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SYSTEMS FORECASTING BY-PARTS: A STUDY ON FED BEEF PRODUCTION

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SYSTEMS FORECASTING BY-PARTS: A CASE STUDY ON FED BEEF PRODUCTION

Abstract: *This study examines forecasts of fed beef production through a by-parts estimation framework to provide possibly more practical alternatives to relatively complex systems of equations methods. Recent shifts in cattle production, including elevated contributions of heifers in the slaughter mix and larger weights of 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 the potential of serial correlation within Deterministic Trend / Deterministic Seasonality models, this study highlights that practical enhancements to forecast accuracy can be sustained by simple procedures. The results of this study demonstrate that (1) historical data selection can significantly impact forecast quality; (2) correcting autocorrelated errors 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.*

Key Words: data quality, survey history, simulation, forecasting, fed beef production

1. Introduction & Background

Forecasting endogenous systems possesses a persistent detachment between econometric theory and observed applied practice. In academic literature, simultaneous frameworks such as vector autoregression (VAR) and related systems-based models, are often favored because they represent jointly determined relationships among variables. This makes such models appealing in settings where supply, demand, and subsequently quantities and prices all evolve as one greater entity. In applied forecasting environments, however, analysts frequently rely on simpler and more modular strategies that model key variables separately rather than as a fully specified system. These approaches are often easier to execute, update, and interpret, and they also allow forecasters to tailor model structure, covariates, and estimation procedures to the behavior of the individual series. Despite this practical appeal, little work has evaluated whether the added complexity and assumptions of simultaneous systems consistently produce superior forecast performance compared to more flexible alternatives.

This distinction is important because forecasting models are ultimately judged by how well they perform out of sample, how they compare with alternatives, and why differences in performance may arise. In Allen's (1994) view, forecast evaluation should center on these questions rather than on model form alone. More broadly, forecast errors reflect either unexpected changes in the market or a failure of the model to adequately use the information available at the time of prediction (Nordhaus, 1987). The appeal of more complex system-based methods is not sufficient justification for their use if that added structure does not translate into improved predictive quality or accuracy. Prior forecasting research has even cautioned that greater complexity may even increase estimation error and therefore worsen accuracy relative to simpler alternatives (Green & Armstrong, 2015; Stock & Watson, 2006).

A related issue is the quality and relevance of the data used to estimate forecasting models. In practice, one of the least discussed, but most consequential modeling decisions, is the length of the historical data used for estimation. Economists often include long time series to capture complete market cycles or improve statistical fit, yet older data may model structural relationships that are no longer informative for prediction. Estimation window choice is therefore not merely a technical detail, but a data quality issue that determines how much historical information remains valuable for prediction. Simulating alternative sample lengths provides one way to evaluate whether forecast performance improves when models are estimated over shorter or longer histories (Svolba, 2012). This concern is relevant for system-style approaches that impose a common estimation history across equations, because such uniformity assumes that different outcomes are best forecast from the same period of market history.

These questions are particularly relevant in cattle markets, where biological lags, cyclical herd dynamics, and rapidly changing market incentives can alter forecasting relationships. As of January 1, 2024, the U.S. cattle inventory fell to 87.2 million head, which marked the lowest January level observed in over half a century. The loss was reflective of combined COVID-19-era supply chain disruptions, widespread drought, elevated production costs, and record beef demand influencing producers to sell their stock. These pressures altered both the level and composition of the market at a time when the industry was already on the downside of its current cattle cycle. A staple of this period was record high cattle weights rallying to offset losses in fed cattle supplies. 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. Within the slaughter mix, however, heifers as a percent of total slaughter were at a staggering 32 percent, rivaling highs from over 20 years prior. What this meant for the industry was temporary relief for beef consumers in the short run, but in the long run it transpired into continued herd contraction. In an environment like this, where structural relationships can shift quickly, forecasting frameworks that depend on fixed, or highly constrained system-driven relationships, may be less adaptable than approaches that allow components of the production equation to be modeled more flexibly.

Prior research on forecasting in cattle markets has not explored alternatives such as this and has rather focused largely on price determination and broader livestock industry relationships within simultaneous system frameworks (e.g., Abidoye & Lawrence, 2009; Maples et al., 2022; Stillman, 1985; Weimar & Stillman, 1990; Zapata & Garcia, 1990). A smaller number of papers have employed more flexible single-equation models for forecasting purposes (e.g., Bacon et al., 1992; Norwood & Schroeder, 2000), but the research questions examined were not centered on whether a system of forecasts built from separately optimized equations could outperform more constrained alternatives. Instead, they examined how proprietary information or newly available public data improved the prediction of a single dependent variable. Limited evidence exists on whether a by-parts system of forecasts can benefit from allowing different component equations to use different covariates and different histories, and whether that flexibility translates into improved aggregate forecast performance.

Considering these dynamics, fed beef production is particularly well suited to this comparison because it can be decomposed into steer slaughter, heifer slaughter, and their associated dressed weights, where the relationship between slaughter and weights otherwise poses an endogenous relationship. This study uses that decomposition to compare a flexible by-parts framework with benchmark models that impose more common structure across equations, most notably through a common starting point in estimation history. Monthly and annual data on inventories, placements, slaughter by class, dressed weights by class, and prices are used to estimate deterministic trend and deterministic seasonal regression models for the major components of beef production. Forecast performance is then evaluated through a pseudo out-of-sample simulation that varies both the estimation window and forecast updating scheme, allowing direct comparisons across fixed, recursive, and rolling specifications.

Taken together, the broader forecasting question and the fed beef application motivate a central contribution of the study. The paper asks whether forecasting fed beef production by-parts provides measurable advantages over more constrained and complex alternatives, and whether those advantages depend on estimation sample choice and forecast updating procedures. In doing so, the paper aims to provide both an empirical assessment of the by-parts approach and a practical forecasting template for applied outlook work in cattle markets and allied industries.

2. Methodology

The forecasting methodology is based on single-equation regression models estimated for the principal components of fed beef production, which mathematically can be defined by equation 1, where steer and heifer slaughter outcomes are federally inspected totals in time period t and $Fed\ Cattle\ Dressed\ Weight_t$ is the weighted average dressed weight of steers and heifers.

$$Fed\ Beef\ Produciton_t = (Steer\ Slaughter_t + Heifer\ Slaughter_t) \times Fed\ Cattle\ Dressed\ Weight_t \tag{1}$$

A weighted average dressed weight is implemented due to comparable feeding practices in feedyards driving structural similarities in their respective time series. This treatment also preserves the decomposition needed for a by-parts system while preventing the forecasting exercise from becoming unnecessarily over-parameterized in a context where more important contrast is between slaughter components.

Model development occurs along two complementary analyses. The first emphasizes predictive efficiency, using simulation-based forecast evaluation to compare alternative specifications, estimation windows, and updating schemes on the basis of out-of-sample performance. The second emphasizes error diagnostics, with particular attention to the mitigation of serial correlation in model residuals. While the present analysis does not address broader issues such as endogeneity or multicollinearity, it focuses on a practical source of misspecification that remains especially relevant in seasonal time series. This dual structure allows the study to first identify whether certain model designs are competitive as forecasting tools and then to evaluate whether additional gains can be achieved through remedial correction once the more important design decisions have already been made.

2.1 Model Specification

Fed cattle slaughter and dressed weight time series exhibit strong seasonal patterns which can be modeled using the Deterministic Trend / Deterministic Season (DTDS) model. Thus, for a given dependent variable *i* in time period *t*, the general model structure for monthly observations is defined:

$$Y_{i,t} = \alpha_i + \delta_i T_t + \sum_{k=1}^{K} \beta_{i,k} x_{i,k,t-p} + \sum_{m=1}^{11} \gamma_{i,m} D_{m,t} + \varepsilon_{i,t} \ \ \forall\, k \in \{1, \dots, K\}, m \in \{1, \dots, 11\} \tag{2}$$

where $Y_{i,t}$ is the dependent variable, α_i is a constant, δ_i is the coefficient on time trend T_t, $\beta_{i,n}$ is the coefficient for the k^{th} explanatory variable, $x_{i,k,t-p}$ is explanatory variable k in time period t lagged p time periods, D_m is a dummy variable for month m, γ_m is the coefficients for the m^{th} dummy variable, and $\varepsilon_{i,t}$ is the error term.

The DTDS structure provides a useful foundation for the present problem for a couple of reasons. Firstly, it is a simple, interpretable, and broadly consistent framework for the type of modeling used by practitioners when building routine production forecasts. Secondly, it permits a wide range of explanatory variables and lag structures without forcing a singular system-wide structure on every equation. For this study's purposes, that flexibility is a feature rather than a weakness. The objective is not to develop a single universal equation that explains every component of fed beef production equally well, but rather it is to identify candidate equations for each major component and then evaluate them based on how they forecast under alternative estimation histories and updating procedures.

Candidate models are constructed from combinations of variables motivated by economic reasoning and prior literature. These include structural variables such as trend and the number of federally inspected slaughter days ($SltrDays$), measures of cattle availability and supplies, profitability ratios, price variables for outputs and feed inputs, and constructed indicators designed to reflect production incentives and bottlenecks. For example, cattle on feed over 150 days ($COF150$) is included in the model of dressed weights because it proxies the volume of cattle retained in feedyards longer than normal feeding durations, thereby capturing conditions when weights may rise as feedlots delay marketings. Similarly, ratios combining cattle prices with hay or corn prices are intended to capture the profitability incentives facing producers when determining whether to retain animals longer, market them sooner, or alter herd-building decisions.

2.2 Forecast Performance

Forecast performance is evaluated using an in- and post-sample design. Models are estimated on data from January 1980 through December 2013 and assessed over a post-sample period from January 2014 through December 2024, allowing evaluation across recent turning points in the cattle cycle and total slaughter. Forecasts are generated under recursive and rolling estimation. Recursive estimation updates parameters using an expanding sample in the post-sample period, while rolling estimation updates parameters using a fixed-length window that moves forward through time. These alternative schemes are intended to determine whether forecast performance improves when parameter estimates are allowed to adjust to information.

The different updating procedures reflect distinct assumptions on how much stability should be imposed on the underlying relationship between predictors and the outcome being forecast. Recursive estimation relaxes more standard fixed assumptions by allowing models to expand with each newly observed data point, thereby incorporating information while preserving older structures. Rolling estimation is more aggressive in adapting to change because it both adds new information and discards older observations, maintaining a constant window length while shifting the window forward through time. In a market such as cattle, where structural change may occur gradually across years or more abruptly in response to drought, supply disruptions, or shifting incentives, these different updating rules are likely to matter. The forecasts subsequent accuracy is then evaluated at various horizons over the post-sample using three evaluation metrics: root mean square error (RMSE), mean absolute percentage error (MAPE), and Theil's U_2 for forecast quality.

2.3 Survey Length

A central component of the forecasting problem is the survey length of the included time series, or alternatively the length of history used during estimation. The purpose of evaluating survey length 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 time horizon, for each dependent variable and subsequent model of assessment, different simulation repetitions are executed at various survey lengths where using the evaluation criteria, the optimal lengths of the time history, and/or estimation window size, are presented. Survey length is selected based on RMSE, which is treated as the primary measure of forecast accuracy and quality.

Simulation procedures for all models begin with a time history truncated to 36 observations, representing the most recent three years of data within the in-sample period, or January 2011 through December 2013. Based on those observations, forecasts are generated over an initial 24-month horizon. In the next step, the available time history is extended backward in 6-month increments until the maximum feasible history is reached. For each iteration, forecast criteria are recalculated. This process creates an empirical comparison of whether a given variable combination performs best with a short and recent history, a moderate-length history, or a much longer historical span. Rather than assuming that more history is always better, the method allows the data to indicate whether older information improves or hinders prediction.

The focus on the 24-month window in the survey-length identification process is deliberate. Lengths are optimized over the 2014–2015 period because that interval corresponds to a trough in slaughter when herd liquidation came to an end and herd rebuilding was beginning. An optimal short-window forecast should therefore minimize error over a period that serves as a plausible analog to more recent market conditions in which high weights and altered slaughter composition offset declining head marketed. If models that best explain the 2014–2015 trough also perform well in the more recent environment, that provides evidence that the selected history captured information that remained relevant beyond the original analog period. If not, it suggests either that structural change was more substantial than expected or that older analog information had limited carryover value.

Forecasts are considered under alternative estimation techniques where a single simulation procedure identifies the best survey length under recursive and rolling estimation. Recursive estimation is used to identify optimal starting dates in history, while rolling estimation is used to identify optimal observation lengths that do not rely on fixed start dates. This design may appear elaborate, but it is central to the paper's contribution because it separates the question of how a survey length is identified from the question of how a model is updated.

2.4 Autocorrelated Errors

Issues may develop as a byproduct of the simulation process due to seasonally induced inertia in the examined time series, most notably is serial correlation in the error terms. While previous papers have intentionally ignored this (e.g., Bacon et al., 1992; Norwood & Schroeder, 2000), lack of correction could be further driving forecast errors. As such, models are assessed over the in-sample period using the partial autocorrelation function (PACF). In the event a model shows signs of significantly autocorrelated errors at the five 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-sample. Alternatively said, minor autocorrelation that would require extensive remedial measures will be neglected.

Autocorrelated error correction is not treated as the primary forecasting innovation. Rather, it is evaluated after candidate equations and survey lengths have already been chosen depending on forecasting performance. This allows the paper to distinguish between two separate sources of improvement for applied practitioners: gains from better structuring the forecasting system itself, and gains from correcting misspecification within otherwise competitive component models.

3. Data

Data used in this analysis are in monthly and annual frequencies spanning from January 1980 to December 2024. The types of data collected encompass factors related to profitability, cattle supplies, and the demand for cattle to slaughter, and are obtained from the Livestock Marketing Information Center (LMIC). Forecasts can be constrained by the quantity of data available. Primary limitations are in the survey history of data and the time-frequency of that information. For instance, most cash and futures prices on cattle are only available starting in 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, and 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.

Data transformations performed include the extrapolation of annual data into monthly frequencies and the division of inventory and price values to derive measures of relative supplies and profitability. For annual data, given monthly forecasts are the objective, annual data is extrapolated in a stairstep manner, meaning a single yearly value is held constant for every month within that year. This process provides the model with a rough idea of where cattle supplies are for the year without making assumptions about intra-year behavior.

4. Results

Results showed that the major components of fed beef production did not share a common optimal estimation history. Instead, model performance varied both in the preferred amount of history included during estimation and in the type of explanatory information that proved most useful. Similarly, corrections for serial correlation were often beneficial to model quality and accuracy, though those gains occurred after more fundamental differences had already emerged across component equations. Because the primary objective of the paper is to evaluate whether a by-parts forecasting system benefits from preserving component-specific structure, the discussion emphasizes select models and simulation outcomes that are most informative for answering that question.

4.1 Selected Models and Optimized Histories

When slaughter troughed in 2015, weights in cattle rose aggressively to record highs as the cost of feed inputs fell, cattle prices rose to all-time highs, and feeder cattle supplies were dwindling. Reflective of these dynamics, the model selected as the top candidate for dressed weights from methods recursive and rolling is defined by equation 3,

$$FedDress_t = \alpha + \delta Trend_t + \beta_1 COF150_t + \beta_2 CornPrice_t + \beta_3 FuturesPremium_t + \sum_{m=1}^{11} \gamma_m D_m + \varepsilon_t \tag{3}$$

where, $COF150_t$ is as previously established, $CornPrice_t$ is the cash corn price for month *t*, and the futures premium is the difference between the nearby live cattle futures contract approaching expiration and the next closest/nearby contract. Economically, this model captures two related incentives. The first is the willingness of feeders to retain cattle on feed longer when relative revenues justify doing so. The second is the physical presence of cattle that have already been on feed for extended periods and are therefore likely to produce heavier market weights. Summary statistics from Table 1 indicate that the preferred dressed weight models ultimately selected histories beginning in July 2010 and January 2011 for recursive and rolling methods, respectively, highlighting that a very recent window outperformed longer spans of older data in forecasting weights. This is consistent with the idea that the relationship between weights, feed costs, supply conditions, and revenue incentives changed over time to the degree that older observations diluted predictive accuracy.

Models of federally inspected steer slaughter showed more mixed results in how they responded to different types of supply information. In particular, the inclusion of annual supply stocks of steers displayed strong ability to produce accurate forecasts, while models built around measures of current feedlot flows, including placements on feed, showed more variable performance. The selected steer slaughter model is defined by equation 4,

$$SteerSlaughter_t = \alpha + \delta Trend_t + \beta_1 SltrDays_t + \beta_2 PctSteers_t + \beta_3 SteerAlfalfaPriceRatio_t + \beta_4 AlfalfaPrice_{t-6} + \sum_{m=1}^{11} \gamma_m D_m + \varepsilon_t \tag{4}$$

where, $SltrDays_t$ is included as a structural parameter, $PctSteers_t$ is the number of steers greater than 500 pounds that came available in the current year based on the calf crop from the previous year, $SteerAlfalfaPriceRatio_t$ is a profitability ratio that assesses the 5 market cash fed cattle price relative to the cash alfalfa hay price, and $AlfalfaPrice_{t-6}$ is the cash alfalfa hay price lagged six months to capture the relative cost of feed when cattle would have possessed a rough timeline of being placed in the feedyard. The optimized histories for steer slaughter differed from those for weights. Where the dressed weight models favored start dates beginning in July 2010 and January 2011 for recursive and rolling methods, respectively, steer slaughter showed preference with dates January 2007 and July 2006. This longer preferred history suggests that steer slaughter and the included explanatory information retained more predictive value from earlier market conditions than did dressed weights.

Table 1: Selected model optimal start dates and forecast errors across horizons

Model	Method	Start Date	Horizon	RMSE*	MAPE	U2
Fed Dressed Weights	Recursive	Jul-2010	1-Month	9.53	1.10	0.011
			6-Month	11.79	1.22	0.014
			12-Month	13.49	1.35	0.016
			18-Month	14.84	1.47	0.017
	Rolling	*Jan-2011*	1-Month	6.88	0.78	0.008
			6-Month	10.72	1.08	0.012
			12-Month	14.54	1.43	0.017
			18-Month	18.36	1.80	0.021
Steer Slaughter	Recursive	Jan-2007	1-Month	40.26	3.15	0.032
			6-Month	53.89	3.47	0.041
			12-Month	60.97	3.75	0.046
			18-Month	67.42	4.03	0.050
	Rolling	*Jul-2006*	1-Month	37.64	2.95	0.029
			6-Month	53.01	3.39	0.040
			12-Month	60.30	3.68	0.045
			18-Month	67.72	4.06	0.051
Heifer Slaughter	Recursive	Jul-1982	1-Month	50.05	6.57	0.066
			6-Month	56.36	6.49	0.073
			12-Month	75.13	7.76	0.096
			18-Month	93.51	9.84	0.119
	Rolling	*Jan-1981*	1-Month	43.74	5.96	0.060
			6-Month	55.67	6.47	0.075
			12-Month	63.12	7.19	0.086
			18-Month	71.52	8.19	0.097

Note: Rolling-Rolling model start dates are italicized to reflect the non-fixed nature of the method.
** RMSE values are in pounds for fed dressed weights and thousands of head for slaughter.*

Similar to equation 5, the identified model of heifer slaughter includes the variable $SltrDays_t$, and uses concepts similar to that of $PctSteers_t$, which is based on extrapolated annual data from the cattle inventory report. Equation 6 contains the variables $PctOtherHeifers_t$ and $PctBeefHeiferReplace_t$ which represent the number of other heifers greater than 500 pounds and the number of beef heifer replacements greater than 500 pounds that came available in the current year relative to the calf crop from the prior year.

$$\begin{aligned} &HeiferSlaughter_t \\ &\quad = \alpha + \delta Trend_t + \beta_1 SltrDays_t + \beta_2 PctOtherHeifers_t \\ &\quad + \beta_3 PctBeefHeiferReplace_t + \beta_4 CullCowPrice_{t-10} + \sum_{m=1}^{11} \gamma_m D_m + \varepsilon_t \end{aligned} \tag{5}$$

Also in equation 6, is the variable $CullCowPrice_{t-10}$, which is the cash value of a cull cow in West Kansas lagged 10 months to reflect the producer's initial decision to liquidate or retain reproductively mature females.

The same broader lesson emerged in heifer slaughter. Although heifer marketing is deeply tied to herd building and liquidation incentives, the selected models for heifer slaughter favored histories that were substantially longer than those for dressed weights and steer slaughter. In other words, the component series collectively rejected a uniform historical starting point. Dressed weights preferred a shortened and recent estimation window, whereas both slaughter components preferred longer, and in cases much older histories. This component specific heterogeneity is central to the paper's main argument. The value of a by-parts framework did not stem only from the ability to estimate equations separately. It stemmed from the ability to let different components preserve differing historical structures.

4.2 Autocorrelated Errors in Selected Component Models

Corrections for serial correlation generally improved the quality of the selected forecasts, although the extent of the gains varied across components and across horizons. In heifer slaughter models, autocorrelated errors were more pronounced over the training sample compared to dressed weights and steer slaughter. Residual diagnostics and PACF examinations indicated that the series required first-order and first-order seasonal autoregressive corrections (i.e., AR(1) and SAR(1)); this was true for both recursive and rolling models.

Re-estimation with an AR(1) and SAR(1) yielded notable improvements in the heifer slaughter forecasts. RMSE reductions on 1-month out forecasts were roughly 45 and 38 percent for recursive and rolling methods, respectively. Over a longer 18-month horizon, accounting for autocorrelated errors again improved performance. The recursive method saw RMSE values fall by 41 percent, while the rolling model saw declines of 21 percent. MAPE and Theil's U_2 values also fell meaningfully relative to the uncorrected versions. Importantly, however, these gains occurred within models that had already been identified as competitive through the survey-length exercise. Thus, the autocorrelation results should be interpreted as complementary to, rather than substitutes for, the broader design gains achieved by selecting component-specific histories and updating procedures.

The same broader interpretation applied across the dressed weight and steer slaughter equations. Both weights and steer slaughter possessed significant first order autocorrelated errors. While dressed weights responded well to AR(1) correction, mixed results were achieved for steer slaughter. Specifically, rolling steer slaughter forecasts improved with the AR(1) process, whereas recursive models observed a decay the further the horizon got. At the 1-month horizon, dressed weights observed RMSE declines of 52 and 35 percent on recursive and rolling models, respectively, where steer slaughter had declines of 13 and 7 percent. By 18-months out, dressed weight RMSE reductions were 6 percent on the recursive model and 8 percent on the rolling model; recursive steer slaughter forecast RMSE increased 2 percent where rolling declined 2 percent. A summary of error inclusion and forecast metrics is provided in Table 2, of which metrics can be contrast with pre-corrected model outputs from Table 1.

Corrections for autocorrelation overall improved forecast performance, but those gains did not overturn the more important result that the component series behaved differently with respect to estimation history and updating method. In practical terms, this implies that analysts

Table 2: Selected model errors across horizons when corrected for serial correlation

Model	Method	AR Order	Horizon	RMSE*	MAPE	U2
Fed Dressed Weights	Recursive	AR(1)	1-Month	4.60	0.53	0.005
			6-Month	9.65	0.97	0.011
			12-Month	12.13	1.20	0.014
			18-Month	13.89	1.38	0.016
	Rolling	AR(1)	1-Month	4.50	0.52	0.005
			6-Month	9.70	0.96	0.011
			12-Month	13.14	1.28	0.015
			18-Month	16.91	1.64	0.019
Steer Slaughter	Recursive	AR(1)	1-Month	35.22	2.75	0.028
			6-Month	52.96	3.42	0.040
			12-Month	61.35	3.79	0.046
			18-Month	68.49	4.12	0.051
	Rolling	AR(1)	1-Month	35.04	2.75	0.028
			6-Month	51.89	3.32	0.039
			12-Month	59.29	3.62	0.045
			18-Month	66.57	3.98	0.050
Heifer Slaughter	Recursive	AR(1) & SAR(1)	1-Month	27.51	3.65	0.037
			6-Month	41.85	4.70	0.055
			12-Month	46.42	5.01	0.061
			18-Month	55.56	5.96	0.074
	Rolling	AR(1) & SAR(1)	1-Month	26.99	3.59	0.036
			6-Month	41.14	4.64	0.054
			12-Month	46.90	5.10	0.062
			18-Month	56.62	6.12	0.075

*Note: * RMSE values are in pounds for fed dressed weights and thousands of head for slaughter.*

confronting similar forecasting systems should first pay attention to whether the right history and updating process have been chosen and then consider residual error correction as a secondary but still worthwhile step. This sequencing aligns with the philosophy of the paper: forecasting gains are more valuable when they are achieved through transparent and operationally realistic decisions before resorting to more intricate statistical repair.

4.3 Aggregate Fed Beef Production Forecasts

The aggregate fed beef production results provide the clearest test of the paper's central question. If the advantage of a by-parts system is real, then forecasts assembled from component equations optimized on their own terms should outperform benchmark forecasts that impose a common historical starting point across components. The prior evidence supported that outcome. The major components of fed beef production did not share a common optimal estimation history. Further investigation found that the preservation of that difference ultimately improved the aggregate forecast.

Table 3: Fed beef production average errors across horizons

Estimation	Method	Start Date	Horizon	RMSE*	MAPE	U2
Without AR Errors	Recursive	Jan-90	1-Month	76,788.54	4.27	0.0427
			6-Month	90,851.90	4.20	0.0497
			12-Month	104,686.63	4.67	0.0570
			18-Month	108,714.80	4.79	0.0592
		Optimized	1-Month	67,112.75	3.74	0.0374
			6-Month	80,141.71	3.70	0.0438
			12-Month	93,720.35	4.15	0.0510
			18-Month	107,629.11	4.82	0.0585
	Rolling	*Jan-90*	1-Month	77,376.03	4.38	0.0438
			6-Month	96,737.64	4.64	0.0535
			12-Month	108,495.39	5.04	0.0598
			18-Month	120,460.63	5.56	0.0665
		Optimized	1-Month	60,873.56	3.45	0.0345
			6-Month	76,343.19	3.60	0.0421
			12-Month	85,532.42	3.92	0.0471
			18-Month	93,026.66	4.23	0.0513
With AR Errors	Recursive	Jan-90	1-Month	53,920.98	3.02	0.0302
			6-Month	84,777.06	4.03	0.0466
			12-Month	94,459.64	4.28	0.0520
			18-Month	106,753.11	4.77	0.0588
		Optimized	1-Month	48,674.51	2.74	0.0274
			6-Month	70,374.80	3.27	0.0387
			12-Month	77,242.70	3.41	0.0424
			18-Month	88,057.67	3.82	0.0485
	Rolling	*Jan-90*	1-Month	52,894.71	2.97	0.0297
			6-Month	84,802.95	4.02	0.0466
			12-Month	95,806.62	4.33	0.0527
			18-Month	108,062.53	4.85	0.0595
		Optimized	1-Month	46,749.61	2.64	0.0264
			6-Month	66,229.39	3.03	0.0363
			12-Month	73,296.03	3.24	0.0401
			18-Month	82,617.76	3.62	0.0454

Note: Rolling-Rolling model start dates are italicized to reflect the non-fixed nature of the method.
** RMSE values are in millions of pounds.*

Across horizons, fed beef production forecasts constructed from optimized component equations outperformed forecasts constrained to use a uniform January 1990 start date. Aggregated recursive model's RMSE fell by 13 percent at the 1-month horizon and 1 percent by the 18-month horizon (average decline of 9 percent from horizons 1 to 18), while rolling model's RMSE fell 21 percent at 1-month and 23 percent by 18-months (average decline of 21 percent from horizons 1-18). These results support that allowing the component equations to retain different estimation histories did not merely redistribute forecast errors across the pieces of the system. Instead, it improved the aggregate production forecast itself.

Autoregressive error correction further improved aggregate fed beef forecasts once the optimized component equations had been assembled. Comparing non-corrected models to corrected in shorter-run horizons (1-month), optimized recursive RMSE fell 10 percent, while optimized rolling RMSE fell 12 percent. Over the longer 18-month horizon, optimized recursive RMSE declined 18 percent and rolling RMSE declined 24 percent. These gains demonstrate that serial correlation still mattered in the aggregate system and that correcting for it yielded further improvement. Also of interest with autocorrelation correction, is that the gains to the non-optimized models also showed major promise. Compared to forecasts that were optimized and had no AR errors included during estimation, AR error inclusive models that started in January 1990 observed average RMSE differences of -0.3 and 10 percent in recursive and rolling models, respectively, from 1 to 18-month horizons. The negative difference means that models that were corrected for autocorrelation but did not go through the simulation procedure for optimal survey history (i.e., started in January 1990) performed marginally better on average; a positive difference indicating that optimized windows of history performed better on average across horizons. On a broader scale, this means meaningful improvements can be made on recursive forecasts by simply considering if AR errors may be necessary, and/or that serial correlation is present, than running models through an entire simulation procedure. Rolling models suggest something that intuitively makes sense: long-term stability is an issue, thus identifying the optimal survey window is meaningful. Table 3 includes forecast model metrics for aggregated fed beef production.

Overall, these findings suggest that regardless of optimizing historical data inclusion, assessing the role of seasonal inertia in time series and how that plays into model specification can drastically improve or reduce forecast quality and accuracy. Even then, the larger contribution still originated from the component-specific design of the by-parts system itself, which showed the largest relative gains in forecast quality and accuracy. The aggregate evidence therefore mirrors the component evidence: the first order gain came from preserving differences in model structure, historical scope, and updating procedure across equations, while residual correction provided a secondary layer of refinement. Figures 1 and 2 graphically summarize these conclusions regarding fed beef production. Three additional figures are provided in the Appendix, containing the in-part component forecasts used to generate Figures 2. The values used are six-month out forecasts of fed dressed weights, steer slaughter, and heifer slaughter, where for each, the four discussed alternative model configurations are presented. Forecasts are visually similar and compete well across the processes considered. As identified previously, based on the component model in question, the success of single forecasting configuration against its competitors is highly dependent on the outcome variable of interest. For instance, recursive methods in the dressed weights models show a greater gravitation towards the mean, with comparatively less outliers. The opposite could be said in the case of steer slaughter.

5. Conclusions

The cumulative results reinforce the broader forecasting contribution of the study. The paper does not claim that simultaneous systems are universally inferior or that complexity is never

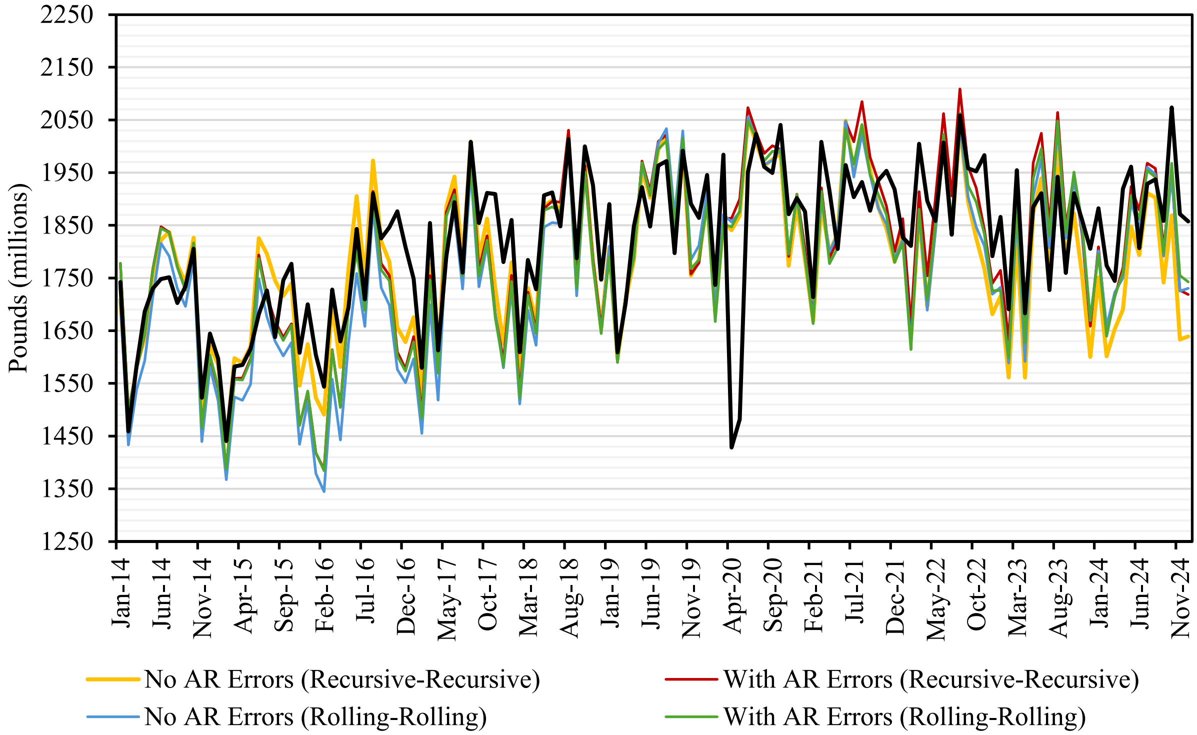

Figure 1: Six-month out fed beef production forecasts with a January 1990 start.

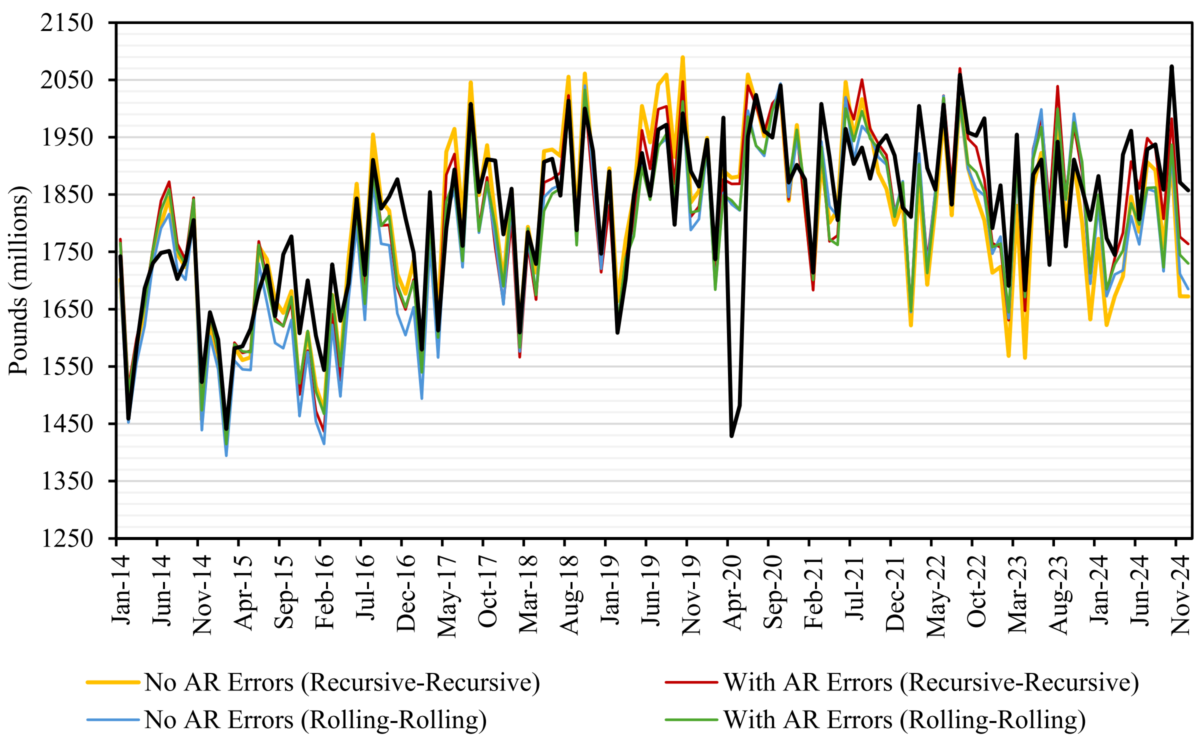

Figure 2: Six-month out fed beef production forecasts with an optimized history.

useful. Rather, it shows that in this endogenous production setting, a by-parts system of separately optimized equations offered measurable forecasting advantages over a more constrained benchmark that imposed common historical structure across the system. The gain arose because the major components of fed beef production did not behave as though they were best forecast from the same history, nor under the same updating rule. A framework that allowed them to differ proved better able to accommodate those distinctions. More broadly, the findings suggest that forecasting design in endogenous production systems should be viewed as a sequence of linked decisions: how to decompose the system, what information to include in each equation, how much history to retain, how the model should be updated once new data arrives, and whether residual misspecification warrants correction. In this study, each of those choices mattered. Most importantly, they mattered in ways that would have been obscured had the analysis begun and ended with a single common history. The contribution of the paper is therefore not simply that fed beef production can be forecast by-parts, but that by-parts systems can benefit from preserving meaningful differences across component series that more constrained approaches are designed to suppress.

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APPENDIX

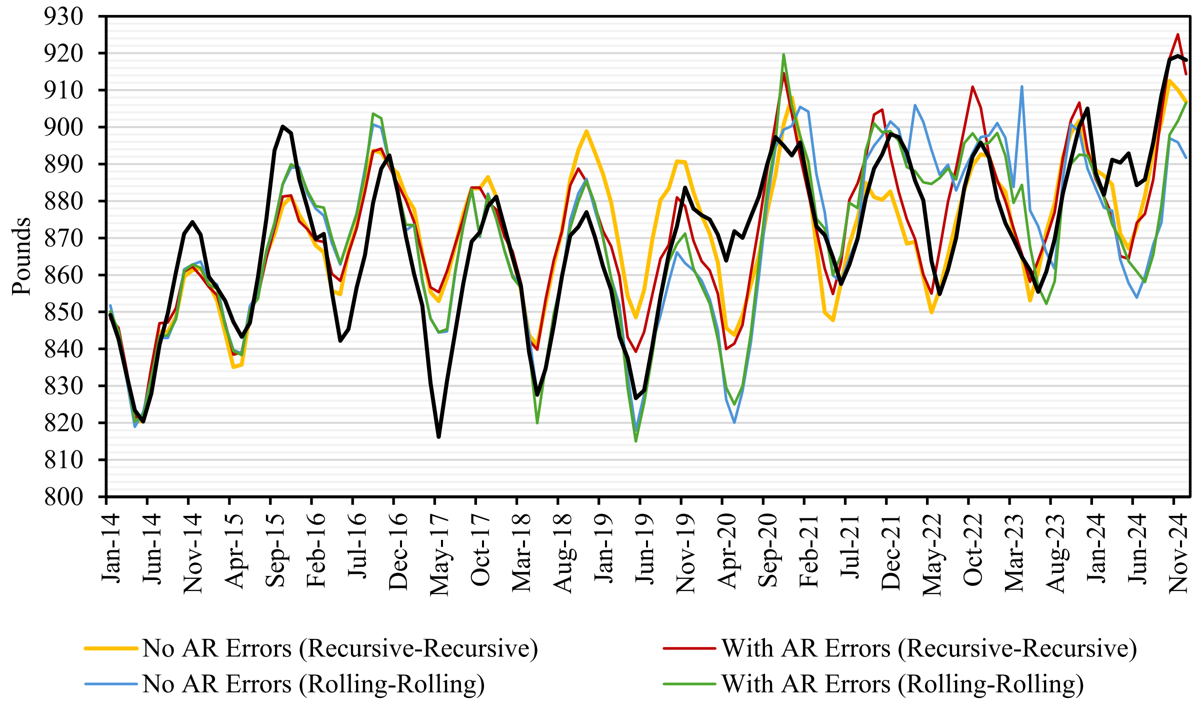

Figure A1: Six-month out fed dressed weight forecasts

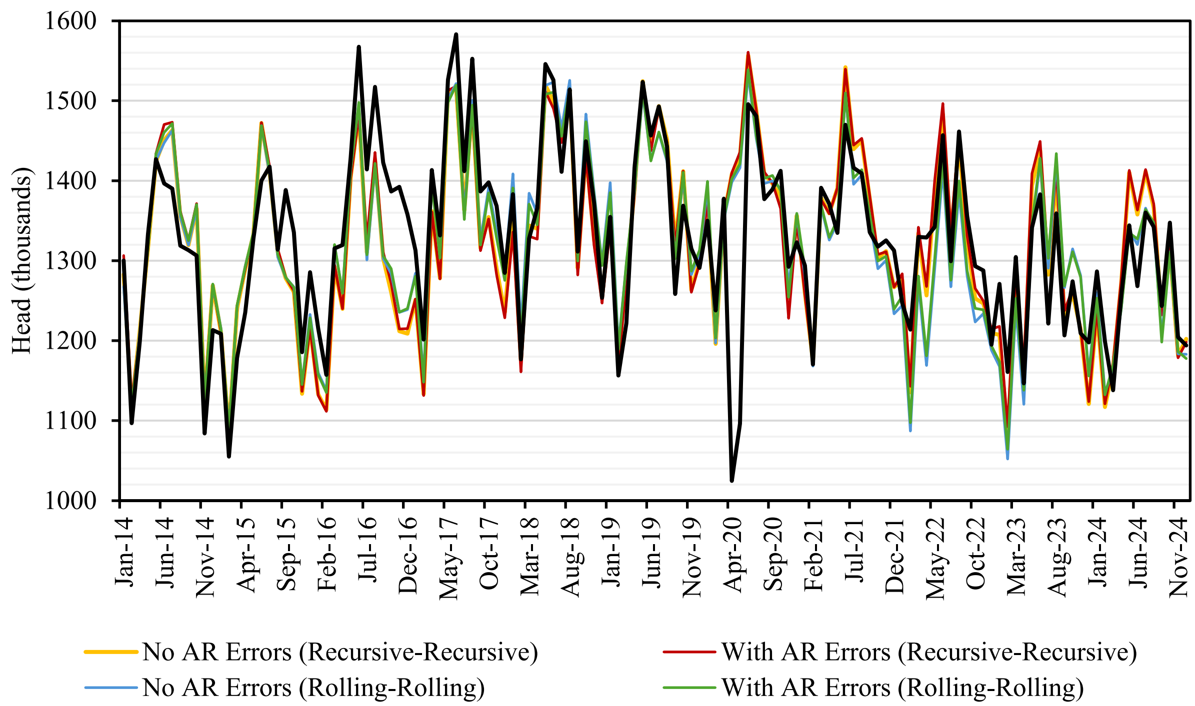

Figure A2: Six-month out steer slaughter forecasts

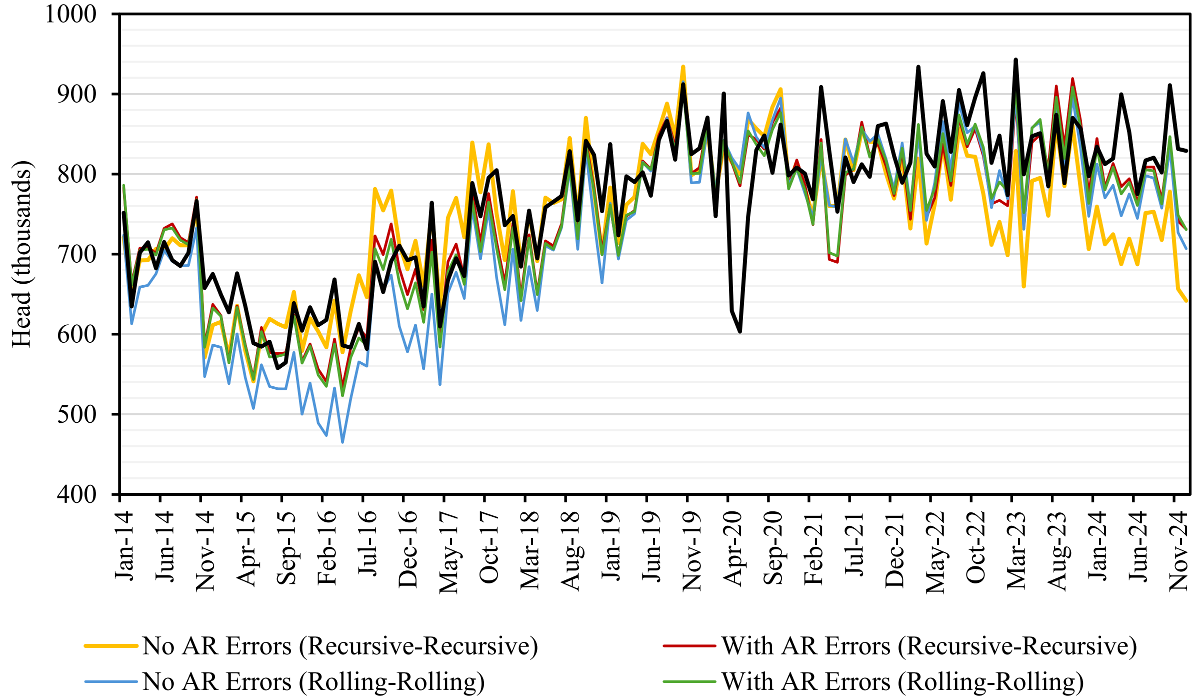

Figure A3: Six-month out heifer slaughter forecasts