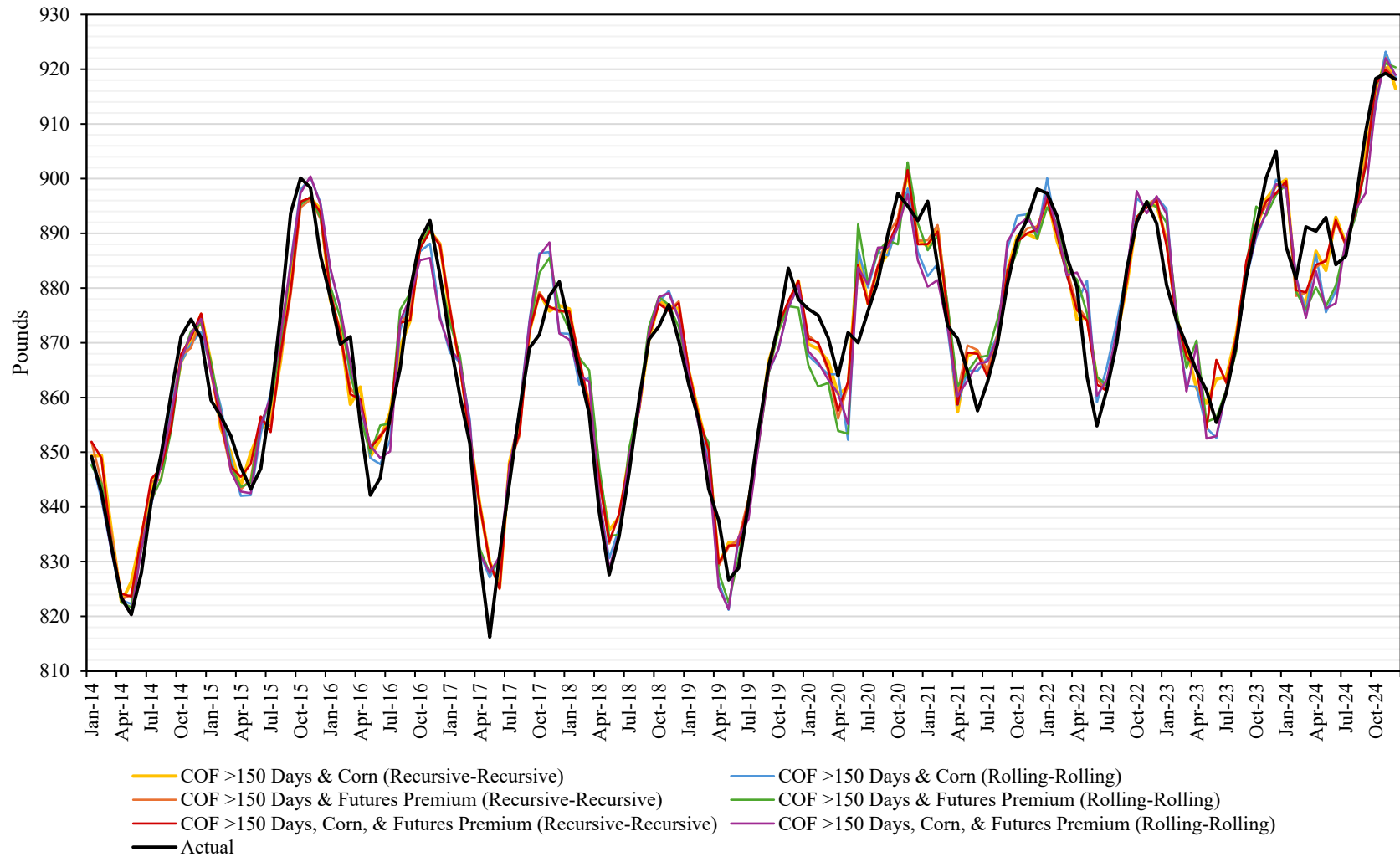


Figure 10: 132-month out fed dressed weight forecasts corrected for autocorrelated errors

6.2 Steer Slaughter

Models of federally inspected steer slaughter showed mixed results in how they responded to different types of supply information. Specifically, the inclusion of annual supply stocks of steers showed great ability in producing accurate forecasts, while models that contained information on supply flows of fed cattle moving through feedlots showed mixed and often inferior performance. The steer slaughter section covers two competing variable combinations that showed similar performance in the 24-month out horizon; one that contains the percentage of steers available from the prior year's calf crop, and the other that uses placements and backlogs of cattle on feed. The two models provide complementarity reflecting that more simplistic assumptions can still produce accurate forecasts.

In the selection process for optimal forecasts of steer slaughter, 50 variable combinations were simulated producing 250 forecast outputs. First considering survey history across all simulations, compared to dressed weights, simulations of steer slaughter showed greater favorability towards earlier starting dates and/or greater numbers of observations in the estimation process. However, overall models of steer slaughter appeared to follow the same patterns. For methods that identify a fixed starting point, fixed estimation again preferred the oldest starting dates while recursive chose the earliest of the sample on average. For optimal rolling windows, results were slightly different from dressed weights and showed that models instead preferred the largest estimation window on average across methods. For estimation and prediction methods, both on average and median, models tended towards starting dates in the 2004 to 2005 time period, where only in a couple of extreme cases, models chose to include data prior to 2000. More information regarding the simulated starting dates, including summary statistics for the optimal number of observations is available in Table 5.

Table 5: Steer slaughter survey history summary for 2014 to 2015 optimal window

Simulation Design	Starting Date			
	<i>Oldest</i>	<i>Most Common</i>	<i>Average Time</i>	<i>Most Recent</i>
Fixed	Jan-90	Jan-05	Sep-04	Jan-11
Recursive	Jan-99	Jul-05	Feb-05	Jan-11
<i>Rolling</i>	<i>Jan-02</i>	<i>Jan-05</i>	<i>Jun-04</i>	<i>Jan-10</i>
Simulation Design	Observations (N)			
	<i>Longest</i>	<i>Most Common</i>	<i>Average Length</i>	<i>Shortest</i>
Fixed	288	108	111	36
Recursive	180	102	106	36
Rolling	144	108	114	48

Note: Observations range from the specified start date to Dec-13, the end of the training window. Rolling estimation start dates are italicized to reflect the non-fixed nature of the method.

In contrast to models of fed cattle dressed weights, estimation methods performance within the 6-, 12-, 18-, and 24-month out horizons showed more ambiguous results as to which method performed best on average; Figure 11 displays a box and whisker plot of the simulation results. First, all methods during the first 6 months contained virtually the same estimate of RMSE on average, with the only difference being the range to which estimates fell in. When only considering the four methods that select optimal starting dates, even the 24-month out horizon showed stark similarities on average. However, at 12- and 18-month out horizons, models began to differentiate themselves. Like dressed weights, models of steer slaughter forecasted using fixed estimation (i.e., fixed-fixed and recursive-fixed) drove larger average errors over time and greater ranges of estimates. Models that recursively updated (i.e., fixed-recursive and recursive-recursive), had the opposite effect in which average errors were lower and succeeded at times, with the range of estimates produced also being smaller. For optimized rolling windows, contrary to dressed weights, average errors were higher at horizons 6, 12, and 18 compared to recursively predicted forecasts. It wasn't until 24 months out that rolling windows showed better ability to reduce RMSE on average. For consistency, models using methods recursive-recursive and rolling-rolling were further considered in the competition mix

of presented forecasts. Tables A7 and A8 in the Appendix D provide the corresponding summary statistics for RMSE and MAPE, respectively.

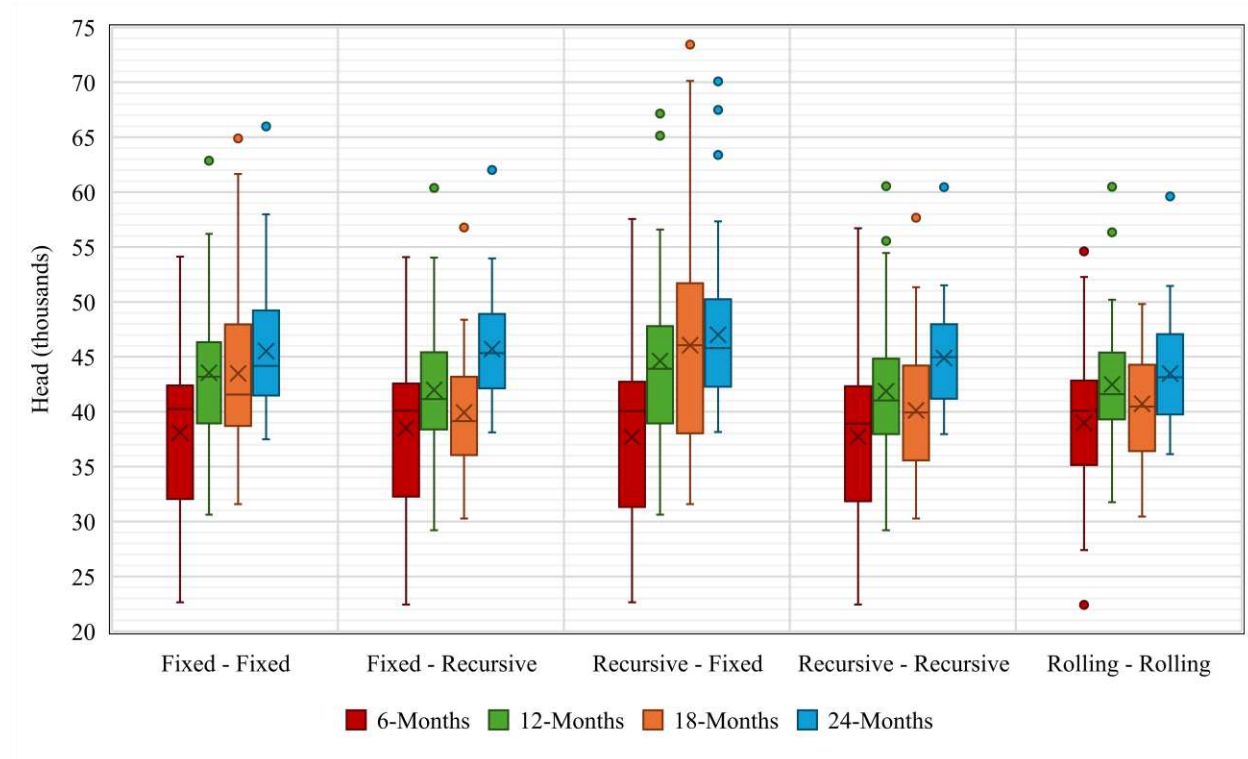


Figure 11: Steer slaughter simulation method box and whisker plot RMSE summary

Out of methods recursive-recursive and rolling-rolling, models that predicted well into the trough of steer slaughter from 2014 to 2015 are defined by equations 13 and 14. Unlike dressed weights, models of steer slaughter often shared the same rankings across methods, and as such were chosen based off their highest mutual ranks for both recursive and rolling estimation.

$$SteerSlaughter_t$$

$$= \alpha + \beta_1 Trend_t + \beta_2 SltrDays_t + \beta_3 PctSteers_t + \beta_4 SteerAlfalpaPriceRatio_t + \beta_5 AlfalfaPrice_{t-6} + \sum_{m=1}^{11} \gamma_m D_m + \varepsilon_t \quad (13)$$

SteerSlaughter_t

$$\begin{aligned}
 &= \alpha + \beta_1 Trend_t + \beta_2 SltrDays_t + \beta_3 COF180_t + \beta_4 COF150_{t-1} \\
 &+ \beta_5 PlcmtGrtr800_{t-4} + \beta_6 Plcmt700to799_{t-5} + \beta_7 Plcmt600to699_{t-6} \quad (14) \\
 &+ \beta_8 PlcmtLess600_{t-7} + \beta_9 SteerAlfalfaPriceRatio_t + \sum_{m=1}^{11} \gamma_m D_m + \varepsilon_t
 \end{aligned}$$

In both equations, two variables showed powerful ability to enhancing forecasts, a structural variable to correct for the number of business days in a month and a profitability ratio. Not all cattle are slaughtered within federally inspected plants, and instead can be allocated towards other facilities that become a part of total commercial slaughter. Including the variable *SltrDays_t* (slaughter days) in both models accounts for FI slaughter only occurring on federally recognized business days. Another common variable in both equations, *SteerAlfalfaPriceRatio_t*, takes the 5 market cash price per hundred pounds of a steer and divides it by the national price per ton of alfalfa hay. Similar to the discussion with dressed weights, the ratio captures the tradeoff at the time of slaughter related to what a feeder can gain in perceived returns against what the relative cost is to feed that animal. During simulations, alfalfa prices were observed to perform more optimally than corn price in slaughter models. Likely reasons being changes in feedlot rations over time incorporating more distillers grains and other feedstuffs that have a more dispersed production geography, of which alfalfa reflects.

Specific to equation 16, what will be referred to as the steer supply stocks model, the variable *PctSteers_t* is introduced to capture the percent of steers that come available into the current year based on the calf crop from the previous year. Other values were assessed related to the number of steers greater than 500 pounds as well as current and past values of calf crop, but those variables possessed less optimal performance. In addition to steer supply stocks, a 6 month

lagged price on alfalfa hay is included to capture the relative costs for feeders when placing cattle on feed as well as for producers who may have cattle on pasture. As previously mentioned, alfalfa production has a larger geographic production area. If drought is affecting populous cattle areas, the inclusion of alfalfa prices picks up on those effects.

In comparison to model 13, model 14 captures supply flows of fed cattle moving through feedlots by using information on placements of cattle on feed by weight category as well as measures of backlogged cattle. Placements are lagged by 4, 5, 6, and 7 months for cattle greater than 800 pounds, cattle between 700 and 799 pounds, cattle between 600 and 699 pounds, and cattle less than 600 pounds, respectively. The lag structure captures the ADG experienced by cattle and makes the assumption that based on when feeder cattle are placed on feed, their weight later dictates when we expect them to be market ready animals.³ In dressed weight models, COF150 was introduced for its ability to capture steers and heifers lengthened stay within the feedlot. In contrast to placements, COF150 and cattle on feed over 180 days (COF180) are used in tangency.⁴ Models of steer slaughter showed strong correlation and predictive relationships with COF150 at a lag of one month and COF180 for the current month. During simulations, models that only considered placements struggled to capture monthly dynamics in FI steer slaughter. The inclusion of cattle on feed over 150 and 180 days supplements placements in that if cattle are held on feed for longer than what may be considered typical, those placement values

³ Placements by weight category could easily be substituted with total placements at the same lags. More general assumptions are made if total placements are used, and a practitioner is likely to experience greater ease in forecasting them as an input variable. Weight based placements are used in this analysis because they showed minor improvement over total placements in simulations.

⁴ COF180 is calculated the same as COF150 in equation 9, but with the inclusion of one additional lagged value of net placements at $t-6$.

are no longer the determining factor. Using weight specific placements supplements COF150 and COF180 further, given the two values only consider net placements of cattle in their derivation.⁵

Both models with supply stocks and with supply flows experienced different simulated behavior in what was chosen as an optimal starting point and/or rolling window. Steer supply stocks preferred a shorter relative window compared to fed cattle supply flows beginning in the 2006 to 2007 period and 2002 to 2003 period, respectively, where in both cases, the rolling-rolling methods for each model preferred the additional years' worth of data. Based on patterns observed during the optimal length selection process, or the internal forecast competition for that specific variable combination, similar to dressed weights, models did not follow any inherent pattern regarding the selection of full or partial seasons; models randomly selected either January or July starting months. However, based on the type of supply information, models did show optimal results at July starts for stocks and January for flows. A summary of the selected starting dates and rolling windows is available in Table 6. Table A9 in Appendix D contains the top 5 starting dates for each model and method, along with their corresponding RMSE and MAPE for the 24-month out window.

Table 6: Selected steer slaughter model start dates and observations summary

Model	Method	Start Date	Observations (N)
Steer Supply Stocks	Recursive-Recursive	Jul-07	78
	Rolling-Rolling	<i>Jul-06</i>	90
Fed Cattle Supply Flows	Recursive-Recursive	Jan-03	132
	Rolling-Rolling	<i>Jan-02</i>	144

Note: Methods begin with the simulation method for optimal length and are followed by the prediction method. Rolling-Rolling model start dates are italicized to reflect the non-fixed nature of the method.

⁵ An important factor in determining slaughter is the packers' willingness to accept cattle which is also a function of packing capacity. In the literature there have been estimates derived in attempt to capture this capacity. However, they often rely on current estimates of slaughter, which invalidates the goal of producing forecasts of slaughter. COF150 and COF180 consider the backlog of cattle produced if there occurs an upset in packing operations that would otherwise effectively force cattle to remain on feed. Conversely, if cattle are moving through feedlots rapidly, the values will capture this movement as well.

First considering estimates of RMSE across the 24-month horizon, shown in Figure 12, rolling estimation models again outperform recursive models, as was seen with dressed weights. However, the margin to which rolling estimation beat recursive was very small. By the end of the forecasting window, the rolling supply stocks model performed better than the supply flows model by a margin of only 40 head, where the recursive supply stocks model followed by a margin of only 830 head. Throughout the entire 2-year sample, supply flow models in both recursive and rolling estimation frameworks maintained lower estimates of RMSE, where performance differences were most noticeable during the first 6 months. Models did not become comparable until the 22-month horizon when rolling supply flow information decreased error better relative to recursive supply stocks information. Supply stock models reduced error the best holistically, but supply flow models delivered consistency in error generation.

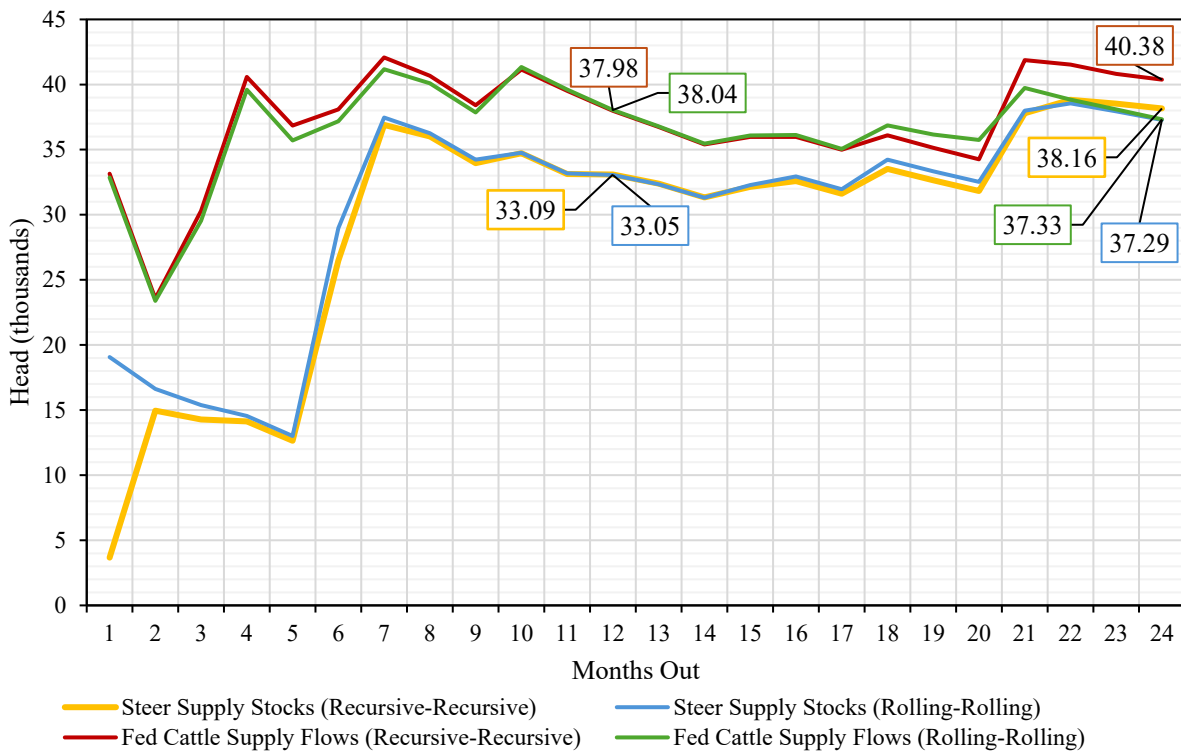


Figure 12: 24-month out steer slaughter forecast RMSE estimates

Over the 11-year testing window, models containing steer supply stocks performed relatively more optimally when compared to models containing fed cattle supply flows. By method, differences were more noticeable between the models based on recursive versus rolling forecasts. Rolling models still appeared to do a better job minimizing forecast error across estimates of RMSE, MAPE, and Theil's U_2 ; Table 7 contains a summary of the error estimates.

With respect to visual quality, Figure 13 graphically shows the forecasts over the 11 year testing window. In the initial 2-year out horizon, models predicted relatively accurately with the only notable struggles occurring with minor over and underestimation of seasonal peaks. Further into the testing window, similar to the observed patterns in dressed weights, forecast's performance visually deteriorated. For years 2022 and 2023 particularly, all models and methods had issues over and underestimating peaks and troughs. Forecasts for 2024 also did not suggest visibly that the explanatory information from our analog years could explain the events that transpired. A larger issue with these forecasts appeared to come from models not handling changes in seasonal variance well. In dressed weights, seasonality was often widened or narrowed in models not corrected for autocorrelated errors. In steer slaughter, we see seasonality shrinking with time and forecast models had trouble predicting and adapting to these changes.

Table 7: Selected steer slaughter model error results for the 132-month out horizon

Model	Method	RMSE	MAPE	U_2
Steer Supply Stocks	Recursive-Recursive	61.615	3.072	0.643
	Rolling-Rolling	60.734	2.971	0.634
Fed Cattle Supply Flows	Recursive-Recursive	68.490	3.797	0.715
	Rolling-Rolling	65.156	3.444	0.680

Note: Methods begin with the simulation method for optimal length and are followed by the prediction method.

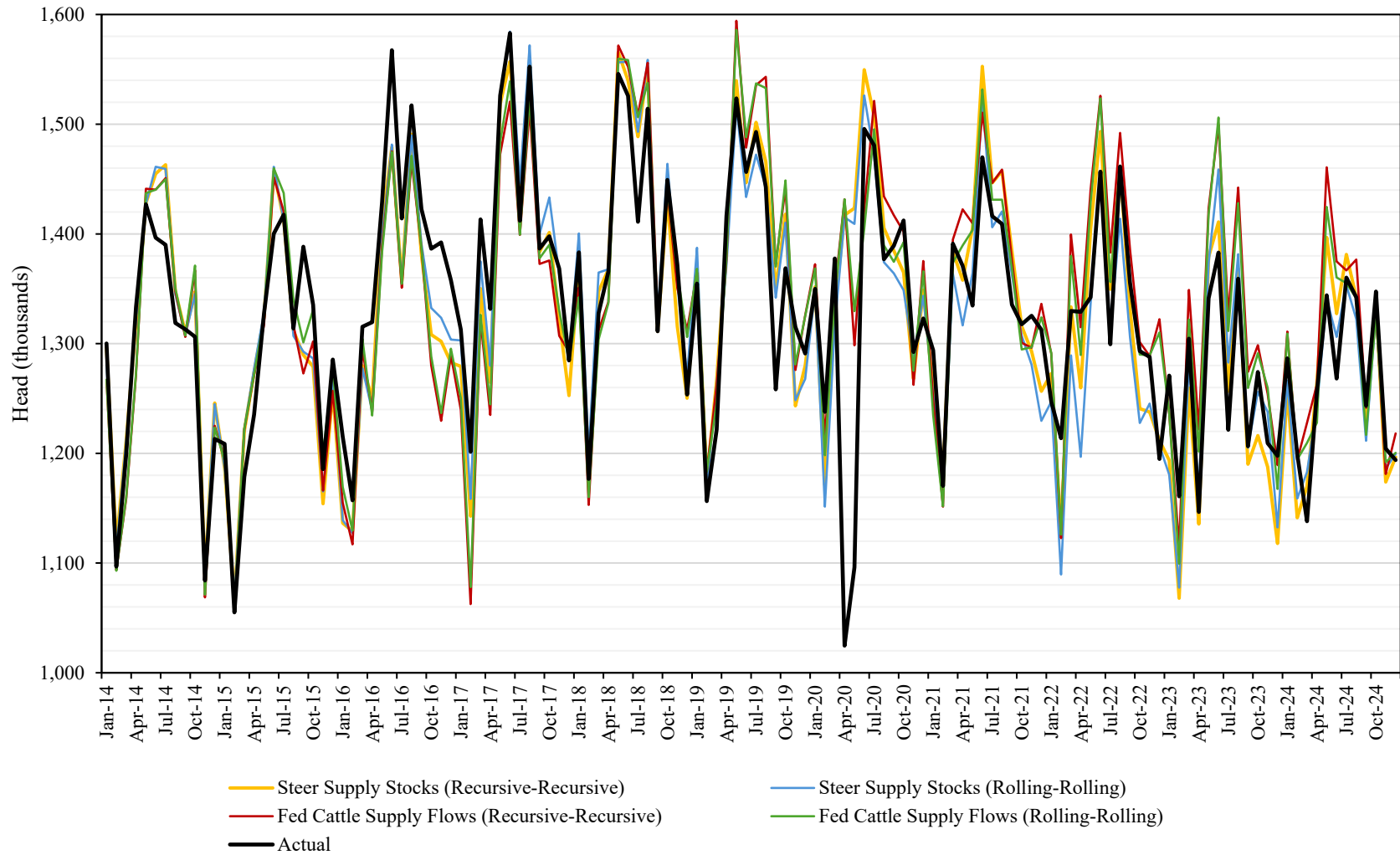


Figure 13: Steer slaughter forecasts

If we again consider the presence of autocorrelated errors as the culprit for deterioration in forecast quality, following inspection of the PACF, requirement of an AR(1) structure was observed across all models.⁶ Figure 14 shows the percent by which forecasts improved from the correction for all months leading to the 24-month out horizon. Overall, models responded well to correction in the short-run and saw large relative gains during the initial 12 months. However, similar to dressed weights, some models did not respond in kind to AR(1) correction. The model containing steer supply stocks forecasted using recursive estimation saw month-to-month losses leading up to month 6. These losses were not substantial in driving errors over the whole 2-year sample though. By month 24, the rolling model containing information on steer supply stocks was the most RMSE minimizing model, followed by recursive steer supply stocks. Models with supply flows were not competitive in the short-run scenario despite near unanimous reductions in RMSE. Table A11 in Appendix D provides the associated error measures for models corrected for autocorrelated errors.

Looking across the 11-year testing sample, improvements overall were sustained, but greater relative improvements were achieved for models containing supply flow information. For estimates of RMSE, decreases for recursive and rolling supply flow models were documented at 6.28 and 8.32 thousand head, respectively. Models of supply stocks had larger declines for recursive forecasts at 11.72 thousand head, but only fell 2.14 thousand head with rolling estimation. Results of the criteria at the 132-month horizon are displayed in Table 8. In Figure 15, forecasts corrected for autocorrelated errors are graphed with the actual observations. Overall, in comparison to the forecasts displayed in Figure 13, corrected models met seasonal

⁶ AR(1) errors solved most issues observed with supply stock models. However, additional complexity was observed in supply flow models. In early run samples, AR(1) inclusion did not entirely reduce autocorrelation issues at lags of 1 and 2. However, by the end of the sample the majority of issues were resolved.

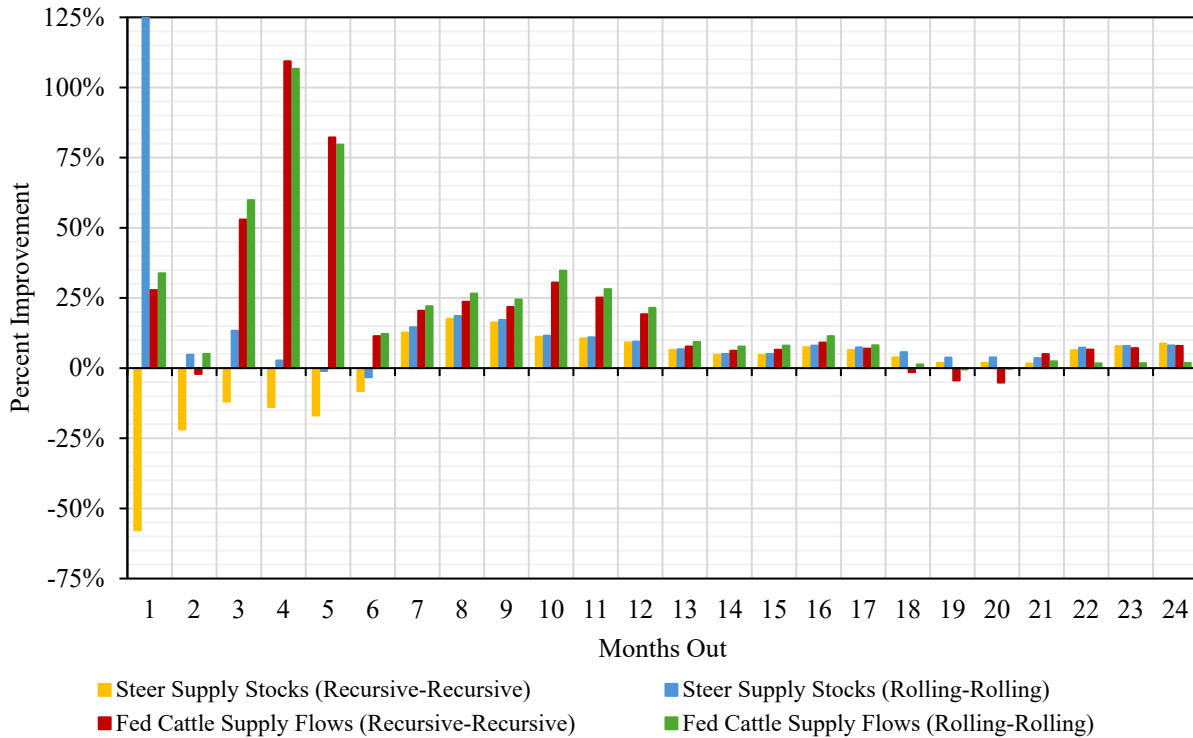


Figure 14: 24-month out steer slaughter forecast RMSE percent change when corrected for autocorrelated errors

peaks and troughs with greater accuracy across the testing window. Forecast estimates were also more in line with changes in seasonal variance. However, severe underestimation and minor overestimation continued to be a problem in the 2022 and 2023 time periods. Considering 2024 in relation to the analog time period, as long as models were corrected for autocorrelated errors, forecasts suggested that information from the 2014 and 2015 time period show promise in their ability to predict the events of 2024.

Table 8: Selected steer slaughter model error results summary at the 132-month horizon when corrected for autocorrelated errors

Model	Method	AR Order	RMSE	MAPE	U_2
Steer Supply Stocks	Recursive-Recursive	AR(1)	55.332	2.697	0.578
	Rolling-Rolling	AR(1)	58.591	2.745	0.612
Fed Cattle Supply Flows	Recursive-Recursive	AR(1)	56.767	2.978	0.593
	Rolling-Rolling	AR(1)	56.839	2.963	0.594

Note: Methods begin with the simulation method for optimal length and are followed by the prediction method.

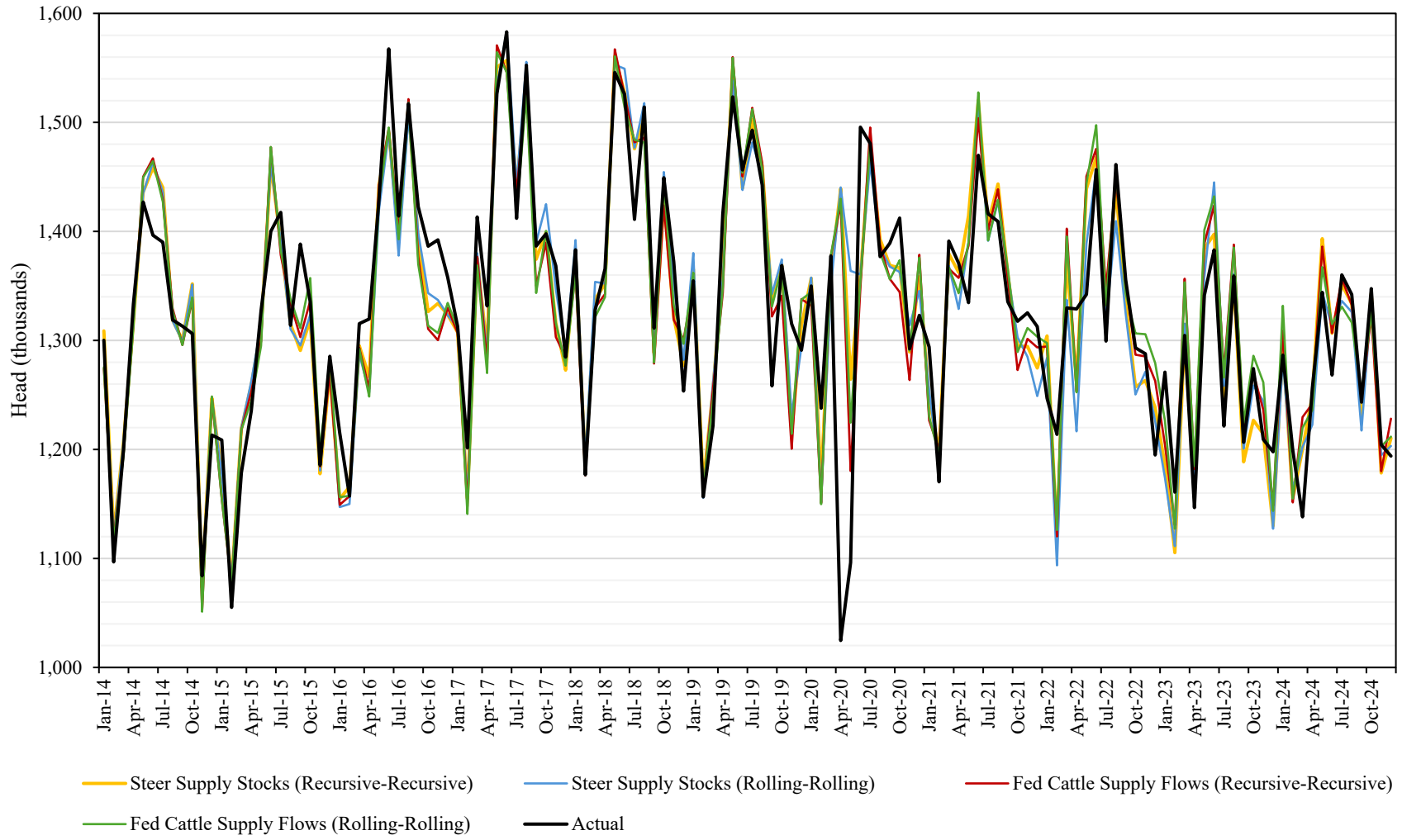


Figure 15: Steer slaughter forecasts corrected for autocorrelated errors

6.3 Heifer Slaughter

Models of federally inspected steer slaughter demonstrated the power of using simple information on supply stocks. Models of federally inspected heifer slaughter echo this trend where every model incorporated in Section 6.3 contains supply information only on heifer supply stocks. During 2015, heifers constituted the smallest contribution to the slaughter mix witnessed in over half a century. As a result, variables documenting the flow of fed cattle through feedlots proved ineffective in producing accurate and quality forecasts. Rather, it was identified that models performed more optimally in the presence of two supply parameters; the percentage of the prior years' calf crop that becomes retained as replacement heifers in the current year and the percentage of the prior years' calf crop that becomes available for slaughter (i.e., other heifers) in the current year.

Starting with summary statistics from simulations, 40 simulations were documented consisting of 200 forecasts. Similar to steer slaughter, models of heifer slaughter preferred the inclusion of greater amounts of history in relativity to dressed weights. However, models of heifer slaughter on average preferred marginally less data compared to steer slaughter. Unlike the other two modeled production outcomes, heifer slaughter possessed no innate pattern among commonly selected starting dates where average and median periods covered a range of roughly two years. For the fixed estimation method that identified optimal starting dates, commonality was observed with steer slaughter models in that both simulations revealed the most commonly selected start date of January 2005. Like both fed cattle dressed weights and steer slaughter, recursive estimation again chose the inclusion of the least amount of data during estimation. Rolling method patterns also persisted with longer relative observation lengths compared to recursive methods. Summary statistics and results are provided in Table 9.

Table 9: Heifer slaughter survey history summary for 2014 to 2015 optimal window

Simulation Design	Starting Date			
	<i>Oldest</i>	<i>Most Common</i>	<i>Average Time</i>	<i>Most Recent</i>
Fixed	Jul-96	Jan-05	Mar-05	Jul-10
Recursive	Jul-01	Jul-07	May-07	Jan-11
<i>Rolling</i>	<i>Jul-94</i>	<i>Jan-07</i>	<i>Apr-06</i>	<i>Jul-10</i>
Simulation Design	Observations (N)			
	<i>Longest</i>	<i>Most Common</i>	<i>Average Length</i>	<i>Shortest</i>
Fixed	210	108	105	42
Recursive	150	78	80	36
Rolling	234	84	93	42

Note: Observations range from the specified start date to Dec-13, the end of the training window. Rolling estimation start dates are italicized to reflect the non-fixed nature of the method.

Different estimation methods performance within the 6-, 12-, 18-, and 24-month out horizons greater aligned with the trends observed in dressed weights. However, like steer slaughter, recursive-recursive and rolling-rolling methods produced ambiguity as to which method possessed greater forecasting ability; at every horizon the margin between the average errors generated was less than 500 head. RMSE ranges acquired from the two methods showed recursive-recursive possessed smaller ranges at months 6 and 12, although box sizes were still very comparable until the 18- and 24-month horizons in which recursive-recursive methods showed to be marginally better. Like both dressed weights and steer slaughter, fixed estimation methods continued to reject fixed forecasting procedures beyond the 12-month horizon. However, in early forecast horizons at 6 and 12 months, fixed-fixed methods delivered only slightly larger errors on average. Visual of the method based performance can be seen in Figure 16 and summary statistics for RMSE and MAPE for the 40 model simulations are provided in Tables A12 and A13 of Appendix D, respectively. To continue with previously established work, recursive-recursive and rolling-rolling models are further developed for their better long-term forecasting ability and to provide contrast between optimized starting dates and observation windows.

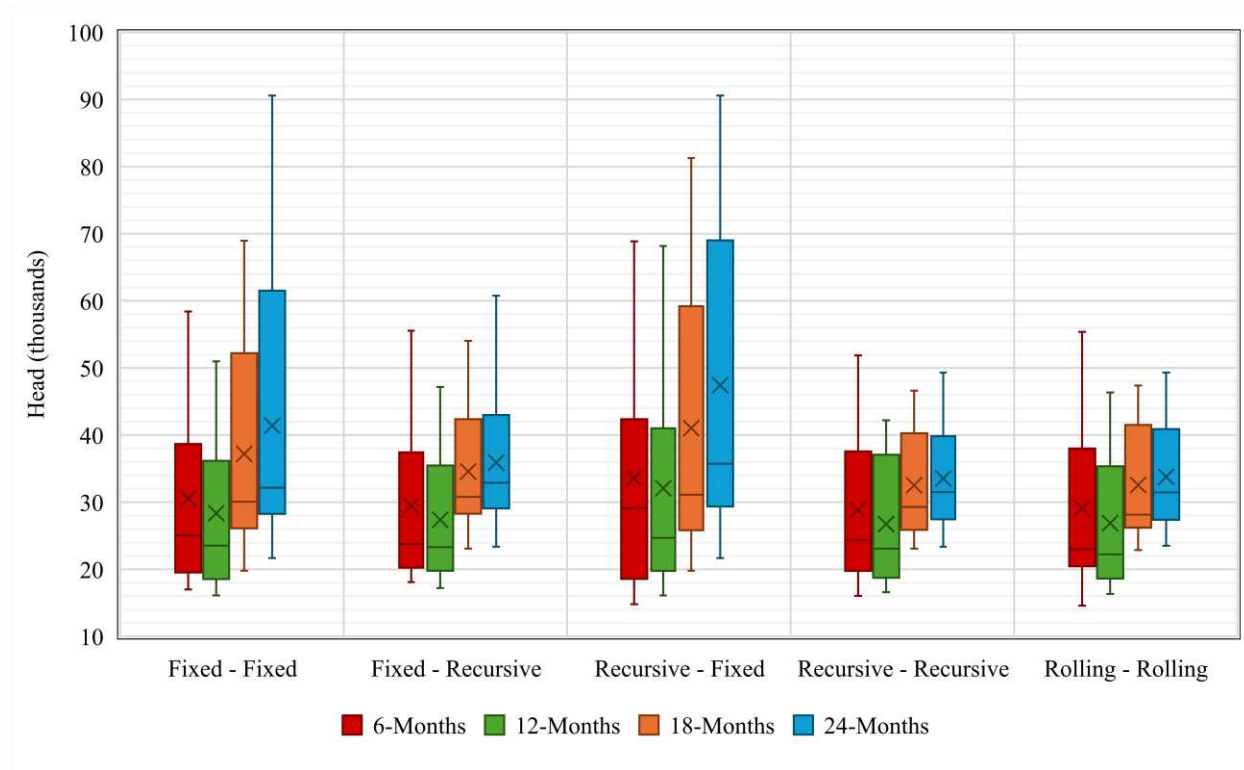


Figure 16: Heifer slaughter simulation method box and whisker plot RMSE summary

Models of FI heifer slaughter that performed well over the 2014 to 2015 time period are characterized by equations 15 through 17. Similar to steer slaughter, criteria and method based rankings of models were relatively uniform in their agreement. Equation 15 defines the universally accepted base model of FI heifer slaughter,

$$\begin{aligned}
 HeiferSlaughter_t &= \alpha + \beta_1 Trend_t + \beta_2 SltrDays_t + \beta_3 PctOtherHeifers_t \\
 &+ \beta_4 PctBeefHeiferReplace_t + \beta_5 CullCowPrice_{t-10} + \sum_{m=1}^{11} \gamma_m D_m + \varepsilon_t
 \end{aligned} \tag{15}$$

where $SltrDays_t$ is as was previously defined for its use in steer slaughter models,

$PctOtherHeifers_t$ is the percent of other heifers available in the current year relative to the calf crop in the prior year, $PctBeefHeiferReplace_t$ is the percent of heifers held as beef cow

replacements in the current year relative to the calf crop in the prior year, and $CullCowPrice_{t-10}$ is the value per hundred pounds of a cull cow from West Kansas included at a lag of 10 months to reflect the producers initial decision to liquidate or retain reproductively mature females.⁷ The lag of 10 months was identified through reviews of cross correlation patterns and was tested at alternative lagged time intervals. Cow slaughter is often driven by cow prices, and tends to have a leading relationship to changes in heifer slaughter; variables of cow slaughter did not produce as near of optimal forecast results as cull cow prices.

Two models that serve as an extension to equation 15 are defined by equations 16 and 17, where models are augmented by the inclusion of price incentives, similar to models of dressed weights and steer slaughter.

$$\begin{aligned}
 &HeiferSlaughter_t \\
 &= \alpha + \beta_1Trend_t + \beta_2SltrDays_t + \beta_3PctOtherHeifers_t \\
 &+ \beta_4PctBeefHeiferReplace_t + \beta_5CullCowPrice_{t-10} \\
 &+ \beta_6HefAlfalfaPriceRatio_t + \sum_{m=1}^{11} \gamma_m D_m + \varepsilon_t
 \end{aligned} \tag{16}$$

$$\begin{aligned}
 &HeiferSlaughter_t \\
 &= \alpha + \beta_1Trend_t + \beta_2SltrDays_t + \beta_3PctOtherHeifers_t \\
 &+ \beta_4PctBeefHeiferReplace_t + \beta_5CullCowPrice_{t-10} \\
 &+ \beta_6FuturesPremium_t + \sum_{m=1}^{11} \gamma_m D_m + \varepsilon_t
 \end{aligned} \tag{17}$$

⁷ Cull cow prices are used from West Kansas due to data availability. A desire during the simulation process was to identify variables that could capture as much historical information as possible. West Kansas prices were the most comprehensive historically for fed and feeder steers and heifers as well as cows. Other cull cow prices from different regions could be used and could produce better results.

In equation 16, similar to steer slaughter, a price ratio is included where the 5 market cash price for a fed heifer per hundred pounds it taken relative to the national price per ton of alfalfa hay. The ratio indicates the same as previously established; a large ratio is indicative of heifer retention from slaughter while a small ratio suggests signals to producers to liquidate fed heifers. In equation 17, as opposed to a profitability ratio, instead the futures premium/discount is reintroduced. In models of steer slaughter, the inclusion of a profitability ratio performed relatively better when compared to models that included the futures premium. Models of heifer slaughter over the long-run responded well to similar information; however, in the short-run the inclusion of the futures premium possessed greater predictive quality. Likely reasons behind such difference include sharp changes in lower percentages of head slaughtered being more easily explained and/or predicted by sharp changes in the futures premium. Steer slaughter consumes the majority of total cattle slaughter, and as such it's possible small changes in the futures premium have trouble capturing larger movements of head slaughtered.

Among the aforementioned models, starting dates and optimal rolling windows were observed to coincide with average and median estimates from the total simulation sample of 200 forecasts; selected models of dressed weights and steer slaughter were not as reflective of their total sample simulation results. Most models gravitated towards starting dates during the 2006 to 2007 time period with only the rolling model containing the profitability ratio choosing a longer history, starting in 2004. Similar to dressed weights and steer slaughter, models of heifer slaughter continue to show no apparent pattern in the selection of full or partial seasons during simulations. A summary of the observed optimal starting periods is available in Table 10. A more comprehensive list of the top 5 competing start dates, along with estimates of RMSE and MAPE for the 24 month out horizon are provided in Table A14 of Appendix D.

Table 10: Selected heifer slaughter model start dates and observations summary

Model	Method	Start Date	Observations (N)
Cull Cow Price	Recursive-Recursive	Jul-06	90
	Rolling-Rolling	<i>Jan-07</i>	84
Cull Cow Price & Heifer Alfalfa Price Ratio	Recursive-Recursive	Jan-06	96
	Rolling-Rolling	<i>Jul-04</i>	114
Cull Cow Price & Futures Premium	Recursive-Recursive	Jul-07	78
	Rolling-Rolling	<i>Jan-07</i>	84

Note: Methods begin with the simulation method for optimal length and are followed by the prediction method. Rolling-Rolling model start dates are italicized to reflect the non-fixed nature of the method.

On the basis of forecast performance, as can be seen in Figure 17, estimates of RMSE grew quickly in response to a large dip in the observed data at the 2-month out forecast horizon (February 2014). During simulations, every variable combination simulated struggled to accommodate for this change.⁸ After the spike in prediction error, values of RMSE stabilized across the models through the end of the 2-year period. In the mix, the models that produced the most RMSE minimizing forecasts at the 24-month horizon were both rolling and recursive forecasts containing the futures premium; the recursive model beat the rolling forecast by a margin of 150 head. The base model containing no measure of price incentive at the time of slaughter also performed well across the sample, and from months 11 to 18, was considered the most accurate forecast. Unlike prior error results observed in dressed weights and steer slaughter, nearly all models of heifer slaughter saw recursive forecasts for a given variable combination outperform their associated rolling forecasts by the end of the sample; the exception to this was the model with no price incentive measure at time t . Estimates of the criteria, including RMSE, MAPE, and Theil's U_2 are available in Table A15 of Appendix D for the 24-month out window.

⁸ Models were re-estimated with the inclusion of a dummy variable at the 1- and 2-month out horizons to smooth RMSE estimates to reflect similar patterns in Figures 6 and 12. Models inclusive of the dummy variable did not dramatically change RMSE. Errors were observed to exhibit smoother behavior at the 2-month horizon if different starting periods were used, but errors across the 24-month period were proportionally larger.

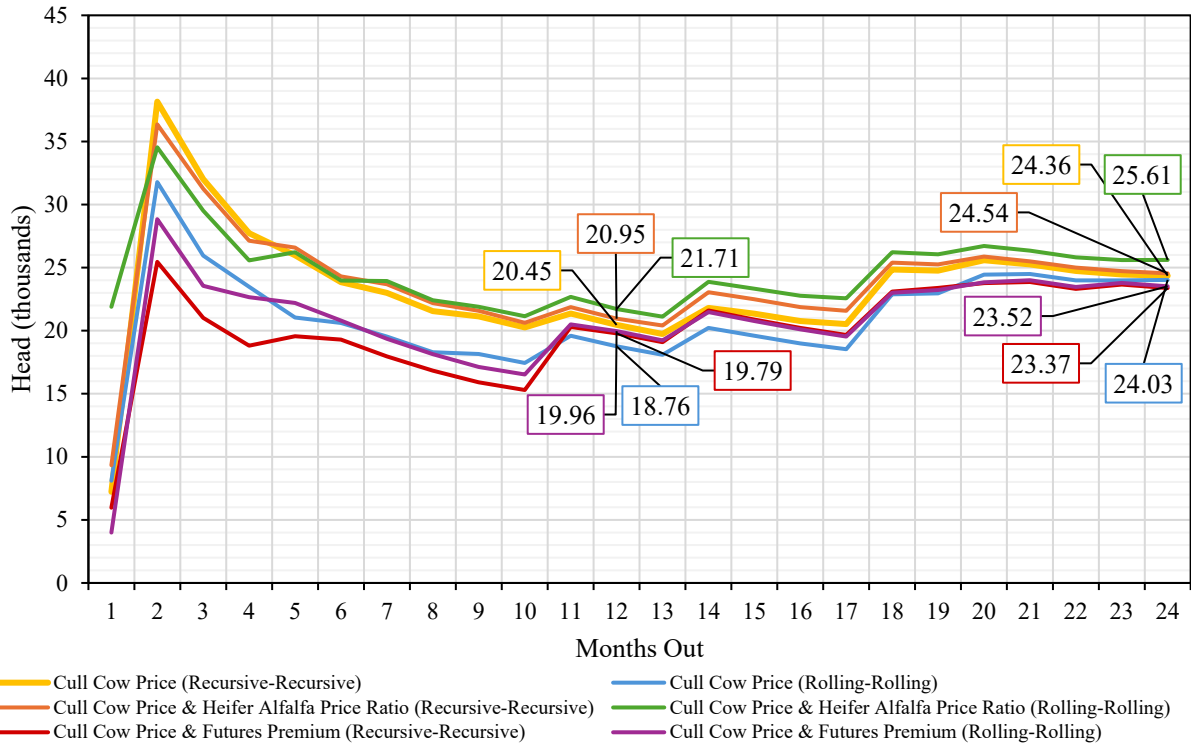


Figure 17: 24-month out heifer slaughter forecast RMSE estimates

It was previously mentioned that the model containing the profitability ratio didn't perform as optimally over the 2-year window, but improved over the 11-year sample. Compared to the model inclusive of the futures premium, the ratio model had lower estimates of RMSE, MAPE, and Theil's U_2 under both recursive and rolling estimation. Out of the 3 models and 6 forecasts, the rolling-rolling model in possession of the ratio minimized error the best. Table 11 displays the long-run error criteria results for the 132-month out horizon. Of more stark interest, was the model not containing either the ratio or futures premium performing competitively in the mix. The cull cow price model possessed the lowest error estimates of all recursive forecasts, and for rolling forecasts was near comparable to the price ratio model. The model inclusive of the futures premium performed the worse of all forecasts in both estimation methods, suggesting revenue incentives during 2014 to 2015 may not have retained their influence by 2024.

Table 11: Selected heifer slaughter model error results for the 132-month out horizon

Model	Method	RMSE	MAPE	U_2
Cull Cow Price	Recursive-Recursive	43.225	4.064	0.622
	Rolling-Rolling	41.671	3.858	0.600
Cull Cow Price & Heifer Alfalfa Price Ratio	Recursive-Recursive	43.604	4.113	0.628
	Rolling-Rolling	40.994	3.797	0.590
Cull Cow Price & Futures Premium	Recursive-Recursive	43.954	4.149	0.633
	Rolling-Rolling	43.029	3.992	0.619

Note: Methods begin with the simulation method for optimal length and are followed by the prediction method.

In Figure 18, forecasts of heifer slaughter are graphed along with the actual values recorded for the series in the 11-year testing window. In comparison to forecasts of dressed weights and steer slaughter, forecasts of heifer slaughter were choppy and frequently missed changes throughout the sample. During analog years of 2014 and 2015, forecasts struggled to predict month-to-month changes where models often over and underestimated slaughter in large movements. Of particular significance, were all models during absolute lows in the summer months of 2015 severely missing the trough. Models predicted heifer slaughter to rise during this time, but heifer slaughter continued to fall. As forecasts pushed further into the 11-year window, similar patterns continued to plague the forecasts and performance remained continually poor. Models performed well during occasional pronounced spikes in heifer slaughter. However, the majority of the time, models struggled with overestimating the magnitude of changes from month-to-month. By 2023 and 2024, forecasts completely deteriorated with not a single forecast following in line with observed values; 2023 was victim to large overestimation, while 2024 was victim to severe underestimation. By method, recursive and rolling models appear to follow no innate pattern aside from recursive forecasts increasingly becoming similar the further into the window they estimated.

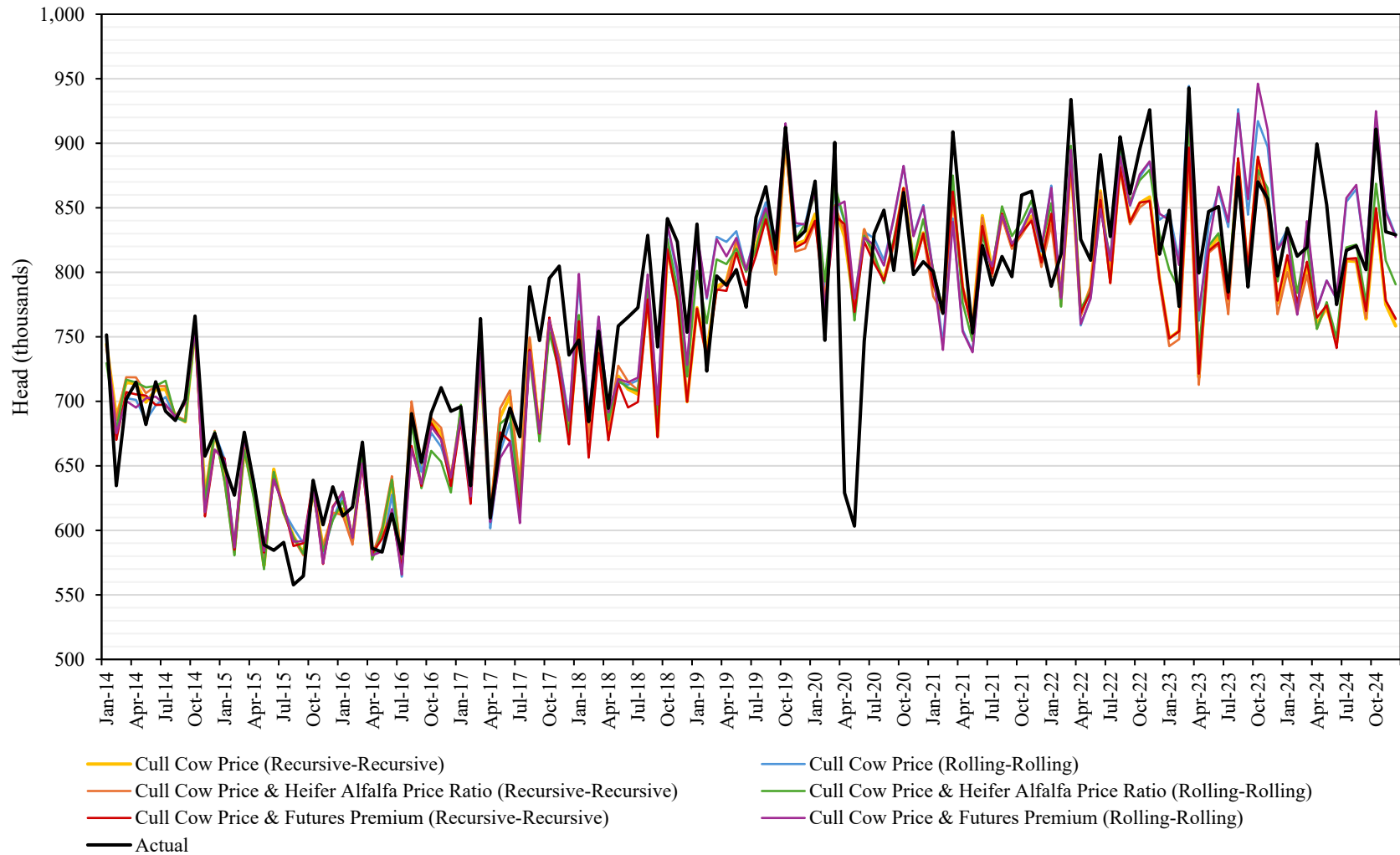


Figure 18: Heifer slaughter forecasts

Compared to dressed weights and steer slaughter, heifer slaughter exhibited the least amount of concern with autocorrelated errors. Although, as model estimation windows were lengthened, first order autocorrelation showed to be an emerging issue. Over short and long-run horizons, the implementation of first order autoregressive errors managed to correct the majority of observed issues.⁹ Figure 19 demonstrates the percentage improvement in forecasts RMSE when corrected for serially correlated errors. Outside of the one-month out horizon, the inclusion of AR(1) errors reduced forecast quality in models for virtually every month of the entire 2-year window. By the 24-month out horizon, some models managed to witness improvement. However, gains made to RMSE were minimal and in the best case only reached 1.7 percent. Expanding the window to the 132-month out horizon, RMSE reductions were more pronounced by estimating models with AR errors because of models observed issues growing with time. For all recursive models, improvements made hovered between 14 and 15 percent, while rolling models achieved gains by from roughly 9 to 11 percent. A summary of model error performance is provided in Table 12 for the 132-month out horizon.

Table 12: Selected heifer slaughter model error results summary at the 132-month horizon when corrected for autocorrelated errors

Model	Method	AR Order	RMSE	MAPE	U_2
Cull Cow Price	Recursive-Recursive	AR(1)	36.971	3.307	0.5321
	Rolling-Rolling	AR(1)	37.910	3.403	0.5456
Cull Cow Price & Heifer Alfalfa Price Ratio	Recursive-Recursive	AR(1)	37.120	3.302	0.5342
	Rolling-Rolling	AR(1)	36.510	3.229	0.5254
Cull Cow Price & Futures Premium	Recursive-Recursive	AR(1)	37.792	3.409	0.5439
	Rolling-Rolling	AR(1)	39.251	3.552	0.5649

Note: Methods begin with the simulation method for optimal length and are followed by the prediction method.

⁹ The model containing cull cow prices and the futures premium in a recursive estimation framework showed negligible concerns with first order autocorrelation in the early testing sample. However, by the end of the sample there inclusion was observed to be necessary. Thus, AR(1) errors were included in the model for comparison against models that neglect the issue for the shorter 24 month out horizon. Most models also had minor autocorrelation at a lag of 3, but the issue was not addressed.

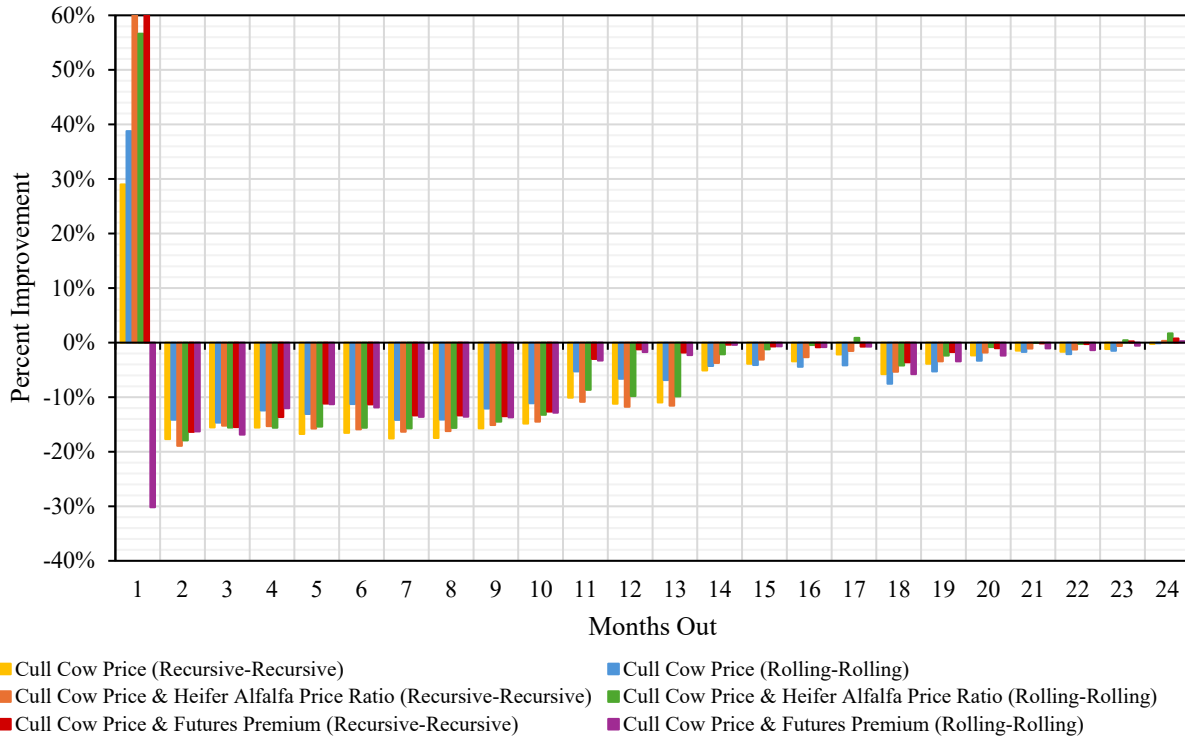


Figure 19: 24-month out heifer slaughter forecast RMSE percent change when corrected for autocorrelated errors

In the 24-month out horizon, lack of improvement in forecast accuracy is demonstrated by models increased fluctuation from months 2 to 7 and by newly observed overestimation in upward changes during months 12 and 15. Figure 20 contains the updated forecasts corrected for autocorrelated errors. Forecasts further into the testing window showed models visibly attained enhancements where month-to-month changes were more subtle and movements tended to agree with actual values. For years 2023 and 2024, forecasts improved slightly. However, generally forecasts still showed choppy and inaccurate behavior with frequent overestimation during 2023 and mixed outcomes in 2024. Holistically, compared to models of steer slaughter and dressed weights, DTDS models of heifer slaughter visually do not appear to provide comparable quality. While all models possess low errors on average, sharp changes were not captured well and inconsistency in error generation remained an issue across horizons.

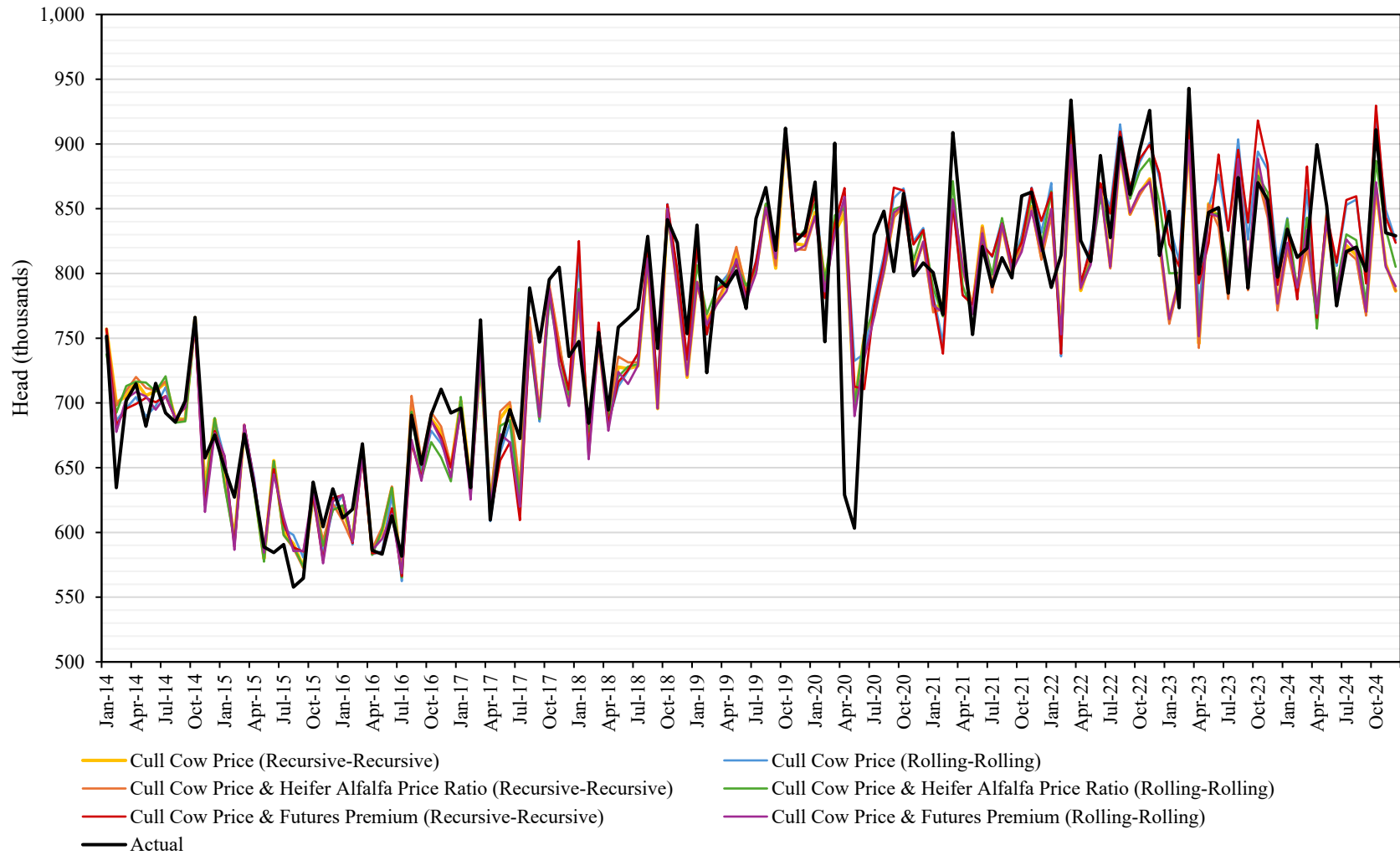


Figure 20: Heifer slaughter forecasts corrected for autocorrelated errors

6.4 Fed Beef Production

A pillar of this work is to demonstrate potential necessity in tailoring single-equation forecasts to their given explanatory power in place of making sweeping assumptions such as entire systems requiring a uniform start date in history. To demonstrate this concept, forecasts are aggregated into estimates of fed beef production based on their inclusion or exclusion of autoregressive errors and also by two different forecast estimation processes: (1) where forecasts are acquired from re-estimated select models of each outcome variable, but all with a uniform start date in January 1990, and (2) where forecasts of the same select models are aggregated based on the forecasts that were optimized to their specific survey history. Models selected from each section are those that performed relatively more optimal in comparison to their competitors and that managed to perform well in long and short term horizons holistically; these models correspond equations 12, 13, and 15.

In the 24-month out forecast window, results almost unanimously support that optimizing forecasts around their specific survey history increases forecast accuracy and quality. Starting with forecasts that neglect the presence of autocorrelated errors, at the 24-month horizon reductions in estimates of RMSE were achieved by 73.9 and 85.3 percent for recursive and rolling methods, respectively. For models that contained autoregressive errors, results continued to support optimized survey history; however, gains were more modest with recursive methods posting increases of 10.9 percent and rolling estimation methods improving by 19.9 percent. Considering forecasts earlier in the testing window, in the case autoregressive errors were not included in models, performance at every horizon increased. Although, in the case autoregressive errors were included, mixed results emerged from months 2 to 10, where in most cases forecasts forced to a January 1990 start date outperformed forecasts with optimized survey history.

Probable sources of this discrepancy come from steer and heifer slaughter models producing mixed feedback to the inclusion of autoregressive errors within initial months. Differences between the optimized forecasts and those started in January 1990 are visually demonstrated in Figure 21, where it can be understood that a positive percent difference indicates an improvement in forecast accuracy based on the premise that optimized start dates reduced errors. Tables of the various error criteria, including RMSE, for fed beef production forecasts are provided in Tables A17 and A18 of Appendix D.

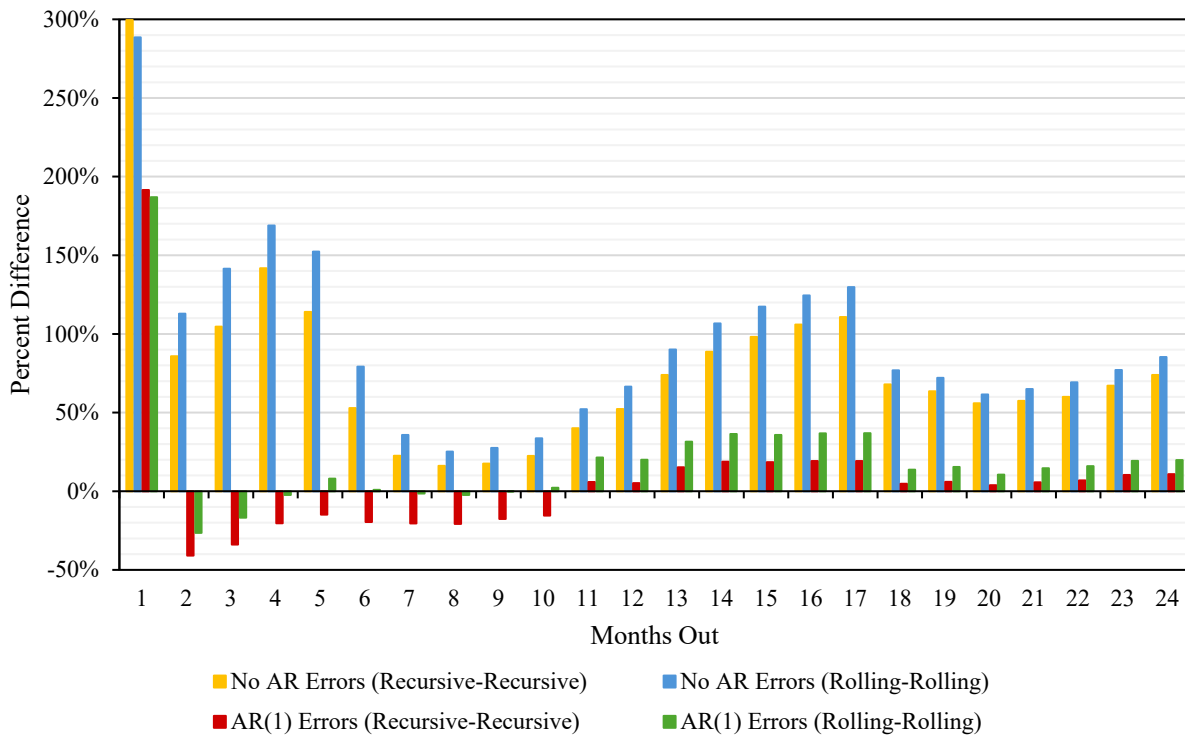


Figure 21: Percentage difference in RMSE estimates for forecasts with optimized survey history versus with uniform estimation beginning in 1990 for fed beef production

Observed differences by the 132-month out horizon confirm that optimizing survey history for by-parts forecasting systems overall boosts forecasts performance. Specifically, for models that exclude autoregressive errors, improvements in RMSE were achieved by 19.2 and 20.7 percent for recursive and rolling estimation, respectively. For models containing

autoregressive errors, similar to the 24-month out horizon, improvements were sustained in more modest levels by 7.6 and 8.1 percent for recursive and rolling estimation, respectively. Changes to RMSE overall indicate improvements made to the average magnitude in errors observed for fed beef production by millions of pounds. If estimates of MAPE are considered, more pronounced gains are acquired reflective of the overall improvements made to the average accuracy of models. Notably, under both estimation methods, models without AR errors witnessed values of MAPE be reduced by 44.5 percent and models that include AR errors seeing improvements in recursive methods by 15.3 percent and rolling methods by 20.9 percent. Estimates of Theil's U_2 echo the same support with percent changes similar to RMSE. Specifically, for models without AR errors, estimates produced with a January 1990 start date placed Theil's U_2 at the cusp of rejection compared to the naïve no-change extrapolation. However, after allowing dynamic start dates within the system, values continue to substantiate quality in the forecast models. Table 13 provides criteria estimates for fed beef production based on differentiated start dates. Visuals of the forecasts over the 11-year testing window are also available in Figures A5 and A6 of Appendix E.

Table 13: 132-month out fed beef production error results summary

Model	Method	Start Date	RMSE	MAPE	U2
No AR Errors	Recursive-Recursive	Jan-90	103.511	4.800	0.858
		Optimized	83.667	2.665	0.693
	Rolling-Rolling	<i>Jan-90</i>	103.085	4.846	0.854
		<i>Optimized</i>	81.798	2.677	0.678
AR Errors	Recursive-Recursive	Jan-90	79.349	2.699	0.658
		Optimized	73.307	2.286	0.608
	Rolling-Rolling	<i>Jan-90</i>	78.919	2.773	0.654
		<i>Optimized</i>	72.554	2.192	0.601

Note: Titles for table sections begin with the simulation method for optimal length and are followed by the prediction method. Rolling-Rolling model start dates are italicized to reflect the non-fixed nature of the method. AR error models include AR(1) for slaughter models and ARMA(1,1) & SAR(1) errors for dressed weights.

CHAPTER 7: CONCLUSION

The methods by which agricultural systems have been understood and forecasted show major disconnect between the academic literature and participants of the private sector. The overarching objective of this paper is to demonstrate that systems based forecasting can be simplified and enhanced when estimated by-parts using single-equation frameworks. Using fed beef production as a case study, this analysis identified four key findings: (1) time and historical data are crucial considerations in forecast development, (2) adjustments for autocorrelated errors in seasonal forecasting models should be considered, (3) the efficacy of a forecast estimation method is contingent upon the forecast horizon, and (4) simplicity in both assumptions and methods can yield competitive and highly accurate forecasts.

Structural changes in markets have been a longstanding focus of economic research. The question of the appropriate survey length of data for forecasting is one of many approaches to examining changes in underlying market fundamentals. During simulations of steer slaughter, heifer slaughter, and fed cattle dressed weights, all models exhibited significant variation in the time periods most likely to produce high-quality forecasts. Among the optimally selected models, results varied considerably regarding how included explanatory information managed error minimization over a two-year horizon. For instance, a single forecast of steer slaughter incorporated the most extensive historical data of all reviewed models, commencing in 2002. On the other hand, nearly all models of fed cattle dressed weights opted for starting periods in 2011, the earliest constrained date. Observations across models revealed that average and median starting periods consistently rejected the inclusion of data predating 2000. For practitioners and analysts in cattle markets, these findings suggest that extensive possession of historical data may

not inherently be necessary and/or beneficial for forecasting monthly series. Instead, reduced historical data that considers more comparable market dynamics is more likely to yield accurate predictions.

In addition to optimal estimation windows, the selection of analog years for error minimization demonstrated their relevance during events in 2024. The subsequent analysis identified the period between 2014 and 2015 as the suspected analog years for total fed beef production. During this time, total cattle slaughter was entering a trough and weights in fed cattle had jumped to record levels, among other events. The efficacy of optimizing forecasts around this period was evident, as models of steer slaughter and dressed weights confirmed that the patterns and selected explanatory information remained relevant in 2024. However, for models of heifer slaughter the selected analog period did not suggest an appropriate fit. During 2014 and 2015, heifers constituted the lowest contribution to total slaughter documented in decades. In 2024, the percentage of heifers in the slaughter mix was among the highest ever recorded. While models of heifer slaughter managed to maintain low errors on average, forecasts for 2024 struggled to match realized values. Probable sources of this discrepancy include the need for an alternative analog period, and it is likely that over the 11-year period from 2014 to 2024, the mechanisms and variables influencing heifer slaughter have changed.

Notable outcomes and errors derived from forecasts of heifer slaughter suggested that monthly models estimated using a DTDS specification may not have provided the best forecast results. Aside from heifer slaughter requiring an alternative analog year compared to other outcomes in the system, seasonal changes and variation in month-to-month outcomes were more challenging to capture with this model. In practice, analysts commonly assess day-to-day and week-to-week changes in heifer slaughter to develop a bias for future values of either monthly or

annual slaughter. In the literature, models were only observed to capture quarter-to-quarter and year-to-year changes. Assessments of monthly models suggest that the economic factors known to influence producers' decisions to retain or market heifers are likely to be more accurately captured over larger intervals of time due to cow-calf producers' budgetary decisions occurring over extended timeframes. Alternatively, spatial characteristics were not explored in this analysis, and variables estimable using weekly data were also not examined. There is a possibility that more complex methods, which can more readily manage higher frequency time intervals and/or panel data approaches, could capture monthly variations more accurately.

In the broader context of forecasting systems by-parts, distinct trends have emerged regarding the necessity for tailored evaluation of autocorrelated error concerns among models. While models of steer slaughter responded effectively to simple remedial measures in both long- and short-term windows, models of dressed weights exhibited significant variability over time, and models of heifer slaughter did not similarly benefit from the inclusion of autoregressive errors in the two-year forecast period. A critical question posed during examinations of forecast performance was whether models could reduce prediction error if they were corrected for autocorrelated errors. Findings that answer this questions largely suggest yes, models are more capable when corrected. However, just as models responded variably to different historical data, they also exhibited dissimilar responses to various corrective measures. Practitioners should approach these concerns with caution. Thorough identification of the appropriate remedial measure for autocorrelated errors should consider not only the patterns observed during the estimable training window but also how these patterns evolve with historical data in applicable testing windows.

The overarching perspective of this paper posits that systems forecasting by components can yield accurate forecasts under subjective constraints of survey history and autocorrelated error corrections. However, the methods by which forecasts are individually produced are critically important for practitioners. Among all reviewed models, 120 simulations were conducted, resulting in 600 different forecast outputs. The methods employed for identifying optimal start dates in models were fixed and recursive estimation, while rolling estimation was used to determine the optimal number of observations in a mobile window over time. During simulations, models using rolling forecast procedures in the two-year testing period performed the best on average. However, horizon-specific error results were often closely comparable to those derived from recursive estimation. In the months leading to the one-year forecast horizon, fixed estimation demonstrated a nearly equivalent ability to produce accurate forecasts. Although, when evaluated at 18- and 24-month horizons, fixed estimation resulted in noticeably greater error. These findings underscore two key takeaways: (1) employing fixed estimation in monthly DTDS models can produce quality and competitive forecasts over one-year horizons, and (2) forecasts extending beyond the one-year timeframe require adaptation to new and changing market information. Seasonality in cattle markets profoundly impacts forecast production. It is plausible that recursive and rolling estimation excel due to their capabilities in capturing these seasonal changes.

The duration required by practitioners to implement the reviewed estimation and simulation methods constitutes a critical factor, as this study seeks to offer prescriptive solutions rather than additional complexity. First, in the context of forecasting within management settings, simulations can be time-intensive and depend on the window, or potential analog period, during which forecasts are desired to minimize error. This analysis employed a 2-year window to

demonstrate a theoretical assumption regarding analog years as a potential weighting measure in forecasting. Models could have been optimized over the entire 11-year testing window or, alternatively, solely over 2024. This consideration is significant because recursive and rolling estimation only demonstrated their importance when testing windows extended beyond the year-out forecast. Recursive and rolling estimation also present more complex methods that may not yield apparent benefits if the practitioner is solely concerned with the forthcoming year; in which case fixed estimation can be more readily accommodated. However, the ease of implementation is contingent upon the explanatory information included within a model and the software used in computations. Regarding explanatory variables, one should evaluate the value of simple assumptions and the time required to forecast input variables for their models. In the steer slaughter section, it was observed that the model incorporating annual steer supply information, the number of business days in a month, and the input and output prices of alfalfa hay and fed steers demonstrated greater accuracy in both short and long-run horizons compared to its competitor, which included a larger number of independent variables, most of which are more complex in derivation and causal assumption. Selecting both the method and variables that align with one's time constraints is a crucial consideration for efficient workflow.

Secondly, for a researcher inclined to employ more complex methods, say to mitigating concerns of endogeneity, this analysis also yields valuable insights. Models using simultaneous systems of equations, such as vector autoregression, can be refined by examining systemic patterns among equations within the system. For instance, Tables A4, A9, and A14 in Appendix D delineate the top five estimation windows identified for the models discussed in Chapter 6. While certain models, such as dressed weights, favored a shorter historical window, others, like steer and heifer slaughter models, identified commonalities in near-optimal survey history among

simulated models. This relationship suggests that simultaneous forecasts should commence where steer and heifer slaughter models converge. Although errors are anticipated to be larger for dressed weights forecasts, the system is likely to yield more accurate results than if all models were initiated in January 1990. Models are also expected to achieve greater concordance in survey history among included equations if simulated by monthly repetitions. In this analysis, models were simulated in backward iterations by six-month steps to ascertain the significance of full or partial seasons in the selection process. No definitive pattern emerged, indicating that the practitioner's choice of historical sampling steps is not of considerable concern.

The findings of this study underscore the pivotal role of data selection and timing in forecast modeling. A model's performance is contingent on the predictive power of the included explanatory information and the manner in which relationships are permitted to evolve. Demonstrated in this analysis, structural shifts in cattle markets necessitate adaptive forecasting approaches that balance theoretical rigor with practical application. Furthermore, the selection of explanatory variables should be guided not only by their causal relevance, but also by their ease of implementation as forecastable inputs. This study substantiates the hypothesis that forecasting systems by-parts offers a practical and effective alternative to more complex, simultaneous systems approaches. By strategically optimizing estimation windows, identifying analog years, and addressing autocorrelated errors, practitioners can enhance forecast accuracy without the added complexity frequently observed in the literature. As market dynamics continue to evolve, so too must approaches to forecasting. To ensure that both academic and industry perspectives remain aligned in their pursuit of actionable solutions, this paper serves as a bridge between theory and practice.

REFERENCES

- Aadland, D. (2004). Cattle cycles, Heterogeneous Expectations and the Age Distribution of Capital. *Journal of Economic Dynamics and Control*, 28(10), 1977-2002.
- Abidoye, B., & J.D. Lawrence. (2009). "A Limited Information Bayesian Forecasting Model of the Cattle SubSector." Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. St. Louis, MO. [<http://www.farmdoc.uiuc.edu/nccc134>].
- Albright, M.L., Schroeder, T.C. & Langemeier, M.R. (1994). Determinants of Cattle Feeding Cost-of-Gain Variability. *Journal of Production Agriculture*, 7, 206-210.
- Allen, P. (1994). Economic Forecasting in Agriculture. *International Journal of Forecasting*, 10, 81-125.
- Bacon, K.J., J.N. Trapp, & S.R. Koontz. (1992). "Forecasting Short-Run Fed Cattle Slaughter." Proceedings of the NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. Chicago, IL. [<http://www.farmdoc.uiuc.edu/nccc134>].
- Balagtas, J.V. & Cooper, J.C. (2021). The Impact of COVID-19 on United States Meat and Livestock Markets. *Choices, The Magazine of Food, Farm, and Resources Issues*, 36(3).
- Barrow, D.K. & Kourentzes, N. (2016). Distributions of forecasting errors of forecast combinations: Implications for inventory management. *International Journal of Production Economics*, 177, 24-33.
- Bliemel, F. (1973). Theil's Forecast Accuracy Coefficient: A Clarification. *Journal of Marketing Research*, 10(4), 444-446.
- Campbell, J.Y., Lo, A.W., & MacKinlay, A.C. (1997). *The Econometrics of Financial Markets*. Princeton University Press.
- Falk, B. & Orazem, P.F. (1985). *A Theory of Future's Market Responses to Government Crop Forecasts*. (Working Paper No. 150). Department of Economics, Iowa State University, Ames.
- Granger, C. & Newbold, P. (1973). Some comments on the evaluation of economic forecasts. *Applied Economics*, 5, 35-47.

- Green, K. & Armstrong, J. S. (2015). Simple versus complex forecasting: The evidence. *Journal of Business Research*, 68(8), 1678-1685.
- Isengildina, O., Irwin, S.H., & Good, D.L. (2006). The Value of USDA Situation and Outlook Information in Hog and Cattle Markets. *Journal of Agricultural and Resource Economics*, 31(2), 262-282.
- Kastens, T. L., Jones, R., & Schroeder, T. C. (1998). Futures-Based Price Forecasts for Agricultural Producers and Businesses. *Journal of Agricultural and Resource Economics*, 23(1), 294–307.
- Kastens, T. L., Schroeder, T. C., & Plain, R. (1998). Evaluation of Extension and USDA Price and Production Forecasts. *Journal of Agricultural and Resource Economics*, 23(1), 244–261.
- Koontz, S. R. (2023). *Perspectives on Cattle Price Forecasting and Cattle/Beef Market Modeling*. Department of Agricultural and Resource Economics – Colorado State University. <https://webdoc.agsci.colostate.edu/koontz/vt-ers/Perspective%20on%20Cattle%20Price%20Forecasting.pdf>
- Langemeier, M., Schroeder, T., & Mintert, J. (1992). Determinants of Cattle Finishing Profitability. *Southern Journal of Agricultural Economics*, 24(2), 1-7.
- Lawrence, J., Mintert, J., Anderson, J.D., & Anderson, D.P. (2008). Feed grains and livestock: Impacts on meat supplies and prices. *Choices, The Magazine of Food, Farm, and Resources Issues*, 23, 11-15.
- Linnell, P.B. (2017). *Forecasting Fed Cattle Prices: Errors and Performance During Periods of High Volatility* (Publication No. 14544) [Master’s thesis, Colorado State University]. Mountain Scholar.
- Lusk, J.L., Tonsor, G.T. & Schulz, L.L. (2021). Beef and Pork Marketing Margins and Price Spreads during COVID-19. *Applied Economic Perspectives and Policy*, 43(1), 4-23.
- MacDonald, J.M. & Hoppe, R.A. (2018). *Examining consolidation in U.S. Agriculture*. U.S. Department of Agricultural, Economic Research Service. <https://www.ers.usda.gov/amber-waves/2018/march/examining-consolidation-in-us-agriculture/>
- Maples, W.E., Brorsen, W.B., Hahn, W.F., MacLachlan, M., & Chalise, L. (2022). *Structure of the USDA Livestock and Poultry Baseline Model*. U.S. Department of Agriculture, Economic Research Service. <https://www.ers.usda.gov/webdocs/publications/103338/tb-1956.pdf?v=7985.9>
- Muth, J. F. (1961). Rational Expectations and the Theory of Price Movements. *Econometrica*, 29(3):315–335.

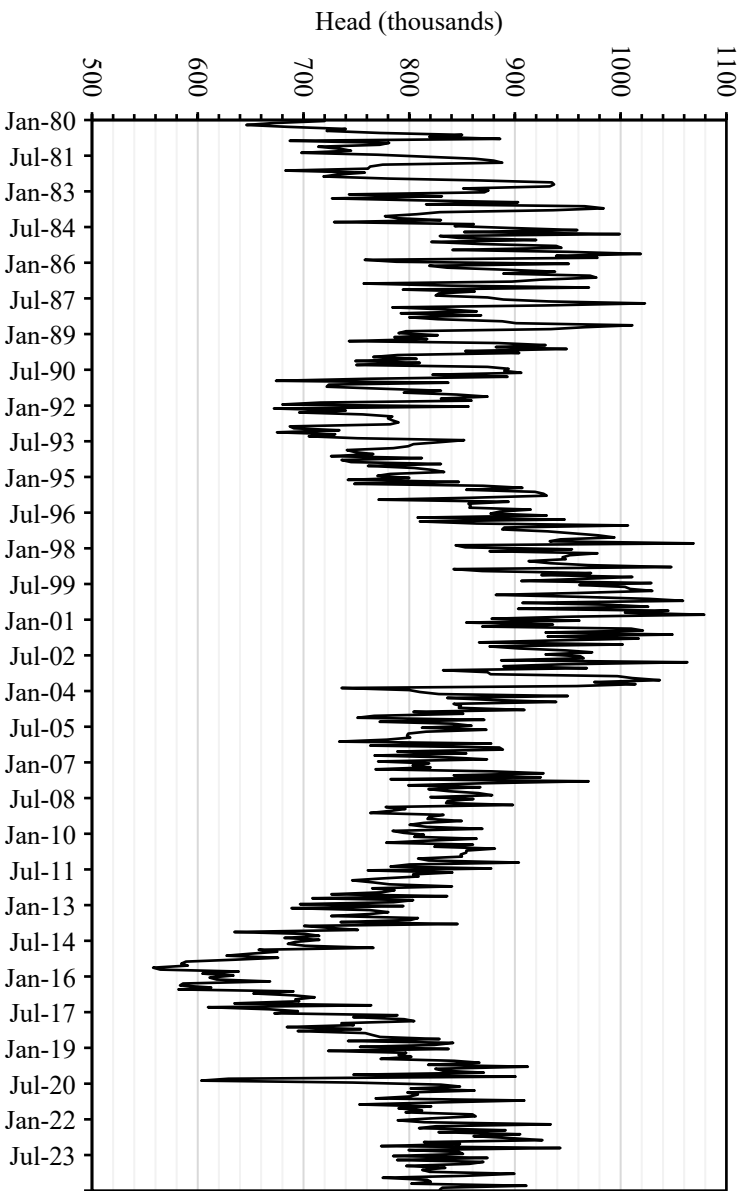
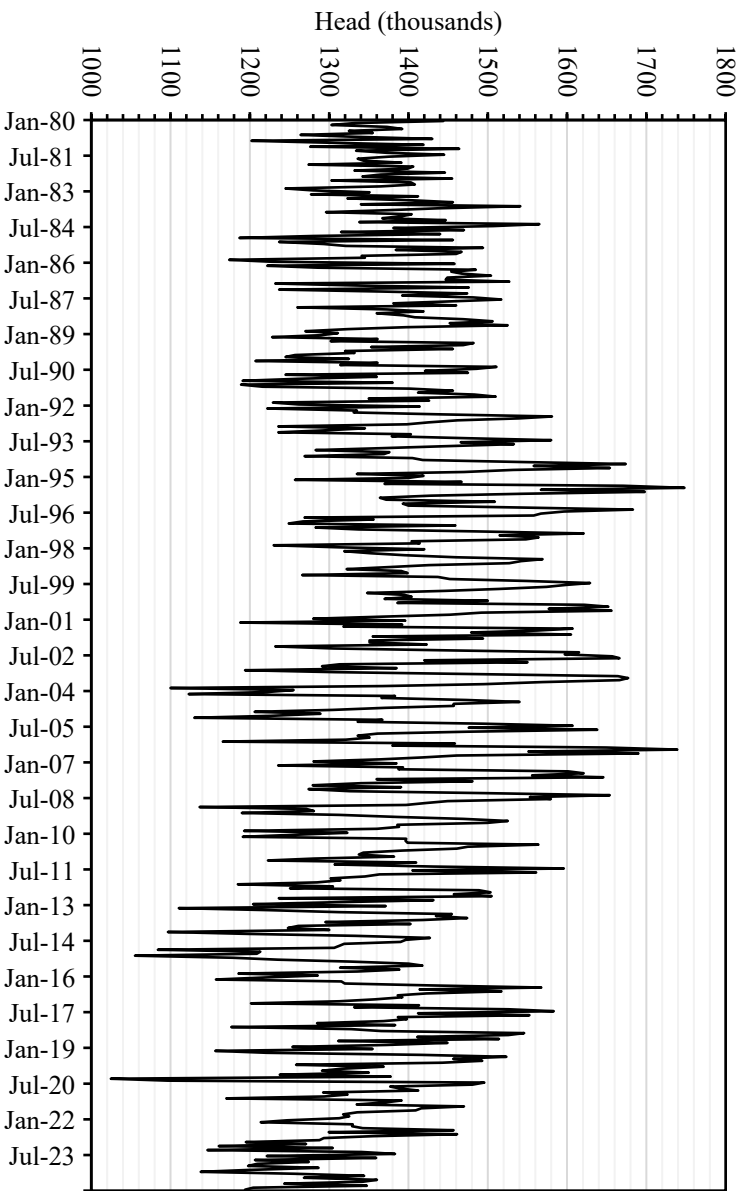
- Muth, M., & Read, Q. 2020, July 7. *Effects of COVID-19 Meat and Poultry Plant Closures on the Environment and Food Security*. RTI International. <https://www.rti.org/insights/covid-19-effect-meat-supply-chain>
- Nelson, B. 2024, August 30. *Beef Price Soar to Record Highs, Yet Farmers Struggle to Reap the Benefits*. American Farm Bureau Federation. <https://www.fb.org/market-intel/beef-prices-soar-to-record-highs-yet-farmers-struggle-to-reap-the-benefits>
- Norwood, F.B. & Schroeder, T.C. (2000). Usefulness of Placement-Weight Data in Forecasting Fed Cattle Marketings and Prices. *Journal of Agricultural and Applied Economics*, 31(1), 63-72.
- Nordhaus, W. D. (1987). Forecasting Efficiency: Concepts and Applications. *Review of Economics and Statistics*, 69(4), 667-674.
- Patalee, M. A. B. & Tonsor, G. T. (2021). Impact of weather on cow-calf industry locations and production in the United States. *Agricultural Systems*, 193, 103212.
- Payne, N., & B. Karali. (2015). "Can Cattle Basis Forecasts Be Improved? A Bayesian Model Averaging Approach." Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. St. Louis, MO. [http://www.farmdoc.illinois.edu/nccc134].
- Rosen, S., Murphy, K.M., and Scheinkman, J.A. (1994). Cattle Cycles. *Journal of Political Economy*, 102(3):468–492.
- Schultz, L. (2022, May). Detailing the supply curve for beef. *Ag Decision Maker Newsletter – Iowa State University Extension and Outreach*. <https://www.extension.iastate.edu/agdm/articles/schulz/SchMay22.html>
- Stehle, A., Peel, D.S., & Riley, J.M. (2018). A Profile of Cattle Feeding: Beyond the Averages. *Western Economic Forum*, 16(2), 62-77.
- Stillman, R. P. (1985). *A Quarterly Model of the Livestock Industry*, 1711, U.S. Department of Agriculture, Economic Research Service.
- Stock, J. H. & Watson, M. W. (2006). *Handbook of Economic Forecasting*. Elsevier.
- Svolba, G. (2012). *Data Quality for Analytics Using SAS*. SAS Institute.
- Tonsor, G. T., Dhuyvetter, K. C., & Mintert, J. R. (2004). Improving Cattle Basis Forecasting. *Journal of Agricultural and Resource Economics*, 29(2), 228–241.
- USDA NASS. (2024). *Cattle*.
- NDMC. (2024). *U.S. Agricultural Commodities in Drought*.

Weimar, M. R., & R. P. Stillman. (1990). "A Long Term Forecasting Model of the Livestock and Poultry Sectors." Proceedings of the NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. Chicago, IL. [<http://www.farmdoc.uiuc.edu/nccc134>].

Zapata, H. O., & Garcia, P. (1990). Price Forecasting with Time-Series Methods and Nonstationary Data: An Application to Monthly U.S. Cattle Prices. *Western Journal of Agricultural Economics*, 15(1), 123–132.

APPENDIX A

Plots of federally inspected slaughter and dressed weights in cattle: visually demonstrating the purpose of (dis)aggregation in dependent variables.



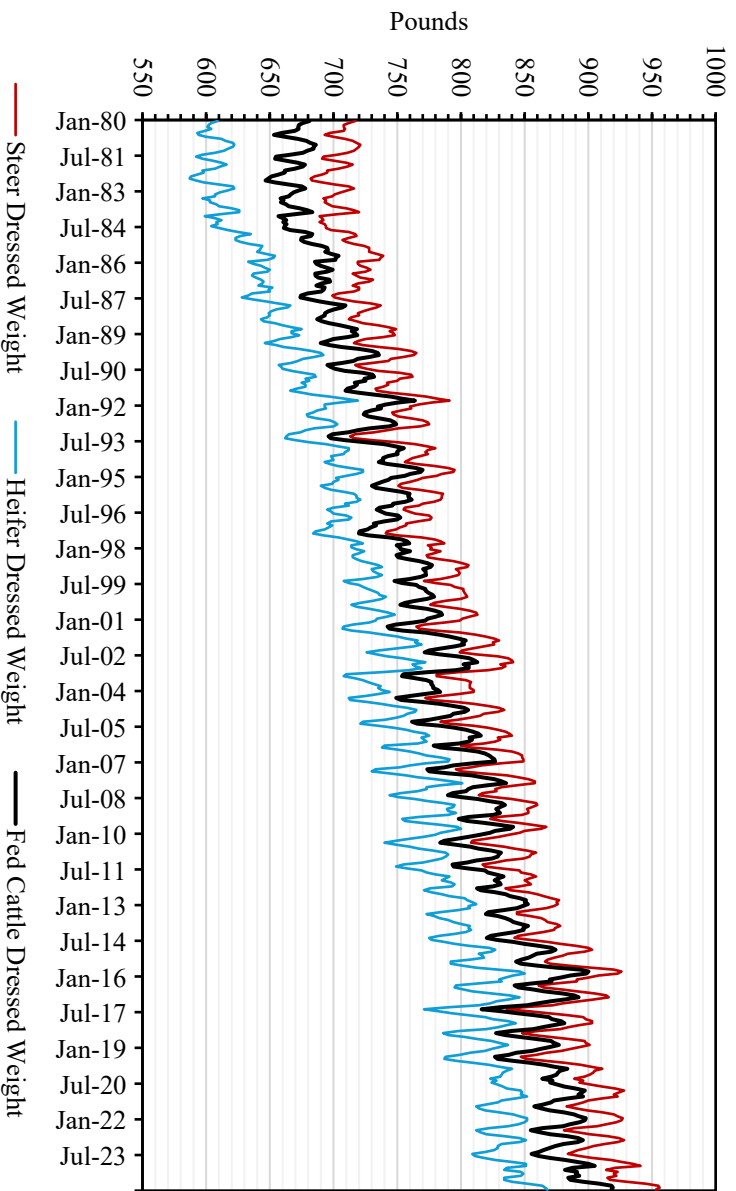


Figure A3: Steer and heifer (fed) dressed weights, 1980 – 2024

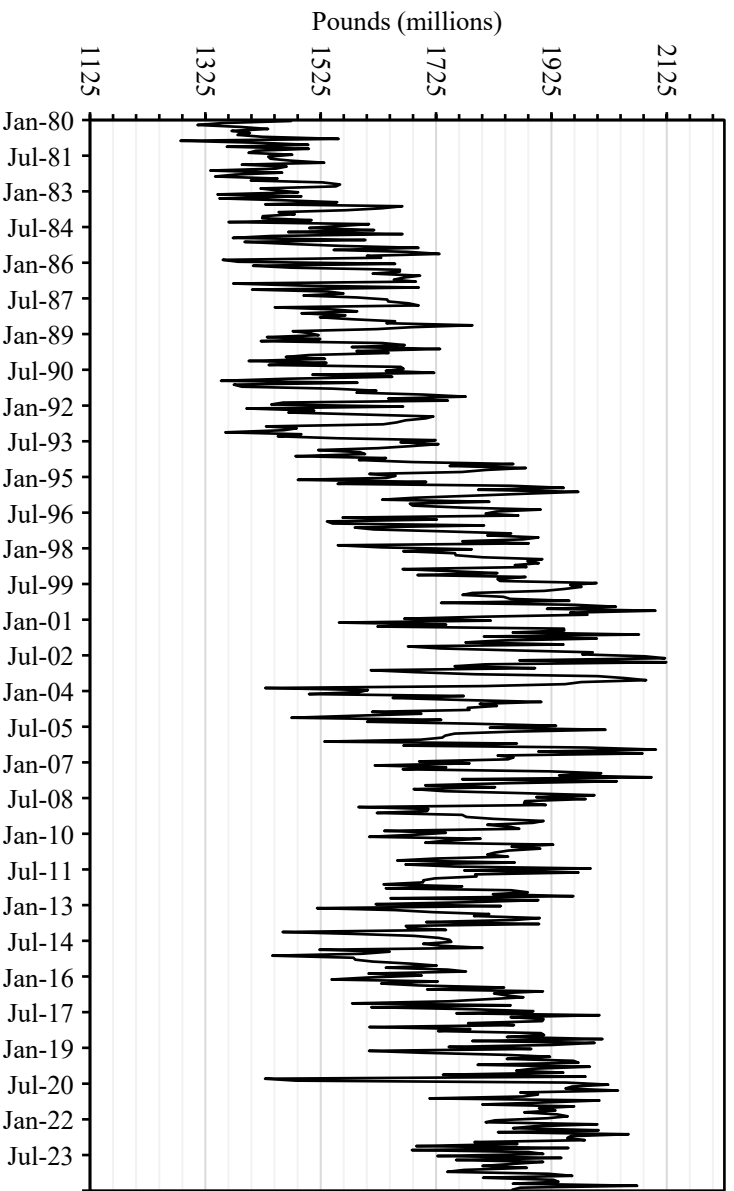


Figure A4: Federally inspected fed beef production, 1980 – 2024

APPENDIX B

Supporting information on the data used in analysis.

Table A1: Data sources including reports, history, and explanatory variables

<i>Report / Database</i>	<i>Agency</i>	<i>Frequency</i>	<i>History Assessed</i>	<i>Relevant Data Points</i>
Cattle	USDA NASS	Annually	1980 – 2024	<ul style="list-style-type: none"> – Calf crop – Heifers larger than 500 pounds kept for beef cow replacements – Other heifers larger than 500 pounds – Steers larger than 500 pounds
Livestock Slaughter	USDA NASS	Monthly	Jan. 1980 – Dec. 2024	<ul style="list-style-type: none"> – FI beef production – FI Slaughter <i>per class</i> – Average dressed weights and <i>per class</i>
Cattle on Feed (7 State)	USDA NASS	Monthly	Jan. 1980 – Jan. 1996	<ul style="list-style-type: none"> – Cattle on feed – Placements on feed
Cattle on Feed	USDA NASS	Monthly	Dec. 1995 – Dec. 2024	<ul style="list-style-type: none"> – Cattle on feed – Placements on feed <i>by weight class</i>
Feed Input Prices (Quickstats)	USDA NASS	Monthly	Jan. 1980 – Dec. 2024	<ul style="list-style-type: none"> – Cash corn price per bushel – Alfalfa hay price per ton
Focus on Feedlots	KSU	Monthly	Jan. 2000 – Dec. 2024	<ul style="list-style-type: none"> – Average days on feed
5 Area Weighted Average Yearly Direct Slaughter Cattle - Negotiated (LM_CT170)	USDA AMS	Weekly	Jan. 1990 – Dec. 2024	<ul style="list-style-type: none"> – Cash steer price per cwt. – Cash heifer price per cwt.
Winter Livestock Auction Weighted Average Report for Dodge City, KS (DC_LS750)	USDA AMS	Weekly	Jan. 1992 – Dec. 2024	<ul style="list-style-type: none"> – Cash cull cow price per cwt.
Live Cattle Futures	CME	Daily	Nov. 1989 – Jan. 2025	<ul style="list-style-type: none"> – Various live cattle futures contracts

Note: *per class* indicates per animal category (i.e., steer, heifer, cow, bull); *by weight class* indicates weight categories including cattle less than 600 pounds, cattle 600-699 pounds, cattle 700-799 pounds, and cattle greater than 800 pounds.

APPENDIX C

To demonstrate, a model with serially correlated error terms is defined by the following relationship:

$$\varepsilon_{i,t} = \phi_1 \varepsilon_{i,t-1} + \phi_2 \varepsilon_{i,t-2} + \dots + w_{i,t}$$

where $\varepsilon_{i,t}$ is a linear combination of errors generated from previous periods and $w_{i,t}$ is an independently and identically distributed residual that follows a normal distribution. If we let $\Phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \dots$, then the ARMA model for the errors can be written as:

$$\Phi(B)\varepsilon_{i,t} = w_{i,t}$$

Making the assumption that an inverse operator exists, we're further provided with, $\varepsilon_{i,t} = \Phi^{-1}(B)w_{i,t}$, allowing for the redefinition of equation 5 with the inclusion of the ARMA errors:

$$Y_{i,t} = \alpha_i + \sum_{n=1}^N \beta_{i,n} x_{i,n,t-k} + \sum_{m=1}^{11} \gamma_{i,m} D_{i,m} + \Phi^{-1}(B)w_{i,t}$$

APPENDIX D

Extended results of simulation summaries and forecast model performance criteria.

Table A2: Fed dressed weight models RMSE summary for all simulated 24-month out forecasts

Months Out	RMSE (Pounds)																	
	Total Sample			Fixed - Fixed			Fixed - Recursive			Recursive - Fixed			Recursive - Recursive			Rolling - Rolling		
	<i>Min</i>	<i>Mean</i>	<i>Max</i>	<i>Min</i>	<i>Mean</i>	<i>Max</i>	<i>Min</i>	<i>Mean</i>	<i>Max</i>	<i>Min</i>	<i>Mean</i>	<i>Max</i>	<i>Min</i>	<i>Mean</i>	<i>Max</i>	<i>Min</i>	<i>Mean</i>	<i>Max</i>
1	0.00	3.12	14.13	0.19	3.00	6.94	0.19	3.00	6.94	0.00	2.66	6.94	0.00	2.66	6.94	0.00	4.30	14.13
2	0.06	3.35	11.40	0.31	3.44	7.25	0.31	3.27	6.56	0.30	3.22	8.14	0.31	3.03	7.10	0.06	3.79	11.40
3	0.07	3.43	9.34	1.10	3.75	8.33	1.07	3.38	7.38	1.10	3.50	9.16	1.03	3.12	7.38	0.07	3.39	9.34
4	0.72	3.28	9.24	0.96	3.74	8.48	0.95	3.21	6.76	0.96	3.42	9.24	0.92	2.87	6.76	0.72	3.17	8.14
5	0.85	3.48	8.98	0.88	4.09	8.89	0.85	3.44	6.87	0.88	3.62	8.98	0.85	3.00	6.82	0.94	3.24	7.29
6	1.41	4.13	9.52	1.99	4.88	9.46	2.06	4.10	7.62	1.78	4.40	9.52	1.78	3.70	7.62	1.41	3.59	6.80
7	1.68	4.39	10.23	1.89	5.22	9.70	1.94	4.37	7.44	1.75	4.73	10.23	1.81	3.89	7.44	1.68	3.71	6.30
8	2.04	4.40	9.90	2.08	5.11	9.33	2.10	4.24	6.99	2.04	4.92	9.90	2.18	4.03	6.99	2.07	3.72	6.06
9	2.02	4.70	9.34	2.34	5.11	8.86	2.37	4.39	6.69	2.87	5.35	9.34	2.94	4.51	6.69	2.02	4.14	6.85
10	2.68	5.29	9.32	3.34	5.51	8.46	3.36	4.98	6.78	3.47	6.01	9.32	3.48	5.21	7.17	2.68	4.75	7.88
11	2.85	5.97	11.31	3.34	6.07	8.25	3.50	5.66	7.14	3.34	6.77	11.31	3.50	5.95	8.26	2.85	5.41	9.07
12	2.84	6.10	12.19	3.24	6.23	8.70	3.36	5.81	7.56	3.24	6.95	12.19	3.36	6.02	8.46	2.84	5.50	9.62
13	3.26	6.05	12.02	3.58	6.19	8.36	3.47	5.71	7.41	3.58	6.90	12.02	3.47	5.93	8.14	3.26	5.51	9.30
14	3.28	5.93	12.01	3.54	6.14	8.08	3.36	5.58	7.44	3.54	6.80	12.01	3.36	5.74	7.85	3.28	5.38	9.05
15	3.26	6.11	12.33	3.69	6.42	9.00	3.74	5.84	7.86	3.69	6.97	12.33	3.74	5.88	7.76	3.26	5.45	9.11
16	3.45	6.52	13.28	4.06	6.94	10.25	4.31	6.32	8.80	4.06	7.41	13.28	4.31	6.23	8.08	3.45	5.70	9.53
17	3.37	6.57	13.73	4.06	7.09	11.06	4.31	6.37	9.19	4.06	7.51	13.73	4.31	6.21	8.11	3.37	5.65	9.53
18	3.62	6.56	13.62	4.23	7.07	10.89	4.37	6.32	9.07	4.23	7.50	13.62	4.37	6.16	7.90	3.62	5.77	9.26
19	3.59	6.46	13.59	4.13	6.99	10.89	4.26	6.19	8.98	4.13	7.42	13.59	4.26	6.03	7.69	3.59	5.67	9.03
20	3.65	6.61	14.40	4.14	7.16	11.08	4.38	6.31	9.42	4.14	7.69	14.40	4.38	6.15	8.02	3.65	5.73	8.85
21	4.16	7.62	15.97	5.21	8.30	12.72	5.28	7.27	11.08	5.21	8.89	15.97	5.28	7.11	9.36	4.16	6.55	9.00
22	4.23	8.45	17.77	6.01	9.41	14.57	5.76	8.03	12.75	6.01	9.98	17.77	5.76	7.80	10.24	4.23	7.05	9.89
23	4.14	8.92	19.38	6.45	10.15	16.14	5.90	8.40	14.10	6.45	10.72	19.38	5.90	8.10	10.69	4.14	7.21	10.40
24	4.54	8.99	19.96	6.42	10.33	16.69	5.78	8.43	14.46	6.42	10.83	19.96	5.78	8.06	10.54	4.54	7.29	10.27

Note: Titles for table sections begin with the simulation method for optimal length and are followed by the prediction method.

Table A3: Fed dressed weight models MAPE summary for all simulated 24-month out forecasts

Months Out	MAPE (Percent)																	
	Total Sample			Fixed - Fixed			Fixed - Recursive			Recursive - Fixed			Recursive - Recursive			Rolling - Rolling		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
1	0.00	0.37	1.66	0.02	0.35	0.82	0.02	0.35	0.82	0.00	0.31	0.82	0.00	0.31	0.82	0.00	0.51	1.66
2	0.01	0.37	1.29	0.03	0.39	0.86	0.03	0.37	0.77	0.03	0.36	0.94	0.03	0.34	0.83	0.01	0.40	1.29
3	0.01	0.37	1.06	0.10	0.42	0.95	0.09	0.37	0.86	0.10	0.39	1.06	0.09	0.34	0.86	0.01	0.34	0.91
4	0.05	0.35	1.09	0.08	0.42	0.98	0.08	0.35	0.78	0.08	0.38	1.09	0.08	0.31	0.78	0.05	0.31	0.74
5	0.07	0.37	1.06	0.08	0.45	1.02	0.07	0.37	0.80	0.08	0.40	1.06	0.07	0.32	0.80	0.10	0.31	0.61
6	0.15	0.42	1.11	0.18	0.52	1.10	0.17	0.42	0.88	0.17	0.46	1.11	0.16	0.37	0.88	0.15	0.35	0.65
7	0.17	0.45	1.19	0.19	0.55	1.12	0.18	0.45	0.86	0.17	0.50	1.19	0.17	0.40	0.86	0.17	0.36	0.67
8	0.18	0.44	1.15	0.21	0.54	1.07	0.21	0.43	0.78	0.20	0.51	1.15	0.21	0.40	0.78	0.18	0.35	0.63
9	0.18	0.46	1.03	0.24	0.52	0.99	0.24	0.44	0.74	0.26	0.52	1.03	0.26	0.43	0.74	0.18	0.39	0.60
10	0.23	0.51	0.95	0.29	0.55	0.93	0.30	0.49	0.75	0.29	0.57	0.95	0.30	0.49	0.75	0.23	0.44	0.69
11	0.27	0.57	0.97	0.27	0.59	0.89	0.31	0.55	0.79	0.27	0.63	0.97	0.31	0.56	0.79	0.28	0.50	0.77
12	0.27	0.58	1.04	0.27	0.61	0.85	0.29	0.56	0.80	0.27	0.65	1.04	0.29	0.57	0.80	0.27	0.51	0.84
13	0.31	0.57	1.04	0.31	0.60	0.86	0.31	0.55	0.76	0.31	0.65	1.04	0.31	0.56	0.76	0.31	0.51	0.81
14	0.30	0.56	1.07	0.31	0.60	0.86	0.30	0.53	0.71	0.31	0.64	1.07	0.30	0.53	0.71	0.32	0.49	0.79
15	0.32	0.58	1.12	0.33	0.62	0.85	0.33	0.56	0.70	0.33	0.66	1.12	0.33	0.55	0.70	0.32	0.51	0.82
16	0.33	0.62	1.22	0.37	0.67	0.96	0.38	0.61	0.76	0.37	0.71	1.22	0.38	0.59	0.74	0.33	0.54	0.87
17	0.32	0.63	1.29	0.37	0.68	1.04	0.39	0.62	0.81	0.37	0.72	1.29	0.39	0.60	0.76	0.32	0.53	0.89
18	0.35	0.63	1.29	0.39	0.68	1.03	0.40	0.61	0.81	0.39	0.72	1.29	0.40	0.59	0.73	0.35	0.54	0.84
19	0.35	0.62	1.30	0.38	0.67	1.04	0.38	0.60	0.81	0.38	0.72	1.30	0.38	0.57	0.73	0.35	0.53	0.81
20	0.36	0.63	1.38	0.39	0.69	1.07	0.40	0.61	0.86	0.39	0.74	1.38	0.40	0.59	0.73	0.36	0.54	0.79
21	0.40	0.70	1.50	0.46	0.76	1.18	0.46	0.67	0.97	0.46	0.82	1.50	0.46	0.65	0.81	0.40	0.59	0.80
22	0.40	0.76	1.60	0.52	0.84	1.30	0.50	0.73	1.09	0.52	0.90	1.60	0.50	0.71	0.89	0.40	0.63	0.86
23	0.39	0.80	1.73	0.56	0.90	1.39	0.51	0.77	1.19	0.56	0.96	1.73	0.51	0.74	0.94	0.39	0.65	0.91
24	0.42	0.81	1.80	0.57	0.93	1.46	0.50	0.77	1.24	0.57	0.98	1.80	0.50	0.73	0.93	0.42	0.66	0.91

Note: Titles for table sections begin with the simulation method for optimal length and are followed by the prediction method.

Table A4: Fed dressed weight models optimal length simulation results for the 24-month horizon of selected models

Model	Method	Rank	Start Date	RMSE (pounds)	MAPE (percent)	Survey Length
COF >150 Days & Corn	Recursive-Recursive	1	1/1/2011	6.518	0.598	36
		2	7/1/2009	6.715	0.688	54
		3	7/1/2010	6.729	0.583	42
		4	1/1/2010	7.014	0.614	48
		5	1/1/2009	7.187	0.713	60
	Rolling-Rolling	1	1/1/2011	4.543	0.427	36
		2	7/1/2010	4.876	0.474	42
		3	1/1/2010	4.884	0.485	48
		4	7/1/2009	6.257	0.635	54
		5	1/1/2009	7.166	0.708	60
COF >150 Days & Futures Premium	Recursive-Recursive	1	1/1/2011	6.022	0.545	36
		2	7/1/2010	7.164	0.621	42
		3	1/1/2010	7.190	0.623	48
		4	7/1/2009	9.075	0.888	54
		5	1/1/2007	11.307	1.150	84
	Rolling-Rolling	1	1/1/2010	4.946	0.459	48
		2	7/1/2010	5.017	0.452	42
		3	1/1/2011	5.075	0.473	36
		4	7/1/2009	6.237	0.638	54
		5	1/1/2009	7.763	0.742	60
COF >150 Days, Corn, & Futures Premium	Recursive-Recursive	1	1/1/2011	6.359	0.589	36
		2	7/1/2010	6.492	0.569	42
		3	7/1/2009	6.694	0.666	54
		4	1/1/2010	6.756	0.609	48
		5	1/1/2009	7.084	0.703	60
	Rolling-Rolling	1	1/1/2011	4.667	0.444	36
		2	7/1/2010	4.826	0.460	42
		3	1/1/2010	4.920	0.479	48
		4	7/1/2009	6.033	0.616	54
		5	1/1/2009	7.072	0.682	60

Note: Methods sections begin with the simulation method for optimal length and are followed by the prediction method.

Table A5: Selected fed dressed weight model performance summary for 24-month out forecasts

Months Out	COF >150 Days & Corn						COF >150 Days & Futures Premium						COF >150 Days, Corn, & Futures Premium					
	<i>Recursive - Recursive</i>			<i>Rolling - Rolling</i>			<i>Recursive - Recursive</i>			<i>Rolling - Rolling</i>			<i>Recursive - Recursive</i>			<i>Rolling - Rolling</i>		
	RMSE	MAPE	U_2	RMSE	MAPE	U_2	RMSE	MAPE	U_2	RMSE	MAPE	U_2	RMSE	MAPE	U_2	RMSE	MAPE	U_2
1	0.00	0.00	0.003	0.00	0.00	0.003	1.99	0.23	2.593	0.38	0.04	0.492	0.14	0.02	0.180	0.14	0.02	0.180
2	1.96	0.16	1.749	1.90	0.16	1.687	1.41	0.12	1.252	0.48	0.06	0.427	1.76	0.16	1.563	2.06	0.18	1.836
3	1.82	0.17	1.750	1.89	0.18	1.813	1.21	0.10	1.163	0.69	0.08	0.663	1.65	0.16	1.588	1.99	0.19	1.915
4	1.78	0.18	1.430	1.73	0.17	1.386	1.05	0.08	0.840	0.89	0.10	0.716	1.61	0.17	1.292	1.78	0.17	1.430
5	1.71	0.18	1.467	1.69	0.17	1.455	0.97	0.08	0.832	0.94	0.11	0.811	1.46	0.15	1.255	1.62	0.15	1.393
6	2.42	0.24	2.160	2.58	0.25	2.303	2.27	0.17	2.028	1.58	0.15	1.412	2.15	0.20	1.922	2.39	0.22	2.133
7	2.28	0.22	0.864	2.56	0.25	0.971	3.13	0.25	1.187	2.21	0.21	0.840	2.14	0.21	0.812	2.61	0.25	0.990
8	2.59	0.26	0.561	2.43	0.24	0.525	3.00	0.24	0.649	2.07	0.18	0.448	2.41	0.24	0.522	2.45	0.23	0.530
9	3.06	0.30	0.391	2.36	0.23	0.301	3.00	0.26	0.383	2.59	0.23	0.331	3.16	0.30	0.403	2.54	0.24	0.323
10	4.01	0.37	0.374	2.68	0.26	0.251	3.54	0.31	0.330	3.17	0.28	0.296	4.06	0.37	0.379	2.78	0.27	0.259
11	4.88	0.44	0.402	2.97	0.29	0.245	4.04	0.36	0.333	3.72	0.33	0.307	4.81	0.43	0.396	2.85	0.28	0.235
12	4.96	0.46	0.375	2.84	0.27	0.215	3.91	0.35	0.296	3.56	0.30	0.270	4.69	0.43	0.355	2.87	0.29	0.217
13	5.08	0.48	0.390	3.26	0.31	0.250	4.23	0.38	0.325	3.94	0.34	0.302	4.87	0.45	0.374	3.26	0.32	0.251
14	4.90	0.45	0.375	3.29	0.32	0.252	4.11	0.37	0.314	3.90	0.35	0.298	4.71	0.43	0.360	3.28	0.33	0.251
15	4.89	0.46	0.358	3.26	0.32	0.238	4.24	0.39	0.310	3.89	0.35	0.285	4.81	0.45	0.352	3.37	0.34	0.247
16	5.15	0.49	0.355	3.45	0.34	0.238	4.47	0.42	0.308	3.97	0.37	0.273	5.04	0.48	0.347	3.51	0.36	0.242
17	5.08	0.49	0.335	3.37	0.33	0.223	4.39	0.41	0.290	3.85	0.35	0.254	4.96	0.48	0.327	3.43	0.35	0.226
18	5.03	0.49	0.327	3.62	0.35	0.235	4.56	0.44	0.297	4.30	0.39	0.280	5.05	0.49	0.328	3.83	0.38	0.249
19	4.93	0.48	0.316	3.59	0.36	0.231	4.49	0.43	0.288	4.34	0.40	0.279	4.94	0.48	0.318	3.78	0.38	0.243
20	5.10	0.50	0.314	3.65	0.36	0.225	4.50	0.44	0.278	4.27	0.39	0.263	4.97	0.49	0.306	3.76	0.38	0.232
21	5.91	0.55	0.340	4.16	0.40	0.239	5.28	0.49	0.304	4.68	0.43	0.269	5.71	0.54	0.328	4.26	0.41	0.245
22	6.42	0.59	0.355	4.23	0.41	0.234	5.90	0.53	0.327	4.96	0.45	0.274	6.28	0.58	0.347	4.37	0.43	0.242
23	6.65	0.62	0.362	4.14	0.40	0.225	6.13	0.56	0.334	5.00	0.46	0.272	6.48	0.60	0.353	4.28	0.41	0.233
24	6.52	0.60	0.357	4.54	0.43	0.249	6.02	0.54	0.330	4.95	0.46	0.271	6.36	0.59	0.349	4.67	0.44	0.256

Note: Titles for table sections begin with the simulation method for optimal length and are followed by the prediction method.

Table A6: Selected fed dressed weight models corrected for autocorrelated errors performance summary for the 24-month out horizon

Months Out	COF >150 Days & Corn						COF >150 Days & Futures Premium						COF >150 Days, Corn, & Futures Premium					
	<i>Recursive - Recursive</i>			<i>Rolling - Rolling</i>			<i>Recursive - Recursive</i>			<i>Rolling - Rolling</i>			<i>Recursive - Recursive</i>			<i>Rolling - Rolling</i>		
	RMSE	MAPE	U_2	RMSE	MAPE	U_2	RMSE	MAPE	U_2	RMSE	MAPE	U_2	RMSE	MAPE	U_2	RMSE	MAPE	U_2
1	0.33	0.04	0.426	0.33	0.04	0.426	0.11	0.01	0.142	1.58	0.19	2.056	0.11	0.01	0.142	0.11	0.01	0.142
2	1.19	0.12	1.062	0.92	0.09	0.815	1.68	0.15	1.493	1.59	0.19	1.418	2.33	0.20	2.074	0.38	0.04	0.342
3	1.33	0.14	1.281	0.91	0.10	0.877	1.53	0.15	1.471	1.44	0.17	1.381	1.94	0.16	1.865	0.53	0.05	0.505
4	1.23	0.13	0.987	0.82	0.09	0.659	1.36	0.13	1.092	1.31	0.15	1.051	1.70	0.14	1.365	0.49	0.05	0.395
5	1.96	0.19	1.684	1.14	0.12	0.981	1.33	0.13	1.141	1.31	0.15	1.124	1.60	0.14	1.373	0.44	0.04	0.380
6	2.62	0.26	2.335	2.26	0.20	2.020	2.32	0.21	2.072	2.17	0.22	1.935	2.65	0.22	2.362	1.87	0.13	1.668
7	2.45	0.24	0.932	2.11	0.18	0.802	2.15	0.18	0.817	2.01	0.19	0.762	2.49	0.21	0.944	1.73	0.11	0.658
8	2.49	0.25	0.538	2.04	0.18	0.442	2.54	0.22	0.550	2.46	0.23	0.533	2.66	0.24	0.575	1.75	0.13	0.379
9	2.93	0.29	0.374	2.01	0.18	0.256	3.20	0.28	0.408	3.21	0.29	0.410	3.52	0.31	0.449	2.08	0.16	0.266
10	3.37	0.33	0.314	2.42	0.22	0.226	3.40	0.31	0.318	3.35	0.31	0.313	3.69	0.33	0.344	2.38	0.19	0.222
11	3.40	0.34	0.280	2.67	0.25	0.221	3.33	0.31	0.274	3.26	0.31	0.269	3.57	0.32	0.294	2.41	0.20	0.199
12	3.27	0.32	0.247	2.58	0.24	0.195	3.26	0.30	0.246	3.21	0.31	0.243	3.49	0.32	0.264	2.52	0.22	0.190
13	3.98	0.37	0.306	2.97	0.27	0.228	3.69	0.34	0.283	3.65	0.34	0.280	3.91	0.36	0.300	2.79	0.25	0.214
14	3.92	0.37	0.299	2.90	0.27	0.222	3.63	0.34	0.277	3.52	0.33	0.269	3.83	0.36	0.293	2.69	0.24	0.206
15	4.03	0.39	0.295	3.00	0.28	0.220	3.97	0.37	0.290	3.67	0.35	0.268	4.13	0.39	0.302	3.09	0.27	0.226
16	4.11	0.40	0.283	3.19	0.30	0.220	4.01	0.39	0.276	3.66	0.35	0.252	4.12	0.39	0.284	3.19	0.29	0.220
17	4.03	0.40	0.266	3.11	0.29	0.205	3.91	0.37	0.258	3.56	0.34	0.235	4.04	0.39	0.267	3.10	0.27	0.205
18	4.18	0.41	0.272	3.37	0.32	0.219	4.23	0.40	0.275	4.02	0.38	0.261	4.38	0.42	0.285	3.55	0.31	0.231
19	4.08	0.40	0.262	3.30	0.31	0.212	4.15	0.40	0.267	3.92	0.36	0.252	4.31	0.41	0.277	3.46	0.30	0.222
20	4.54	0.44	0.280	3.42	0.32	0.211	4.40	0.42	0.271	3.99	0.37	0.246	4.53	0.44	0.279	3.47	0.30	0.214
21	5.11	0.48	0.294	3.87	0.36	0.223	5.14	0.47	0.296	4.42	0.41	0.255	5.24	0.48	0.301	3.94	0.34	0.227
22	5.09	0.48	0.282	3.81	0.35	0.211	5.17	0.48	0.286	4.45	0.41	0.246	5.25	0.49	0.291	3.89	0.34	0.215
23	4.98	0.46	0.271	3.74	0.34	0.204	5.06	0.46	0.275	4.36	0.40	0.237	5.14	0.47	0.280	3.83	0.33	0.209
24	5.19	0.48	0.284	4.17	0.38	0.229	5.10	0.47	0.280	4.51	0.42	0.247	5.19	0.48	0.285	4.21	0.36	0.231

Note: Titles for table sections begin with the simulation method for optimal length and are followed by the prediction method.

Table A7: Steer slaughter models RMSE summary for all simulated 24-month out forecasts

Months Out	RMSE (Thousands of Head)																	
	Total Sample			Fixed - Fixed			Fixed - Recursive			Recursive - Fixed			Recursive - Recursive			Rolling - Rolling		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
1	0.06	21.68	65.41	0.06	22.34	65.41	0.06	22.34	65.41	0.06	20.05	63.52	0.06	20.05	63.52	0.57	23.62	64.72
2	1.53	19.62	54.65	2.62	19.21	47.50	2.36	18.91	47.05	2.10	19.40	46.04	2.04	19.11	46.16	1.53	21.50	54.65
3	1.53	22.78	61.73	2.78	22.47	55.75	2.63	21.99	56.12	4.64	23.02	61.73	4.81	22.46	61.72	1.53	23.93	56.43
4	8.82	32.25	55.98	13.96	32.94	55.98	13.56	31.83	55.56	12.42	32.30	54.80	9.95	31.39	54.74	8.82	32.80	55.84
5	9.10	31.03	50.81	14.02	32.12	50.49	14.10	30.86	49.78	11.84	31.05	49.19	9.10	30.10	49.10	10.41	31.02	50.81
6	22.41	38.20	57.56	22.65	38.10	54.13	22.44	38.51	54.07	22.65	37.70	57.56	22.44	37.73	56.70	22.41	38.97	54.60
7	26.72	43.98	60.83	27.46	43.63	58.44	26.74	44.29	58.18	27.46	43.70	56.27	26.74	43.72	55.17	26.72	44.56	60.83
8	25.92	43.35	63.57	26.98	43.24	62.27	25.97	43.49	60.61	26.98	43.47	63.57	25.97	42.93	60.62	25.92	43.60	61.01
9	24.85	41.38	59.98	26.19	41.38	59.25	24.95	41.45	58.19	26.19	41.61	59.98	24.95	40.89	57.51	24.85	41.59	58.59
10	30.73	43.81	61.94	30.78	44.08	57.98	30.73	43.46	55.93	30.78	44.67	61.94	30.73	43.00	54.87	31.94	43.84	59.13
11	29.32	42.66	67.27	29.68	43.07	65.53	29.32	42.14	63.05	29.68	43.86	67.27	29.32	41.76	63.00	30.59	42.46	63.16
12	29.20	42.90	67.15	30.63	43.55	62.86	29.20	41.99	60.37	30.63	44.62	67.15	29.20	41.87	60.54	31.76	42.48	60.48
13	31.10	41.60	65.18	31.10	42.17	61.21	31.84	40.78	58.50	31.10	43.31	65.18	31.89	40.59	58.86	31.55	41.15	58.64
14	29.97	40.52	65.56	29.97	41.06	61.79	30.83	39.50	57.89	29.97	42.60	65.56	30.96	39.44	58.68	30.48	40.00	58.29
15	30.12	41.58	67.80	30.12	42.19	63.32	30.57	40.17	57.78	30.12	44.28	67.80	30.57	40.38	58.72	31.59	40.91	58.48
16	29.97	41.46	68.08	29.97	42.10	62.54	30.06	39.83	56.66	29.97	44.54	68.08	30.06	40.16	57.95	31.40	40.70	57.72
17	29.15	40.61	69.95	29.15	41.24	64.89	29.50	39.15	57.87	29.15	43.59	69.95	29.50	39.30	58.83	31.00	39.77	58.72
18	30.27	42.06	73.43	31.59	43.49	64.89	30.27	39.93	56.78	31.59	46.05	73.43	30.27	40.11	57.66	30.45	40.71	57.64
19	29.94	41.31	73.69	30.75	42.67	63.16	29.97	39.20	55.68	30.75	45.38	73.69	29.97	39.35	56.50	29.94	39.94	56.48
20	29.54	40.90	73.60	30.00	42.24	65.36	29.54	38.87	56.09	30.00	44.98	73.60	29.54	38.91	56.21	31.51	39.51	56.23
21	37.44	46.10	71.91	37.44	46.58	68.53	38.43	45.67	62.14	37.44	48.56	71.91	37.79	45.27	61.18	38.00	44.41	60.97
22	37.40	46.11	70.71	38.92	46.39	67.07	39.71	46.17	61.34	38.93	48.09	70.71	38.83	45.57	60.45	37.40	44.32	60.21
23	36.71	45.69	70.29	38.07	45.96	65.60	38.84	45.92	60.28	38.51	47.53	70.29	38.54	45.21	59.43	36.71	43.83	59.10
24	36.14	45.32	70.07	37.49	45.52	65.97	38.12	45.71	62.01	38.16	47.01	70.07	37.96	44.90	60.44	36.14	43.48	59.61

Note: Titles for table sections begin with the simulation method for optimal length and are followed by the prediction method.

Table A8: Steer slaughter models MAPE summary for all simulated 24-month out forecasts

Months Out	MAPE (Percent)																	
	Total Sample			Fixed - Fixed			Fixed - Recursive			Recursive - Fixed			Recursive - Recursive			Rolling - Rolling		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
1	0.00	1.67	5.03	0.00	1.72	5.03	0.00	1.72	5.03	0.00	1.54	4.89	0.00	1.54	4.89	0.04	1.82	4.98
2	0.11	1.47	4.41	0.21	1.44	3.49	0.20	1.40	3.56	0.15	1.47	3.76	0.15	1.43	3.83	0.11	1.59	4.41
3	0.12	1.67	4.91	0.19	1.64	4.46	0.20	1.59	4.51	0.31	1.72	4.89	0.32	1.66	4.91	0.12	1.77	4.50
4	0.42	2.15	4.16	0.95	2.18	4.16	0.96	2.10	4.05	0.69	2.18	4.16	0.69	2.11	4.12	0.42	2.21	4.00
5	0.68	1.98	3.46	0.95	2.03	3.46	0.95	1.95	3.37	0.88	1.99	3.46	0.68	1.92	3.41	0.74	2.00	3.34
6	1.39	2.33	3.88	1.39	2.33	3.77	1.40	2.33	3.79	1.39	2.31	3.88	1.40	2.30	3.86	1.39	2.38	3.79
7	1.66	2.67	3.82	1.71	2.66	3.70	1.66	2.69	3.61	1.71	2.65	3.82	1.66	2.66	3.72	1.69	2.72	3.78
8	1.64	2.67	4.30	1.71	2.67	4.22	1.64	2.66	4.13	1.71	2.68	4.30	1.64	2.64	4.13	1.67	2.69	4.14
9	1.58	2.51	3.96	1.62	2.52	3.95	1.58	2.50	3.95	1.62	2.54	3.88	1.58	2.47	3.84	1.60	2.53	3.96
10	1.79	2.72	3.84	1.79	2.73	3.78	1.80	2.68	3.70	1.79	2.78	3.84	1.80	2.66	3.63	1.83	2.73	3.80
11	1.67	2.65	4.46	1.75	2.69	4.44	1.67	2.59	4.31	1.75	2.76	4.46	1.67	2.59	4.24	1.74	2.64	4.31
12	1.72	2.71	4.35	1.85	2.76	4.17	1.72	2.62	3.97	1.87	2.85	4.35	1.72	2.63	4.01	1.89	2.67	3.97
13	1.84	2.60	4.28	1.91	2.64	4.07	1.91	2.53	3.84	1.84	2.75	4.28	1.87	2.53	3.91	1.89	2.56	3.84
14	1.74	2.53	4.55	1.78	2.57	4.25	1.80	2.42	3.90	1.74	2.74	4.55	1.81	2.45	4.01	1.83	2.49	3.93
15	1.89	2.66	4.78	1.89	2.70	4.43	1.89	2.53	3.95	1.89	2.89	4.78	1.89	2.57	4.08	1.95	2.61	4.02
16	1.86	2.67	4.81	1.92	2.71	4.40	1.88	2.52	3.89	1.86	2.93	4.81	1.88	2.58	4.05	1.99	2.61	3.99
17	1.84	2.59	4.97	1.84	2.63	4.56	1.85	2.46	3.99	1.84	2.85	4.97	1.85	2.50	4.13	1.92	2.53	4.08
18	1.76	2.68	4.98	1.97	2.76	4.57	1.91	2.51	3.90	1.76	2.98	4.98	1.91	2.55	4.03	1.89	2.59	3.99
19	1.80	2.61	4.92	1.87	2.68	4.34	1.90	2.45	3.81	1.80	2.92	4.92	1.90	2.48	3.92	1.86	2.52	3.88
20	1.80	2.58	4.95	1.80	2.65	4.49	1.86	2.42	3.86	1.80	2.90	4.95	1.83	2.44	3.92	1.90	2.48	3.89
21	2.08	2.80	4.96	2.08	2.85	4.67	2.11	2.70	4.14	2.08	3.06	4.96	2.08	2.71	4.15	2.14	2.70	4.12
22	2.18	2.81	4.78	2.20	2.85	4.52	2.25	2.75	4.09	2.20	3.02	4.78	2.18	2.74	4.11	2.21	2.70	4.07
23	2.14	2.80	4.69	2.14	2.83	4.35	2.22	2.76	4.01	2.20	2.99	4.69	2.20	2.74	4.04	2.16	2.68	3.98
24	2.11	2.78	4.71	2.11	2.81	4.40	2.21	2.76	4.15	2.15	2.95	4.71	2.18	2.73	4.13	2.14	2.67	4.04

Note: Titles for table sections begin with the simulation method for optimal length and are followed by the prediction method.

Table A9: Steer slaughter models optimal length simulation results for the 24-month horizon of selected models

Model	Method	Rank	Start Date	RMSE <i>(thousand head)</i>	MAPE <i>(percent)</i>	Survey Length
Steer Supply Stocks	Recursive-Recursive	1	7/1/2007	38.160	2.202	78
		2	1/1/2008	39.011	2.312	72
		3	1/1/2007	39.411	2.316	84
		4	7/1/2006	40.242	2.362	90
		5	7/1/2005	40.483	2.286	102
	Rolling-Rolling	1	7/1/2006	37.285	2.145	90
		2	1/1/2007	37.371	2.187	84
		3	1/1/2006	37.788	2.190	96
		4	1/1/2005	39.202	2.232	108
		5	7/1/2005	39.303	2.223	102
Fed Cattle Supply Flows	Recursive-Recursive	1	1/1/2003	40.380	2.358	132
		2	7/1/2002	41.210	2.404	138
		3	1/1/2002	42.389	2.490	144
		4	1/1/1999	43.777	2.611	180
		5	7/1/2001	43.807	2.594	150
	Rolling-Rolling	1	1/1/2002	37.329	2.220	144
		2	7/1/2001	40.419	2.247	150
		3	1/1/2001	41.206	2.345	156
		4	7/1/2002	42.137	2.478	138
		5	7/1/2000	43.147	2.523	162

Note: Methods sections begin with the simulation method for optimal length and are followed by the prediction method.

Table A10: Selected steer slaughter model performance summary for 24-month out forecasts

Months Out	Steer Supply Stocks						Fed Cattle Supply Flows					
	<i>Recursive - Recursive</i>			<i>Rolling - Rolling</i>			<i>Recursive - Recursive</i>			<i>Rolling - Rolling</i>		
	RMSE	MAPE	U_2	RMSE	MAPE	U_2	RMSE	MAPE	U_2	RMSE	MAPE	U_2
1	3.67	0.28	0.052	19.07	1.47	0.268	33.16	2.55	0.466	32.86	2.53	0.461
2	14.95	1.09	0.292	16.63	1.36	0.324	23.56	1.43	0.460	23.39	1.44	0.456
3	14.28	1.08	0.327	15.39	1.26	0.352	30.30	2.08	0.694	29.54	2.04	0.677
4	14.13	1.07	0.361	14.54	1.16	0.372	40.58	2.72	1.037	39.60	2.67	1.012
5	12.65	0.87	0.341	13.01	0.93	0.350	36.85	2.37	0.993	35.71	2.27	0.962
6	26.48	1.42	0.710	28.98	1.55	0.777	38.09	2.50	1.022	37.18	2.42	0.997
7	36.89	1.97	0.787	37.46	2.04	0.799	42.08	2.77	0.898	41.17	2.69	0.878
8	36.01	2.00	0.642	36.26	2.03	0.646	40.67	2.70	0.725	40.10	2.65	0.715
9	33.97	1.80	0.638	34.24	1.86	0.643	38.41	2.46	0.722	37.85	2.40	0.711
10	34.72	1.93	0.589	34.76	1.97	0.590	41.15	2.67	0.698	41.34	2.66	0.701
11	33.13	1.79	0.427	33.17	1.83	0.428	39.51	2.56	0.510	39.61	2.53	0.511
12	33.09	1.87	0.442	33.05	1.89	0.441	37.98	2.43	0.507	38.04	2.39	0.508
13	32.39	1.87	0.424	32.35	1.89	0.424	36.74	2.34	0.482	36.79	2.30	0.482
14	31.34	1.81	0.421	31.31	1.83	0.421	35.40	2.17	0.476	35.46	2.15	0.477
15	32.15	1.92	0.446	32.27	1.95	0.448	35.97	2.27	0.499	36.09	2.26	0.501
16	32.58	2.00	0.441	32.95	2.04	0.446	35.98	2.31	0.487	36.12	2.30	0.489
17	31.61	1.89	0.418	31.96	1.93	0.422	35.00	2.22	0.463	35.06	2.19	0.463
18	33.52	2.01	0.456	34.23	2.06	0.466	36.10	2.30	0.491	36.86	2.30	0.501
19	32.64	1.92	0.454	33.34	1.97	0.464	35.14	2.19	0.489	36.16	2.25	0.503
20	31.82	1.83	0.454	32.53	1.90	0.464	34.26	2.10	0.489	35.74	2.24	0.510
21	37.79	2.08	0.538	38.00	2.14	0.541	41.87	2.39	0.596	39.74	2.44	0.565
22	38.83	2.18	0.563	38.55	2.21	0.559	41.53	2.40	0.602	38.83	2.34	0.563
23	38.54	2.20	0.545	37.94	2.18	0.537	40.82	2.36	0.577	38.09	2.29	0.539
24	38.16	2.20	0.539	37.29	2.14	0.527	40.38	2.36	0.571	37.33	2.22	0.528

Note: Titles for table sections begin with the simulation method for optimal length and are followed by the prediction method.

Table A11: Selected steer slaughter models corrected for autocorrelated errors performance summary for the 24-month out horizon

Months Out	Steer Supply Stocks						Fed Cattle Supply Flows					
	<i>Recursive - Recursive</i>			<i>Rolling - Rolling</i>			<i>Recursive - Recursive</i>			<i>Rolling - Rolling</i>		
	RMSE	MAPE	U_2	RMSE	MAPE	U_2	RMSE	MAPE	U_2	RMSE	MAPE	U_2
1	8.70	0.67	0.1221	1.32	0.10	0.0185	25.94	2.00	0.3643	24.56	1.89	0.3450
2	19.13	1.50	0.3732	15.88	1.07	0.3097	24.06	2.00	0.4693	22.27	1.84	0.4343
3	16.21	1.21	0.3713	13.58	0.91	0.3111	19.80	1.46	0.4536	18.48	1.39	0.4233
4	16.40	1.23	0.4192	14.16	0.98	0.3619	19.39	1.43	0.4955	19.17	1.44	0.4898
5	15.22	1.11	0.4100	13.15	0.89	0.3541	20.22	1.47	0.5448	19.88	1.47	0.5356
6	28.83	1.66	0.7733	29.97	1.55	0.8037	34.21	2.07	0.9174	33.14	2.03	0.8889
7	32.76	1.94	0.6988	32.70	1.80	0.6975	34.93	2.17	0.7452	33.73	2.12	0.7195
8	30.64	1.70	0.5461	30.59	1.58	0.5452	32.89	2.00	0.5862	31.68	1.94	0.5647
9	29.20	1.62	0.5486	29.22	1.53	0.5489	31.54	1.93	0.5925	30.42	1.87	0.5715
10	31.24	1.81	0.5298	31.16	1.72	0.5285	31.53	1.97	0.5348	30.70	1.93	0.5207
11	29.96	1.73	0.3865	29.89	1.65	0.3856	31.58	2.06	0.4074	30.91	2.03	0.3988
12	30.31	1.82	0.4047	30.19	1.74	0.4032	31.87	2.13	0.4256	31.31	2.11	0.4181
13	30.41	1.88	0.3986	30.31	1.81	0.3973	34.13	2.31	0.4473	33.65	2.29	0.4410
14	29.91	1.90	0.4022	29.81	1.83	0.4008	33.34	2.29	0.4483	32.93	2.27	0.4428
15	30.71	2.00	0.4263	30.71	1.94	0.4264	33.77	2.36	0.4688	33.40	2.34	0.4637
16	30.32	2.00	0.4102	30.50	1.96	0.4127	32.98	2.30	0.4463	32.42	2.24	0.4387
17	29.69	1.95	0.3925	29.76	1.90	0.3933	32.72	2.29	0.4325	32.42	2.26	0.4285
18	32.28	2.09	0.4390	32.40	2.04	0.4406	36.63	2.47	0.4981	36.39	2.44	0.4949
19	32.05	2.08	0.4461	32.13	2.04	0.4473	36.77	2.48	0.5118	36.34	2.44	0.5058
20	31.24	1.98	0.4461	31.33	1.95	0.4473	36.13	2.43	0.5158	35.82	2.41	0.5115
21	37.19	2.22	0.5290	36.70	2.17	0.5220	39.88	2.61	0.5673	38.80	2.56	0.5520
22	36.50	2.18	0.5293	35.94	2.11	0.5212	38.96	2.50	0.5650	38.20	2.52	0.5540
23	35.74	2.11	0.5056	35.17	2.04	0.4975	38.11	2.39	0.5391	37.45	2.45	0.5298
24	35.11	2.07	0.4963	34.50	1.99	0.4876	37.43	2.34	0.5290	36.66	2.36	0.5182

Note: Titles for table sections begin with the simulation method for optimal length and are followed by the prediction method.

Table A12: Heifer slaughter models RMSE summary for all simulated 24-month out forecasts

Months Out	RMSE (Thousands of Head)																	
	Total Sample			Fixed - Fixed			Fixed - Recursive			Recursive - Fixed			Recursive - Recursive			Rolling - Rolling		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
1	0.35	19.29	68.23	0.35	23.05	68.23	0.35	23.05	68.23	0.35	16.63	57.74	0.35	16.63	57.74	0.35	17.09	57.76
2	12.38	37.95	73.68	12.38	35.74	73.68	17.86	37.39	73.26	18.14	38.86	73.11	19.87	39.53	71.64	18.10	38.22	69.60
3	14.16	34.06	77.58	14.16	31.85	60.71	18.35	32.29	60.14	15.70	37.06	77.58	16.42	35.40	71.22	16.98	33.71	69.00
4	13.79	31.52	74.80	15.93	29.27	56.20	17.76	29.13	52.29	13.79	35.50	74.80	14.22	32.33	62.73	15.52	31.34	62.93
5	13.46	32.24	71.29	17.43	32.14	58.45	17.51	31.34	56.18	14.06	35.64	71.29	13.46	31.04	56.68	14.26	31.03	59.94
6	14.60	30.30	68.86	17.01	30.56	58.42	18.11	29.46	55.55	14.81	33.58	68.86	16.04	28.85	51.86	14.60	29.05	55.39
7	14.58	31.02	75.68	16.71	31.42	58.57	17.41	29.77	55.29	15.28	35.31	75.68	15.82	28.97	51.18	14.58	29.60	56.07
8	15.29	29.86	75.53	15.78	30.13	56.88	16.29	28.32	52.19	15.29	34.74	75.53	16.60	27.59	48.27	15.64	28.54	53.88
9	15.21	28.92	74.45	15.21	29.00	54.33	15.90	27.49	50.12	16.31	33.59	74.45	15.90	26.95	46.23	16.46	27.58	51.16
10	14.45	27.89	71.74	14.45	28.08	55.16	15.30	26.60	50.72	15.53	32.33	71.74	15.30	25.90	43.97	15.62	26.52	50.36
11	16.26	29.07	68.40	16.83	29.17	53.24	17.93	28.25	49.25	16.26	32.56	68.40	17.00	27.58	43.62	16.68	27.78	48.12
12	16.12	28.29	68.17	16.12	28.37	50.99	17.22	27.38	47.16	16.12	32.09	68.17	16.61	26.73	42.21	16.33	26.88	46.36
13	15.57	28.11	67.53	15.57	28.45	51.03	16.65	27.22	46.87	16.05	31.88	67.53	16.08	26.23	40.84	15.78	26.74	45.51
14	16.45	29.42	66.92	17.85	30.11	49.34	20.08	28.90	45.17	16.45	32.56	66.92	18.42	27.61	39.37	17.96	27.93	43.88
15	15.90	29.49	68.88	17.48	30.74	50.15	19.48	28.62	45.32	15.90	33.31	68.88	17.84	27.24	38.91	17.40	27.53	42.66
16	16.13	29.56	72.35	17.01	31.15	51.44	18.87	28.30	45.49	16.13	34.19	72.35	17.66	26.91	39.81	17.14	27.23	42.93
17	16.32	29.43	72.22	17.13	31.48	53.41	18.50	28.13	46.86	16.32	34.31	72.22	17.36	26.43	39.03	16.68	26.81	41.70
18	19.80	35.57	81.27	19.80	37.18	68.95	23.09	34.56	54.05	19.80	41.03	81.27	23.09	32.51	46.63	22.88	32.56	47.37
19	20.39	36.66	85.88	20.39	38.75	76.42	23.39	35.27	57.50	20.57	43.35	85.88	23.39	32.98	47.71	22.96	32.93	46.84
20	21.33	38.16	88.72	21.33	40.31	82.57	23.77	36.30	60.05	21.33	46.02	88.72	23.77	34.09	50.79	23.84	34.08	50.29
21	22.22	38.82	92.15	22.22	41.33	88.86	23.86	36.53	60.67	22.22	47.76	92.15	23.86	34.24	51.41	23.74	34.23	50.02
22	21.82	38.50	91.64	21.82	41.36	90.65	23.31	36.14	62.15	21.82	47.75	91.64	23.31	33.63	50.94	23.41	33.64	50.28
23	22.05	38.61	90.14	22.05	41.50	90.14	23.66	36.16	61.31	22.05	47.69	90.14	23.66	33.77	49.87	23.78	33.92	49.20
24	21.67	38.42	90.59	21.67	41.42	90.59	23.37	35.91	60.77	21.67	47.42	90.59	23.37	33.54	49.32	23.52	33.78	49.33

Note: Titles for table sections begin with the simulation method for optimal length and are followed by the prediction method.

Table A13: Heifer slaughter models MAPE summary for all simulated 24-month out forecasts

Months Out	MAPE (Percent)																	
	Total Sample			Fixed - Fixed			Fixed - Recursive			Recursive - Fixed			Recursive - Recursive			Rolling - Rolling		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
1	0.05	2.57	9.08	0.05	3.07	9.08	0.05	3.07	9.08	0.05	2.21	7.68	0.05	2.21	7.68	0.05	2.27	7.69
2	1.78	5.02	10.75	1.78	4.79	10.75	2.58	5.05	10.68	2.54	5.09	10.07	2.74	5.17	9.90	2.54	5.02	9.64
3	2.00	4.32	10.79	2.00	4.09	8.26	2.20	4.06	7.94	2.12	4.84	10.79	2.04	4.46	9.94	2.07	4.17	9.65
4	1.55	3.88	10.39	1.84	3.63	7.66	1.97	3.50	6.95	1.75	4.54	10.39	1.55	3.91	8.25	1.81	3.82	8.62
5	1.53	4.01	9.93	2.13	4.00	8.09	1.88	3.80	7.26	1.84	4.62	9.93	1.53	3.77	7.36	1.74	3.84	8.24
6	1.82	3.68	9.48	2.08	3.76	7.73	2.07	3.50	6.59	1.89	4.27	9.48	1.83	3.37	6.48	1.82	3.52	7.36
7	1.86	3.84	10.35	2.12	3.93	8.07	1.99	3.61	6.83	2.04	4.54	10.35	1.89	3.46	6.73	1.86	3.65	7.55
8	1.77	3.65	10.42	1.89	3.73	7.90	1.77	3.35	6.41	1.96	4.49	10.42	1.93	3.22	5.96	1.81	3.48	7.30
9	1.76	3.50	10.29	1.90	3.53	7.15	1.76	3.24	6.06	1.95	4.27	10.29	1.76	3.14	5.56	1.78	3.34	6.78
10	1.68	3.32	9.78	1.74	3.37	6.73	1.68	3.09	6.02	1.75	4.04	9.78	1.69	2.97	5.12	1.69	3.14	6.66
11	1.84	3.49	8.91	2.03	3.53	6.49	2.01	3.34	5.90	1.84	4.02	8.91	1.94	3.24	5.39	1.93	3.33	6.20
12	1.85	3.37	8.98	1.87	3.40	6.04	1.89	3.20	5.44	1.85	3.97	8.98	1.92	3.10	5.21	1.89	3.19	5.91
13	1.79	3.35	8.99	1.79	3.43	6.15	1.83	3.18	5.53	1.89	3.95	8.99	1.86	3.02	5.01	1.81	3.16	5.85
14	2.08	3.51	9.01	2.08	3.62	5.88	2.21	3.36	5.15	2.09	4.07	9.01	2.18	3.19	4.71	2.16	3.30	5.49
15	1.96	3.53	9.32	2.05	3.70	6.08	2.13	3.35	5.27	1.96	4.15	9.32	2.08	3.16	4.70	2.07	3.26	5.46
16	1.95	3.54	9.84	1.98	3.77	6.25	2.02	3.31	5.41	1.95	4.28	9.84	2.06	3.12	4.94	1.98	3.24	5.69
17	1.85	3.56	9.96	1.99	3.86	6.76	2.01	3.33	5.74	1.85	4.34	9.96	1.99	3.08	4.79	1.95	3.20	5.40
18	2.33	4.20	11.06	2.33	4.48	7.76	2.47	3.99	6.56	2.33	5.03	11.06	2.47	3.70	5.63	2.43	3.79	6.10
19	2.49	4.41	11.78	2.49	4.74	8.47	2.59	4.16	7.12	2.49	5.39	11.78	2.59	3.84	5.90	2.52	3.92	6.09
20	2.65	4.70	12.37	2.65	5.03	9.42	2.73	4.40	7.63	2.65	5.82	12.37	2.73	4.08	6.34	2.72	4.16	6.37
21	2.78	4.86	13.00	2.83	5.25	10.42	2.82	4.51	7.87	2.83	6.15	13.00	2.78	4.17	6.56	2.80	4.24	6.48
22	2.70	4.83	12.98	2.77	5.28	10.81	2.70	4.45	8.14	2.77	6.19	12.98	2.70	4.07	6.55	2.72	4.14	6.54
23	2.80	4.85	12.54	2.84	5.30	10.91	2.80	4.47	8.06	2.84	6.13	12.54	2.80	4.12	6.34	2.82	4.21	6.31
24	2.78	4.83	12.44	2.79	5.31	11.11	2.78	4.45	8.03	2.79	6.09	12.44	2.78	4.10	6.30	2.81	4.21	6.39

Note: Titles for table sections begin with the simulation method for optimal length and are followed by the prediction method.

Table A14: Heifer slaughter models optimal length simulation results for the 24-month horizon of selected models

Model	Method	Rank	Start Date	RMSE <i>(thousand head)</i>	MAPE <i>(percent)</i>	Survey Length
Cull Cow Price	Recursive-Recursive	1	7/1/2006	24.355	2.982	90
		2	7/1/2007	24.484	2.966	78
		3	1/1/2006	24.507	3.074	96
		4	1/1/2008	24.926	3.035	72
		5	7/1/2005	24.955	3.201	102
	Rolling-Rolling	1	1/1/2007	24.029	2.895	84
		2	7/1/2007	24.429	2.991	78
		3	1/1/2006	25.158	3.058	96
		4	7/1/2004	25.321	3.251	114
		5	1/1/2005	25.475	3.193	108
Cull Cow Price & Heifer Alfalfa Price Ratio	Recursive-Recursive	1	1/1/2006	24.542	3.078	96
		2	7/1/2006	24.619	2.941	90
		3	7/1/2005	25.010	3.210	102
		4	1/1/2005	25.359	3.287	108
		5	7/1/2004	25.659	3.278	114
	Rolling-Rolling	1	7/1/2004	25.608	3.299	114
		2	1/1/2004	25.957	3.375	120
		3	1/1/2005	26.255	3.267	108
		4	7/1/2003	26.845	3.470	126
		5	1/1/2003	27.578	3.360	132
Cull Cow Price & Futures Premium	Recursive-Recursive	1	7/1/2007	23.373	2.782	78
		2	7/1/2006	23.596	2.903	90
		3	1/1/2008	24.086	2.891	72
		4	1/1/2006	24.245	2.958	96
		5	7/1/2005	24.506	3.072	102
	Rolling-Rolling	1	1/1/2007	23.515	2.808	84
		2	1/1/2006	24.039	2.871	96
		3	7/1/2007	24.167	2.918	78
		4	7/1/2004	24.746	3.177	114
		5	1/1/2008	25.276	3.024	72

Note: Methods sections begin with the simulation method for optimal length and are followed by the prediction method.

Table A15: Selected heifer slaughter model performance summary for 24-month out forecasts

Months Out	Cull Cow Price						Cull Cow Price & Heifer Alfalfa Price Ratio						Cull Cow Price & Futures Premium					
	<i>Recursive - Recursive</i>			<i>Rolling - Rolling</i>			<i>Recursive - Recursive</i>			<i>Rolling - Rolling</i>			<i>Recursive - Recursive</i>			<i>Rolling - Rolling</i>		
	RMSE	MAPE	U_2	RMSE	MAPE	U_2	RMSE	MAPE	U_2	RMSE	MAPE	U_2	RMSE	MAPE	U_2	RMSE	MAPE	U_2
1	7.22	0.96	0.168	8.10	1.08	0.189	9.33	1.24	0.218	21.89	2.91	0.510	5.97	0.79	0.139	4.00	0.53	0.093
2	38.16	4.69	0.782	31.78	4.02	0.651	36.36	4.60	0.745	34.54	4.90	0.707	25.46	3.19	0.521	28.84	3.46	0.591
3	32.02	3.74	0.603	25.95	2.72	0.489	31.25	3.87	0.588	29.52	3.98	0.556	21.02	2.39	0.396	23.56	2.37	0.444
4	27.73	2.84	0.491	23.48	2.51	0.416	27.13	3.04	0.481	25.57	2.99	0.453	18.81	2.12	0.333	22.65	2.47	0.401
5	25.97	2.78	0.419	21.05	2.10	0.340	26.58	3.14	0.429	26.22	3.24	0.423	19.56	2.35	0.316	22.20	2.57	0.358
6	23.85	2.46	0.420	20.61	2.18	0.363	24.30	2.69	0.428	23.97	2.77	0.423	19.29	2.38	0.340	20.80	2.41	0.367
7	23.00	2.46	0.336	19.53	2.09	0.285	23.68	2.71	0.346	23.94	2.86	0.350	17.96	2.14	0.263	19.36	2.17	0.283
8	21.55	2.22	0.283	18.29	1.87	0.241	22.18	2.43	0.292	22.41	2.56	0.295	16.83	1.93	0.221	18.13	1.95	0.239
9	21.13	2.25	0.291	18.16	1.93	0.250	21.58	2.41	0.298	21.89	2.54	0.302	15.90	1.76	0.219	17.13	1.78	0.236
10	20.26	2.14	0.276	17.44	1.85	0.238	20.62	2.28	0.281	21.14	2.45	0.288	15.30	1.69	0.209	16.52	1.73	0.225
11	21.36	2.36	0.301	19.59	2.16	0.276	21.87	2.51	0.308	22.67	2.71	0.319	20.30	2.18	0.286	20.50	2.17	0.288
12	20.45	2.17	0.294	18.76	1.98	0.269	20.95	2.32	0.301	21.71	2.50	0.312	19.79	2.16	0.284	19.96	2.15	0.287
13	19.74	2.08	0.272	18.09	1.90	0.249	20.41	2.29	0.281	21.11	2.44	0.291	19.09	2.07	0.263	19.23	2.04	0.265
14	21.80	2.39	0.311	20.22	2.20	0.289	23.05	2.64	0.329	23.87	2.80	0.341	21.60	2.40	0.308	21.47	2.36	0.307
15	21.35	2.36	0.314	19.60	2.12	0.288	22.48	2.58	0.331	23.33	2.75	0.343	20.88	2.27	0.307	20.76	2.23	0.305
16	20.77	2.29	0.302	18.99	2.01	0.276	21.87	2.50	0.318	22.77	2.69	0.331	20.22	2.13	0.294	20.10	2.09	0.292
17	20.52	2.32	0.291	18.53	1.97	0.263	21.58	2.52	0.306	22.56	2.72	0.320	19.67	2.06	0.279	19.53	2.02	0.277
18	24.85	2.79	0.331	22.88	2.43	0.305	25.39	2.95	0.338	26.22	3.15	0.349	23.09	2.47	0.308	23.00	2.43	0.307
19	24.77	2.85	0.323	22.96	2.52	0.299	25.26	3.00	0.329	26.05	3.19	0.340	23.39	2.59	0.305	23.22	2.54	0.303
20	25.58	3.04	0.320	24.44	2.79	0.306	25.88	3.17	0.324	26.71	3.36	0.334	23.77	2.73	0.297	23.84	2.72	0.298
21	25.25	3.05	0.302	24.49	2.87	0.293	25.50	3.16	0.305	26.34	3.35	0.315	23.86	2.82	0.285	23.99	2.81	0.287
22	24.74	2.97	0.287	23.99	2.80	0.279	25.01	3.08	0.291	25.81	3.26	0.300	23.31	2.70	0.271	23.47	2.72	0.273
23	24.46	2.96	0.288	23.98	2.85	0.283	24.72	3.08	0.291	25.60	3.27	0.302	23.66	2.80	0.279	23.78	2.82	0.280
24	24.36	2.98	0.292	24.03	2.89	0.288	24.54	3.08	0.294	25.61	3.30	0.307	23.37	2.78	0.280	23.52	2.81	0.282

Note: Titles for table sections begin with the simulation method for optimal length and are followed by the prediction method.

Table A16: Selected heifer slaughter models corrected for autocorrelated errors performance summary for the 24-month out horizon

Months Out	Cull Cow Price						Cull Cow Price & Heifer Alfalfa Price Ratio						Cull Cow Price & Futures Premium					
	<i>Recursive - Recursive</i>			<i>Rolling - Rolling</i>			<i>Recursive - Recursive</i>			<i>Rolling - Rolling</i>			<i>Recursive - Recursive</i>			<i>Rolling - Rolling</i>		
	RMSE	MAPE	U_2	RMSE	MAPE	U_2	RMSE	MAPE	U_2	RMSE	MAPE	U_2	RMSE	MAPE	U_2	RMSE	MAPE	U_2
1	5.60	0.75	0.131	5.84	0.78	0.136	4.45	0.59	0.104	13.98	1.86	0.326	2.07	0.27	0.048	5.72	0.76	0.133
2	46.36	5.52	0.950	37.01	4.49	0.758	44.83	5.28	0.918	42.07	5.49	0.862	30.44	3.53	0.623	34.45	4.19	0.706
3	37.91	3.85	0.714	30.41	3.27	0.573	36.87	3.88	0.694	34.97	4.20	0.658	24.87	2.43	0.468	28.34	3.08	0.534
4	32.84	2.94	0.582	26.82	2.81	0.475	32.04	3.09	0.568	30.30	3.20	0.537	21.77	2.05	0.386	25.75	2.86	0.456
5	31.20	3.04	0.504	24.22	2.46	0.391	31.55	3.34	0.509	31.00	3.55	0.500	22.02	2.31	0.355	25.02	2.93	0.404
6	28.58	2.67	0.504	23.23	2.46	0.409	28.89	2.92	0.509	28.41	3.10	0.501	21.75	2.40	0.383	23.60	2.78	0.416
7	27.90	2.77	0.408	22.75	2.51	0.333	28.31	3.00	0.414	28.40	3.24	0.415	20.73	2.33	0.303	22.40	2.65	0.327
8	26.12	2.47	0.344	21.29	2.22	0.280	26.48	2.65	0.348	26.57	2.85	0.349	19.43	2.09	0.256	20.98	2.37	0.276
9	25.07	2.42	0.346	20.65	2.21	0.285	25.42	2.58	0.350	25.60	2.78	0.353	18.38	1.94	0.253	19.85	2.19	0.274
10	23.79	2.18	0.325	19.62	2.03	0.268	24.12	2.33	0.329	24.36	2.58	0.332	17.51	1.81	0.239	18.95	2.06	0.259
11	23.76	2.31	0.334	20.68	2.25	0.291	24.53	2.51	0.345	24.82	2.75	0.349	20.93	2.22	0.294	21.20	2.38	0.298
12	23.03	2.27	0.331	20.09	2.21	0.289	23.74	2.45	0.341	24.07	2.68	0.346	20.04	2.06	0.288	20.32	2.22	0.292
13	22.17	2.15	0.305	19.43	2.13	0.268	23.08	2.41	0.318	23.42	2.63	0.322	19.45	2.01	0.268	19.68	2.15	0.271
14	22.98	2.36	0.328	21.12	2.40	0.302	23.94	2.62	0.342	24.39	2.84	0.348	21.68	2.34	0.310	21.56	2.44	0.308
15	22.21	2.23	0.327	20.44	2.28	0.301	23.21	2.52	0.341	23.62	2.71	0.348	21.02	2.25	0.309	20.90	2.34	0.308
16	21.51	2.10	0.313	19.88	2.21	0.289	22.47	2.36	0.327	22.88	2.57	0.333	20.39	2.15	0.297	20.27	2.24	0.295
17	20.98	2.07	0.298	19.33	2.14	0.275	21.92	2.31	0.311	22.36	2.53	0.318	19.81	2.07	0.281	19.68	2.14	0.279
18	26.38	2.63	0.352	24.74	2.67	0.330	26.82	2.84	0.357	27.36	3.06	0.365	23.96	2.53	0.319	24.42	2.63	0.325
19	25.77	2.57	0.336	24.24	2.64	0.316	26.16	2.76	0.341	26.69	2.97	0.348	23.80	2.58	0.310	24.05	2.64	0.314
20	26.20	2.74	0.328	25.28	2.87	0.316	26.36	2.89	0.330	26.93	3.10	0.337	24.02	2.70	0.300	24.42	2.78	0.305
21	25.63	2.69	0.307	24.92	2.86	0.298	25.78	2.82	0.308	26.35	3.02	0.315	23.89	2.75	0.286	24.25	2.82	0.290
22	25.16	2.64	0.292	24.51	2.83	0.285	25.33	2.78	0.294	25.87	2.97	0.301	23.37	2.67	0.272	23.80	2.77	0.277
23	24.75	2.62	0.292	24.35	2.85	0.287	24.87	2.73	0.293	25.49	2.95	0.300	23.61	2.75	0.278	23.91	2.84	0.282
24	24.41	2.61	0.292	24.06	2.84	0.288	24.46	2.70	0.293	25.18	2.93	0.301	23.20	2.70	0.278	23.46	2.76	0.281

Note: Titles for table sections begin with the simulation method for optimal length and are followed by the prediction method.

Table A17: 24-month out fed beef production performance summary for forecasts with optimal survey lengths

Months Out	No AR Errors						AR(1) Errors					
	<i>Recursive - Recursive</i>			<i>Rolling - Rolling</i>			<i>Recursive - Recursive</i>			<i>Rolling - Rolling</i>		
	RMSE	MAPE	U_2	RMSE	MAPE	U_2	RMSE	MAPE	U_2	RMSE	MAPE	U_2
1	26.37	1.54	0.277	27.12	1.58	0.285	12.80	0.73	0.134	13.00	0.74	0.137
2	41.96	2.03	0.528	36.68	1.92	0.462	62.21	1.95	0.783	48.53	1.66	0.611
3	35.27	2.02	0.461	30.00	1.81	0.392	50.91	2.05	0.665	39.75	1.72	0.520
4	31.12	1.93	0.455	28.07	1.73	0.411	44.42	2.00	0.650	35.56	1.70	0.520
5	31.58	1.89	0.436	26.87	1.67	0.371	44.74	2.00	0.617	34.44	1.69	0.475
6	40.94	1.92	0.599	35.02	1.69	0.512	48.80	2.04	0.713	38.03	1.72	0.556
7	49.41	1.99	0.575	44.68	1.75	0.520	48.73	2.08	0.567	38.54	1.75	0.449
8	49.54	2.05	0.506	45.97	1.82	0.470	45.89	2.09	0.469	36.50	1.75	0.373
9	47.66	2.09	0.514	43.98	1.86	0.474	47.48	2.11	0.512	38.66	1.78	0.417
10	46.05	2.12	0.494	42.17	1.87	0.452	45.14	2.11	0.484	36.84	1.78	0.395
11	51.00	2.16	0.511	46.97	1.92	0.471	46.89	2.13	0.470	40.85	1.81	0.409
12	49.49	2.20	0.516	45.19	1.95	0.471	45.27	2.14	0.472	39.64	1.83	0.413
13	48.60	2.22	0.483	43.94	1.97	0.437	43.74	2.14	0.435	38.19	1.83	0.380
14	47.70	2.25	0.491	43.11	1.98	0.444	42.20	2.13	0.435	36.88	1.83	0.380
15	46.08	2.26	0.491	41.69	1.99	0.445	40.97	2.12	0.437	35.90	1.83	0.383
16	44.67	2.26	0.474	40.72	1.99	0.432	39.76	2.10	0.422	34.92	1.82	0.371
17	43.33	2.25	0.454	39.58	1.99	0.414	38.57	2.08	0.404	33.87	1.81	0.355
18	53.39	2.26	0.567	50.38	2.01	0.535	49.68	2.08	0.527	45.38	1.82	0.482
19	53.39	2.27	0.581	50.46	2.02	0.549	48.41	2.08	0.527	44.19	1.82	0.481
20	54.63	2.28	0.602	52.42	2.04	0.578	48.55	2.08	0.535	45.30	1.82	0.500
21	54.65	2.30	0.617	52.11	2.06	0.589	51.47	2.08	0.581	47.69	1.84	0.539
22	55.00	2.32	0.634	52.12	2.08	0.601	50.52	2.09	0.583	46.83	1.84	0.540
23	54.90	2.33	0.634	52.00	2.10	0.600	49.52	2.09	0.571	46.00	1.85	0.531
24	54.21	2.34	0.633	51.07	2.11	0.597	48.48	2.09	0.566	45.03	1.86	0.526

Note: Titles for table sections begin with the simulation method for optimal length and are followed by the prediction method.

Table A18: 24-month out fed beef production performance summary for forecasts with a January 1990 start date

Months Out	No AR Errors						AR(1) Errors					
	<i>Recursive - Recursive</i>			<i>Rolling - Rolling</i>			<i>Recursive - Recursive</i>			<i>Rolling - Rolling</i>		
	RMSE	MAPE	U_2	RMSE	MAPE	U_2	RMSE	MAPE	U_2	RMSE	MAPE	U_2
1	105.36	6.44	1.106	105.36	6.44	1.106	37.31	2.19	0.392	37.31	2.19	0.392
2	77.97	5.40	0.981	78.08	5.41	0.983	36.75	2.25	0.463	35.69	2.21	0.449
3	72.18	5.00	0.943	72.44	5.01	0.947	33.63	2.20	0.440	33.07	2.16	0.432
4	75.25	4.86	1.101	75.48	4.88	1.104	35.38	2.19	0.517	34.72	2.16	0.508
5	67.56	4.63	0.932	67.79	4.65	0.936	38.06	2.21	0.525	37.20	2.17	0.513
6	62.60	4.42	0.915	62.76	4.44	0.918	39.23	2.23	0.574	38.38	2.19	0.561
7	60.55	4.25	0.705	60.65	4.26	0.706	38.73	2.23	0.451	37.97	2.20	0.442
8	57.54	4.10	0.588	57.57	4.11	0.588	36.35	2.21	0.371	35.62	2.17	0.364
9	56.03	3.97	0.605	56.07	3.99	0.605	39.11	2.21	0.422	38.64	2.17	0.417
10	56.39	3.88	0.605	56.36	3.89	0.604	38.13	2.20	0.409	37.65	2.16	0.404
11	71.42	3.87	0.716	71.45	3.88	0.716	49.65	2.24	0.498	49.61	2.21	0.497
12	75.36	3.88	0.785	75.24	3.89	0.784	47.61	2.26	0.496	47.58	2.23	0.496
13	84.54	3.94	0.840	83.52	3.94	0.830	50.42	2.29	0.501	50.23	2.26	0.499
14	89.99	4.02	0.927	89.10	4.02	0.918	50.14	2.33	0.517	50.29	2.30	0.518
15	91.32	4.10	0.974	90.62	4.10	0.967	48.55	2.34	0.518	48.73	2.32	0.520
16	92.01	4.17	0.976	91.43	4.17	0.970	47.39	2.36	0.503	47.77	2.33	0.507
17	91.33	4.24	0.956	90.92	4.24	0.952	45.97	2.36	0.481	46.37	2.34	0.485
18	89.65	4.29	0.952	89.10	4.29	0.946	52.05	2.37	0.553	51.58	2.36	0.548
19	87.31	4.33	0.951	86.83	4.32	0.945	51.29	2.38	0.558	51.03	2.37	0.556
20	85.19	4.35	0.939	84.69	4.34	0.934	50.43	2.39	0.556	50.09	2.38	0.552
21	86.03	4.37	0.972	85.97	4.36	0.971	54.38	2.41	0.614	54.66	2.40	0.617
22	88.00	4.39	1.015	88.22	4.39	1.017	53.97	2.42	0.622	54.28	2.42	0.626
23	91.76	4.43	1.059	92.08	4.43	1.063	54.66	2.44	0.631	54.90	2.43	0.634
24	94.28	4.47	1.102	94.62	4.46	1.106	53.74	2.45	0.628	53.97	2.45	0.631

Note: Titles for table sections begin with the simulation method for optimal length and are followed by the prediction method.

APPENDIX E

Fed beef production forecast graphs over the 11-year testing window.

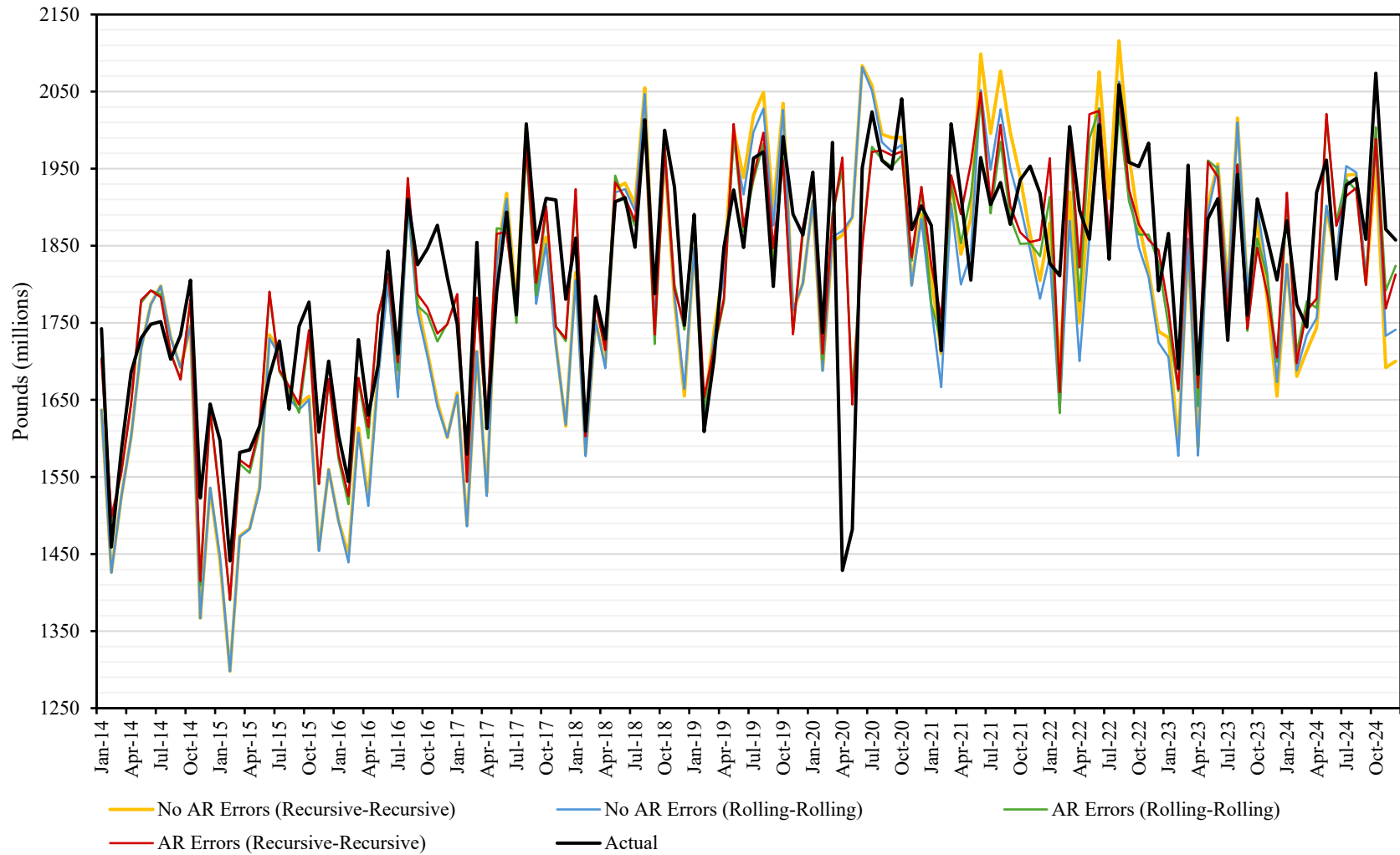


Figure A5: Fed beef production forecasts with training estimation window from Jan. 1990 to Dec. 2013

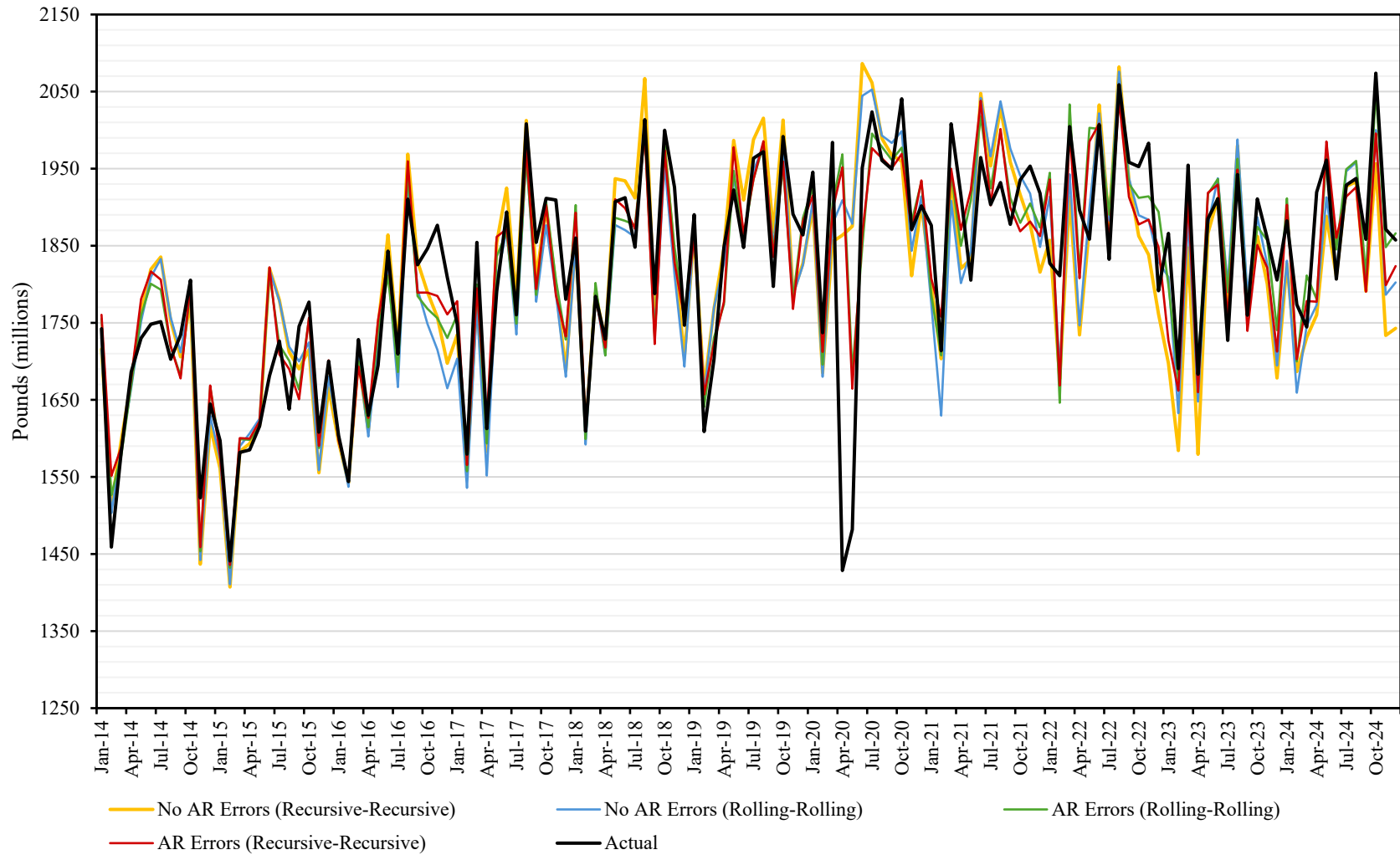


Figure A6: Fed beef production forecasts with training estimation window from optimized start dates to Dec. 2013

APPENDIX F

Parameter estimates for the forecast models not adjusted for autocorrelated errors in the initial training window with a December 2013 end date.

Note: Parameters are displayed for the recursive and rolling methods covered in the results sections. Fixed estimation parameters are not provided as those models were not discussed and did not show as optimal of forecasts.

Table A19: Recursive fed cattle dressed weight forecast model parameters from each model's optimized start date to December 2013

Variable	COF150 & Corn Price	COF150 & Futures Premium	COF150, Corn Price, & Futures Premium
	<i>(Equation 10)</i>	<i>(Equation 11)</i>	<i>(Equation 12)</i>
Intercept	479.965 (25.885)	493.124 (26.851)	480.774 (26.684)
COF150	0.010 (0.003)	0.012 (0.002)	0.010 (0.003)
Corn Price	2.214 (1.174)	-	2.133 (1.245)
Futures Premium	-	0.220 (0.318)	0.078 (0.315)
Trend	0.850 (0.066)	0.841 (0.071)	0.849 (0.068)
February	-9.423 (3.149)	-9.075 (3.423)	-9.274 (3.277)
March	-23.439 (3.149)	-25.183 (3.785)	-23.525 (3.748)
April	-40.887 (4.252)	-44.431 (4.602)	-41.362 (4.754)
May	-42.061 (4.421)	-44.358 (4.510)	-41.997 (4.530)
June	-28.726 (3.800)	-29.514 (4.134)	-28.494 (4.000)
July	-19.223 (3.525)	-19.285 (3.847)	-19.037 (3.684)
August	-13.531 (3.254)	-11.740 (3.708)	-13.164 (3.644)
September	-5.813 (3.167)	-5.569 (3.436)	-5.673 (3.289)
October	1.076 (3.196)	0.308 (3.385)	1.111 (3.273)
November	-0.353 (3.240)	-1.547 (3.401)	-0.406 (3.322)
December	-1.027 (3.200)	-1.044 (3.548)	-0.802 (3.398)
Adj. R-squared	0.943	0.935	0.940
RMSE	3.792	4.055	3.880
N	36	36	36

Note: Paratheses beneath parameter estimates contain their associated standard errors.

Table A20: Rolling fed cattle dressed weight forecast model parameters from each model's optimized start date to December 2013

Variable	COF150 & Corn Price	COF150 & Futures Premium	COF150, Corn Price, & Futures Premium
	<i>(Equation 10)</i>	<i>(Equation 11)</i>	<i>(Equation 12)</i>
Intercept	479.965 (25.885)	547.518 (23.475)	480.774 (26.684)
COF150	0.010 (0.003)	0.008 (0.003)	0.010 (0.003)
Corn Price	2.214 (1.174)	-	2.133 (1.245)
Futures Premium	-	0.260 (0.325)	0.078 (0.315)
Trend	0.850 (0.066)	0.716 (0.066)	0.849 (0.068)
February	-9.423 (3.149)	-8.751 (3.547)	-9.274 (3.277)
March	-23.439 (3.149)	-23.148 (3.965)	-23.525 (3.748)
April	-40.887 (4.252)	-40.741 (4.934)	-41.362 (4.754)
May	-42.061 (4.421)	-40.790 (4.643)	-41.997 (4.530)
June	-28.726 (3.800)	-26.539 (4.123)	-28.494 (4.000)
July	-19.223 (3.525)	-15.783 (3.861)	-19.037 (3.684)
August	-13.531 (3.254)	-9.120 (3.620)	-13.164 (3.644)
September	-5.813 (3.167)	-2.400 (3.466)	-5.673 (3.289)
October	1.076 (3.196)	4.065 (3.463)	1.111 (3.273)
November	-0.353 (3.240)	2.060 (3.466)	-0.406 (3.322)
December	-1.027 (3.200)	2.259 (3.599)	-0.802 (3.398)
Adj. R-squared	0.943	0.928	0.940
RMSE	3.792	4.845	3.880
N	36	48	36

Note: Paratheses beneath parameter estimates contain their associated standard errors.

Table A21: Recursive steer slaughter forecast model parameters from each model's optimized start date to December 2013

Variable	Steer Supply Stocks (Equation 13)	Fed Cattle Supply Flows (Equation 14)
Intercept	867.222 (691.834)	-500.662 (238.036)
Slaughter Days	56.173 (6.443)	64.822 (6.359)
Percent Steers	-714.784 (1306.694)	-
Alfalfa Price (t - 6)	-0.380 (0.264)	-
Steer Alfalfa Price Ratio	-44.167 (76.418)	-60.774 (54.757)
COF180	-	-0.206 (0.064)
COF150 (t - 1)	-	0.259 (0.065)
Placements 800+ lbs. (t - 4)	-	0.253 (0.078)
Placements 700 - 799 lbs. (t - 5)	-	0.135 (0.111)
Placements 600 - 699 lbs. (t - 6)	-	0.212 (0.104)
Placements < 600 lbs. (t - 4)	-	0.031 (0.072)
Trend	-0.886 (0.411)	-0.841 (0.203)
February	-68.491 (25.167)	-37.256 (28.015)
March	-28.417 (25.188)	51.870 (36.762)
April	21.184 (24.828)	29.794 (49.214)
May	180.503 (25.421)	158.399 (44.066)
June	208.992 (25.550)	150.706 (44.043)
July	168.614 (24.483)	114.313 (36.017)
August	119.946 (24.919)	113.501 (35.924)
September	89.032 (24.522)	101.042 (29.444)
October	22.049 (24.901)	84.761 (33.334)
November	7.266 (24.324)	65.890 (30.101)
December	-5.582 (23.787)	38.633 (22.360)
Adj. R-squared	0.871	0.874
RMSE	42.573	48.730
N	78	132

Note: Paratheses beneath parameter estimates contain their associated standard errors.

Table A22: Rolling steer slaughter forecast model parameters from each model's optimized start date to December 2013

Variable	Steer Supply Stocks (Equation 13)	Fed Cattle Supply Flows (Equation 14)
Intercept	1370.817 (556.775)	-532.649 (223.457)
Slaughter Days	55.659 (5.965)	63.762 (5.918)
Percent Steers	-1594.518 (1084.855)	-
Alfalfa Price (t - 6)	-0.275 (0.245)	-
Steer Alfalfa Price Ratio	-10.935 (69.731)	-37.722 (46.676)
COF180	-	-0.184 (0.058)
COF150 (t - 1)	-	0.237 (0.060)
Placements 800+ lbs. (t - 4)	-	0.249 (0.074)
Placements 700 - 799 lbs. (t - 5)	-	0.176 (0.099)
Placements 600 - 699 lbs. (t - 6)	-	0.232 (0.095)
Placements < 600 lbs. (t - 4)	-	0.032 (0.069)
Trend	-1.244 (0.301)	-0.705 (0.171)
February	-64.027 (23.100)	-41.236 (26.301)
March	-21.651 (22.721)	47.689 (34.053)
April	28.280 (22.392)	33.357 (45.572)
May	189.341 (23.076)	157.736 (41.188)
June	225.192 (23.190)	155.128 (40.340)
July	182.771 (22.337)	121.539 (32.958)
August	136.880 (22.670)	123.026 (33.204)
September	101.046 (22.557)	106.673 (27.458)
October	24.465 (22.419)	90.197 (31.133)
November	9.918 (22.233)	70.559 (28.283)
December	-3.644 (21.764)	37.417 (20.931)
Adj. R-squared	0.885	0.883
RMSE	41.734	47.625
N	90	144

Note: Paratheses beneath parameter estimates contain their associated standard errors.

Table A23: Recursive heifer slaughter forecast model parameters from each model's optimized start date to December 2013

Variable	Cull Cow Price <i>(Equation 15)</i>	Cull Cow Price & Heifer Alfalfa Price Ratio <i>(Equation 16)</i>	Cull Cow Price & Futures Premium <i>(Equation 17)</i>
Intercept	-265.413 (510.097)	-307.319 (503.452)	-376.923 (518.127)
Slaughter Days	29.541 (4.239)	30.663 (4.122)	29.174 (3.887)
Percent Other Heifers	2695.511 (1567.346)	2606.485 (1561.674)	3497.822 (1539.841)
Percent Beef Heifer Replacements	709.054 (1124.714)	719.174 (1099.741)	1282.987 (1112.269)
Cull Cow Price (t - 10)	-1.520 (0.557)	-1.687 (0.525)	-0.991 (0.553)
Heifer Alfalfa Price Ratio	-	2.360 (34.860)	-
Futures Premium	-	-	-1.622 (1.094)
Trend	-0.834 (0.292)	-0.715 (0.277)	-1.406 (0.297)
February	-4.646 (18.014)	-4.309 (16.885)	-18.119 (17.019)
March	2.066 (17.663)	6.794 (16.727)	-0.397 (16.980)
April	-23.308 (17.532)	-18.132 (16.325)	-16.948 (17.924)
May	-2.546 (17.665)	7.540 (16.650)	-10.676 (17.047)
June	15.562 (17.648)	22.919 (16.674)	-7.392 (17.082)
July	-14.706 (17.116)	-8.899 (16.835)	-25.721 (17.103)
August	-7.973 (18.040)	-4.109 (17.666)	-13.812 (18.246)
September	-8.451 (18.405)	-2.658 (17.815)	-7.845 (18.445)
October	8.754 (17.947)	12.454 (17.535)	7.786 (18.268)
November	7.136 (17.337)	13.135 (16.796)	-3.194 (17.129)
December	-24.650 (16.436)	-18.254 (15.984)	-37.387 (15.972)
Adj. R-squared	0.678	0.680	0.765
RMSE	29.677	30.098	25.487
N	90	96	78

Note: Paratheses beneath parameter estimates contain their associated standard errors.

Table A24: Rolling heifer slaughter forecast model parameters from each model's optimized start date to December 2013

Variable	Cull Cow Price <i>(Equation 15)</i>	Cull Cow Price & Heifer Alfalfa Price Ratio <i>(Equation 16)</i>	Cull Cow Price & Futures Premium <i>(Equation 17)</i>
Intercept	145.890 (554.864)	-354.709 (386.194)	211.057 (556.243)
Slaughter Days	29.133 (4.348)	29.374 (3.887)	28.621 (4.359)
Percent Other Heifers	1786.081 (1636.517)	2971.714 (1347.687)	1660.573 (1635.798)
Percent Beef Heifer Replacements	-36.333 (1180.628)	705.365 (754.132)	-92.691 (1178.535)
Cull Cow Price (t - 10)	-0.934 (0.629)	-1.623 (0.419)	-0.826 (0.634)
Heifer Alfalfa Price Ratio	-	-8.774 (33.405)	-
Futures Premium	-	-	-1.431 (1.231)
Trend	-1.052 (0.311)	-0.781 (0.271)	-1.106 (0.313)
February	-0.301 (18.024)	-4.732 (15.461)	-2.219 (18.053)
March	6.626 (17.701)	11.190 (15.502)	8.419 (17.721)
April	-17.357 (17.670)	-15.850 (14.802)	-8.840 (19.085)
May	4.518 (17.904)	14.598 (14.837)	7.999 (18.106)
June	22.987 (17.930)	27.324 (14.804)	21.425 (17.934)
July	-5.897 (18.295)	0.978 (14.336)	-5.567 (18.249)
August	7.907 (19.513)	1.061 (14.933)	7.256 (19.470)
September	7.210 (19.931)	3.342 (14.696)	11.318 (20.190)
October	25.037 (19.531)	22.671 (14.538)	27.769 (19.621)
November	11.299 (18.499)	10.915 (14.297)	14.648 (18.674)
December	-18.291 (17.117)	-8.293 (14.096)	-19.877 (17.126)
Adj. R-squared	0.693	0.658	0.694
RMSE	29.382	30.145	29.305
N	84	114	84

Note: Paratheses beneath parameter estimates contain their associated standard errors.