Analysis of USDA Livestock Price Forecasting Accuracy for Cattle, Hogs, and Broilers

Patalee, M.A.B.

Department of Agricultural Economics, University of Kentucky, USA

**Corresponding Author:*
Email: pataleema@uky.edu

ABSTRACT

Agricultural markets, compared to other sectors, are typically characterized by uncertainty and high price fluctuations. High price volatility in livestock markets leads to inefficient resource allocation and production planning. Expert price forecasts are not always affordable for all market players, so readily available public forecasts have risen in popularity. This study uses accuracy-based testing methods to evaluate the accuracy of the United States Department of Agriculture (USDA) livestock price forecasting by utilizing the World Agricultural Supply and Demand Estimates (WASDE) quarterly data for slaughter cattle, hogs, and broilers. The study also employs a vector error correction (VEC) model to compare USDA price forecasts. Results suggest that the USDA forecast was more accurate than the competing VEC model across three sectors, suggested by low RMSE and MAE. The beta efficiency test results showed that USDA price forecasts were efficient for all three price series, whereas VEC forecasts were biased for hogs and broiler prices. The findings of the study also confirm that USDA price forecasts are biased for cattle prices with a tendency to repeat past forecast error in all three markets. Results from the forecast encompassing tests showed that USDA cattle and broiler forecasts captured the information contained in VEC forecasts. However, because the hog prices did not show any improvement over time, there is room for improvement of the USDA price forecasts. Overall, results suggest that USDA price forecasts for slaughter cattle, hogs and broilers provide useful information to the market. However, the results also indicate that USDA price forecasts reduce forecast error by economically significant levels.

KEYWORDS: Forecasting, Forecast efficiency, Livestock prices, Time series models

Introduction

Agricultural commodity prices are the key determinants of cost, revenue, and profitability of large- and small-scale agricultural operations, meaning agricultural price forecasts are vital for farmers, policymakers, and agricultural industries (Jha and Sinha, 2013). Price forecasting captures the attention of market participants because future market for commodities and contract maturity dates relies on expert forecast information (Brandt and Bessler, 1991). Although the purpose of agricultural price forecasting is to increase social welfare through resource allocation (Brorsen and Irwin, 1996), the uncertainty of future prices and production can adversely affect the agricultural market by changing market strategies and investment planning (Brandt and Bessler, 1983), resulting in resource misallocation (Sanders and Manfredo, 2003).

Traditionally, public forecasting of price expectations has been based on naïve assumptions, but naïve predictions have significant forecasting errors that may lead to resource misallocations (Brorsen and Irwin, 1996). Extension outlook price forecasts of the United States Department of Agriculture (USDA), a primary public price forecaster, typically have not been specific to product, location, or time, and broad forecasting has been produced only for quarterly or annual national commodity prices (Kastens et al., 1998). For example, spot price forecasts for agricultural commodities have been available only from 1976 (Just and Rausser, 1981). The USDA, however, has utilized considerable resources to prepare their price forecasts since their price forecasting serves as the benchmark for evaluating forecasting performance of futures markets (Irwin et al., 1994). In addition, agricultural producers who do not have resources or expertise in forecasting can use these public forecasts to make production and planning decisions, meaning social welfare of agricultural producers' increases due to forward-looking forecasts rather than naïve forecasts (Brorsen and Irwin, 1996).

Agricultural price modeling differs from non-farm goods and services due to seasonality of production, derived demand, and price (in)elastic demand and supply functions (Jha and Sinha, 2013). In practice, the most common agricultural commodity price forecasting is one-quarter-ahead forecasts. Short-term agricultural forecasting models are extremely useful for crisis situations such as unexpected droughts to make appropriate production planning and resource allocation (Rajaraman and Datta, 2003). In recent years, forecasts have applied the rational expectation assumption, or the notion that producers use all available information (Brorsen and Irwin, 1996). However, if producers have rational expectations, the research on price forecasting is unnecessary, or rational expectation assumption is implausible, and adjustments such as knowledge of supply and demand functions and zero information cost should be made (Brorsen and Irwin, 1996). These limitations highlight the necessity of publicly available reliable price forecasting information for agricultural products. Consequently, many studies have evaluated USDA production forecasts in terms of both crops and livestock (Sanders and Manfredo, 2003). Although assisting producers with production and marketing decisions via price forecasts is essential to obtain maximum prices (Jadhav et al., 2017), up-to-date accuracy evaluation for livestock prices is lacking.

The U.S. livestock industry plays an important role in country's economic development. With the largest fed-cattle industry in the world, the United States is the foremost global producer of beef. In fact, in 2019, the U.S. cattle industry accounted for $66.2 billion in cash receipts (ERS-USDA, 2020). However, the United States is also the world's largest consumer of beef (ERS-USDA, 2020). Cattle prices significantly impact cattle cycle, which determines the size of the national cattle herd, meaning high expected prices lead producers to slowly build up their herd numbers and low expected prices lead them to cull older cows and keep fewer heifers (ERS-USDA, 2020).

The United States is also one of the world's largest exporters of pork and pork products. Hog operations are geographically concentrated mostly in the Midwest and eastern North Carolina. However, the U.S. hog industry underwent a significant structural change associated with technological change.

Production specialization has increased the use of production contracts (ERS-USDA, 2020). Under the efficient market hypothesis, price quoted for immediate and future delivery incorporate the same set of information (Jin, 2017; Peck, 1985). The hog industry progression towards more production and marketing contracts increases the importance of accurate market price predictions to exchange price risks. Similarly, the robust poultry industry in the United States has evolved from fragmented, locally oriented business into highly efficient large-scale operations (ERS-USDA, 2020). In fact, the U.S. poultry industry is the world's largest producer and second largest exporter (ERS-USDA, 2020).

Market information and interventions require knowledge about present and future prices of agricultural products. Price forecasting is also crucial to business decision making (Jin, 2017), and producers often use price forecasts to aid their business decision making and budgeting and coordinate supply and demand signals (Jadhav et al., 2017). However, compared to storable commodities, price forecasting of perishable products such as meat is challenging. Given the high volatility of commodity prices, accurate price forecasts are of great interest market players. The objective of this paper is to evaluate the USDA forecasting accuracy of prices for slaughter cattle, hogs, and broilers. The findings will help industry participants efficiently use USDA price forecasts in their economic decision making.

Methodology

Data

This study utilized the one-quarter-ahead USDA price forecasts for slaughter cattle, hogs, and broilers reported in the World Agricultural Supply and Demand Estimates (WASDE) monthly reports for the period of 1998 first quarter to 2017 second quarter to estimate price forecasting accuracy. Cattle price forecasts were for 1100–1300-pound Nebraska Direct Slaughter cattle, and hog price forecasts were for 51%–52% lean hog carcasses. Broiler prices were 12 city average wholesale broiler price forecasts. Since the WASDE reports are monthly reports, the prices were collected from the January, April, July, and October reports to obtain quarterly price forecasts. The realized prices were collected through subsequent WASDE reports to ensure that the prices reported in subsequent reports were tallied with the USDA quarterly price forecasts (Sanders and Manfredo, 2003).

Model Specification and Estimation

To evaluate USDA price forecasting accuracy, a competing time series model was developed using pre-sample data from 1987 first quarter to 1997 fourth quarter. The nature of agricultural production and the relationships between various product groups make agriculture forecasts unique from other economic forecasts, thereby requiring testing for cointegrating relationships for cattle, hogs, and broiler forecasting models. Cointegration tests identify where two or more non-stationary time series are integrated together in the long term. The intuition behind the error correction model is that if the markets are integrated, changes in one market price impact prices in the second market (Bachmeier and Griffin, 2006).

Failure to include cointegrating relationships implies that the model is specified incorrectly (Bachmeier and Griffin, 2003). The Granger causality test and the Johansen test are the most commonly used methods of testing for co-integration. In the Granger causality test, residuals are tested for the presence of unit roots. Augmented Dicky-Fuller method tests for stationarity of the residuals. Compared to the Granger causality test, the Johansen test allows for more than one cointegration relationship.

The first step in time-series analysis is to determine whether the data levels are stationary; if not, the first difference of the data is used. Because evidence from the augmented Dickey-Fuller test for three price series suggested the presence of unit root and results from the Johansen test suggested cointegration in three price series, a vector error correction (VEC) model with two lags was selected as the best model for price forecasting. Appropriate lag selection was based on results of Akaike information criterion (AIC). The existing relationship between the three time series data suggested that they are integrated in a way that they cannot deviate from the long-run equilibrium.

Vector Error Correction Model

$$\Delta CP = \sum_{i=1}^{2} \alpha_{ci} \Delta CP_{t-i} + \sum_{i=1}^{2} \alpha_{hi} \Delta HP_{t-i} + \sum_{i=1}^{2} \alpha_{bi} \Delta BP_{t-i} + \theta z_{t-i} + \varepsilon_{cp} \quad [1]$$

$$\Delta HP = \sum_{i=1}^{2} \beta_{hi} \Delta HP_{t-i} + \sum_{i=1}^{2} \beta_{ci} \Delta CP_{t-i} + \sum_{i=1}^{2} \beta_{bi} \Delta BP_{t-i} + \rho z_{t-i} + \varepsilon_{hp} \quad [2]$$

$$\Delta BP = \sum_{i=1}^{2} \gamma_{bi} \Delta BP_{t-i} + \sum_{i=1}^{2} \gamma_{ci} \Delta CP_{t-i} + \sum_{i=1}^{2} \gamma_{hi} \Delta HP_{t-i} + \sigma z_{t-i} + \varepsilon_{bp} \quad [3]$$

Where, $\Delta CP, \Delta\ HP$, and ΔBP represent the change in cattle, hog, and broiler prices, respectively; θ, ρ, σ measure the long-run equilibrium adjustment parameters; and z_{t-i} is the long-run relationship between the three price series. In the U.S. meat-demand analysis, beef, pork, and poultry are close substitutes.

Demand and supply for cattle, hogs, and broilers were shown to interact with each other over the long-run time horizon, exhibiting persistent upward or downward movement resulting in stochastic trends in integrated variables. Since the same stochastic trend was applicable to all three livestock markets due to their close economic relationships, cointegration between cattle, hog, and broiler prices was economically justifiable.

According to existing literature, previous research only used a simple autoregressive model or autoregressive integrated moving average (ARIMA) to forecast livestock prices, claiming that these simple models demonstrate similar performance to sophisticated models (Sanders and Manfredo, 2003). However, evidence from the Granger causality test and the Johansen test for cointegration suggested that the VEC model is the best model to forecast livestock prices.

Results and Discussion

Accuracy-Based Test Results

Two types of tests can be used to evaluate the forecasting performance of competing models: accuracy-based tests and classification tests. This study focused on accuracy-based tests that included error measures comparison (most traditional), optimality in terms of bias and efficiency, forecast encompassing, and forecast improvement over time. Table 1 presents the summary statistics of the data used in the analysis.

Table 1: Summary Statistics (1998.1–2017.2)

Description	Cattle ($/cwt)	Hogs($/cwt)	Broilers (cents/lb)
Price observed			
Mean	97.44	49.45	74.79
Standard Deviation	27.51	12.04	17.04
USDA forecast			
Mean	96.17	48.56	75.13
Standard Deviation	27.69	11.93	15.02
VEC forecast			
Mean	95.36	50.16	73.05
Standard Deviation	26.71	11.36	17.26

As shown in the table, none of the mean prices were statistically different from the mean price observed at the 5% level of the two-tailed t-test. However, a high variation in cattle prices was observed between the USDA forecast and the VEC forecast, accounting for approximately 27% of the standard deviation in actual prices. The second highest price variation was shown in broiler prices, with approximately 17% of standard deviation.

Measures of Forecast Error

Root mean squared error (RMSE) is the most widely reported accuracy measure. In this study, the forecasting errors were measured using RMSE[1]and mean absolute error (MAE)[1]. Results of the forecast error measurement and the Diebold-Mariano test (DMT) are presented in Table 2.

Table 2: Forecast Accuracy Measures

Description	Cattle	Hogs	Broilers
USDA forecast			
MAE	0.04	0.04	0.05
RMSE	0.06	0.05	0.11
VEC forecast			
MAE	0.07	0.08	0.09
RMSE	0.10	0.10	0.16
MAE DMT	-3.07	-3.94	-4.76
RMSE DMT	-4.06	-5.58	-5.47

Results suggest that the USDA forecast was more accurate than the competing VEC model across three sectors, suggested by low RMSE and MAE. However, the standard test should be used to compare the performances of competing models. The one-step-ahead forecast error for two models (e_{1t}, e_{t2}) and the loss function $g(e)$ entered into the DMT with the null hypothesis of equal forecasting performance of two models $(H_0: E[g(e_{1t}) - g(e_{2t})] = 0)$. Test results showed that the forecasting errors of the USDA forecast were statistically smaller than the errors of the VEC model. Figure 1 represents the forecasting accuracy of both USDA and VEC models.

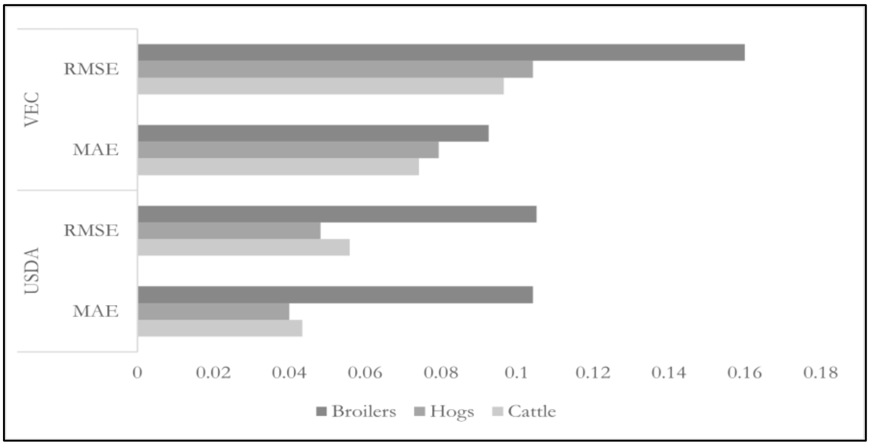

Figure 1: Forecasting Accuracy Measures USDA vs VEC

[1] Notes: For n observations the calculations of RMSE and MAE as RMSE $=(\sum e^2/n)^{0.5}$, MAE=$\sum abse/n$

Tests for Bias and Efficiency

Forecasts are considered optimal if they are unbiased and efficient (Diebold and Lopez, 1996). Efficiency tests deal with forecast errors and OLS regression technique is used to estimate the forecast efficiency. The forecast bias can be estimated as follows:

$$e_t = \gamma + \mu_t \quad [4]$$

The forecast error e_t was regressed with the intercept, and the optimal forecasts were expected to have a mean error equal to zero (c and Lopez, 1996). Under forecast efficiency, the null hypothesis would be $\gamma = 0$. Following the methods of Sanders and Manfredo (2003), the forecast efficiency was measured using beta efficiency and rho efficiency tests. The estimated model for beta and rho efficiency was

$$e_t = \alpha_1 + \beta P_t + \mu_t \quad [5]$$

$$e_t = \alpha_2 + \rho e_{t-1} + \mu_t \quad [6]$$

The beta and rho efficiency tests have null hypotheses of $\beta = 0 \; and \; \rho = 0$, respectively. Table 3 presents the test results for the forecast bias.

Table 3: Test Results for Forecast Bias

Description	Cattle	Hogs	Broilers
USDA forecast			
Estimated γ	1.27***	0.89	-0.62
(t-statistic)	(2.04)	(1.63)	(-0.52)
P value	0.045	0.108	0.61
VEC forecast			
Estimated γ	2.08**	-0.72	1.74
(t-statistic)	(1.92)	(-0.60)	(0.95)
P value	0.06	0.55	0.34

*Note: *** and ** represent statistical significance at levels 5% and 10%, respectively.*

The test results for bias estimates were significant for both USDA and VEC cattle price forecasts, meaning that both forecasts underestimated cattle prices (γ>0). In contrast, USDA and VEC forecasts were unbiased for hog and broiler price series. The forecast bias could be attributed to misspecification of the model.

Tables 4 and 5 show results for the beta and rho efficiency tests. The beta efficiency test results showed that USDA price forecasts were efficient for all three price series, whereas VEC forecasts were biased for hogs and broiler prices (Table 4). However, VEC forecasts failed to reject the null hypothesis of weak efficiency for hogs and broiler price series.

Table 4: Test Results for Beta Efficiency

Description	Cattle	Hogs	Broilers
USDA forecast			
Estimated β	-0.03	-0.07	-0.10
(t-statistic)	(-1.10)	(-1.57)	(-1.22)
P value	0.28	0.12	0.23
VEC forecast			
Estimated β	-0.03	-0.36***	-0.44***
(t-statistic)	(-0.80)	(-3.71)	(-4.71)
P value	0.43	0.00	0.00

*Note: *** and ** represent statistical significance at levels 5% and 10%, respectively.*

Table 5: Test Results for Rho Efficiency

Description	Cattle	Hogs	Broilers
USDA forecast			
Estimated ρ	0.53***	0.50***	0.50***
(t-statistic)	(6.43)	(6.54)	(9.40)
P value	0.00	0.00	0.00
VEC forecast			
Estimated ρ	0.54***	0.51***	0.52***
(t-statistic)	(5.19)	(6.44)	(5.82)
P value	0.00	0.00	0.00

*Note: *** and ** represent statistical significance at levels 5% and 10%, respectively.*

The rho efficiency test (Table 5) for USDA and VEC price forecasts failed to reject the null hypothesis, leading to a consistent tendency of past forecast errors to be repeated in all three markets. The forecast could be adjusted using estimated rho values. For example, estimated ρ for the USDA cattle forecast was 0.5266 (Table 5). If the forecast error of one period prior was 5%, then the actual current period forecast would be 2.633% less of the previous forecast value (0.5266*0.05).

Forecast Encompassing

Forecast encompassing examines whether information content of one forecasting model dominates another forecasting model, rendering it redundant. USDA forecasting is considered the preferred model for evaluating forecast encompassing, which can be measured as follows:

$$e_{1t} = \alpha_3 + \lambda(e_{1t} - e_{2t}) + \varepsilon_t \qquad [7]$$

Where e_{1t} is the forecast error series of the preferred model and e_{2t} is the forecast error series of the VEC model.

The null hypothesis would be $\lambda = 0$, which means the error covariance is zero as tested against $\lambda > 0$. Table 6 presents the results of the forecast encompassing test.

Table 6: Test Results for Forecast Encompassing

Description	USDA Encompassing VEC		
	Cattle	Hogs	Broilers
Estimated λ	-0.08	-0.08**	-0.03
P value	0.34	0.07	0.66

*Note: *** and ** represent statistical significance at levels 5% and 10%, respectively.*
The results suggest that the USDA price forecasts encompassed the VEC forecast for cattle and broilers but not hog prices.

Forecast Improvement

According to methods used by Bailey and Brorosen (1998), forecast improvement is measured by regressing the absolute values of forecast errors of cattle, hog, and broiler price series on a time trend to evaluate whether the forecasts have improved over time.

$$abse_t = \theta_1 + \theta_2 Trend + \mu_t \quad [8]$$

The null hypothesis tests whether $\theta_2 = 0$, and rejection of the null hypothesis contains two important facts: if $\theta_2 < 0$, the forecast improved over time, and if $\theta_2 > 0$, the forecast worsened. Table 7 shows the test results for forecast improvement tests. Although the USDA forecast for cattle and broiler prices did not show improvement over time, the VEC model did not improve the forecasts for all three price series.

Table 7: Test Results for Time Improvement

Description	Cattle	Hogs	Broilers
USDA forecast			
Estimated θ_2	0.05***	0.01	0.13***
(t-statistic)	2.83	0.98	2.86
P value	0.016	0.333	0.005
VEC forecast			
Estimated θ_2	0.12***	0.08***	0.28***
(t-statistic)	4.06	2.36	4.60
P value	0.000	0.021	0.000

*Note: *** and ** represent statistical significance at levels 5% and 10%, respectively.*

This study evaluated performances of the USDA's one-quarter-ahead price forecasts for slaughter cattle, hogs, and broilers. For comparison, similar price forecasts were generated using the VEC model, which was selected via several screening tests.

Accuracy-based tests showed that USDA price forecasts had smaller mean squared errors than forecasts generated by the VEC model. Although the USDA forecasts for hogs and broiler prices were unbiased, cattle prices were underestimated by 4.5%. However, the competing VEC forecast underestimated cattle prices by 5.8%, meaning the VEC error margin was greater than the USDA error margin.

Beta efficiency test results showed that USDA price forecasts efficiently used the available information, resulting in efficient price forecasts. However, the USDA price forecasts inefficiently repeated forecast errors. The positive serial correlation in both the USDA and VEC models as found in the results of the rho efficiency test may indicate structural changes or slow growth of livestock prices (Sanders and Manfredo, 2003).

Results from the forecast encompassing tests showed that USDA cattle and broiler forecasts captured the information contained in VEC forecasts. However, because the hog prices did not show any improvement over time, there is room for improvement of the USDA price forecasts. Overall, evidence from the study highlight the need for improvement of the USDA and VEC forecasts. However, continuous structural changes, high price volatility, and overall performance of the economy increase forecasting difficulty of livestock prices. Further research should incorporate structural shifters to improve price forecasting for cattle, hogs, and broilers.

Conclusion and Policy Implications

Food demands from wealthy nations and a rapidly growing world population are expected to be the major instigators of global environmental change, especially in the agricultural sector, over the next 50 years (Tilman et al., 2001). Unfortunately, research on agricultural price forecasting is limited (Brorsen and Irwin, 1996; Colino et al., 2011), and rapidly changing agricultural markets hinder the development of predictive models to forecast price. This study attempted to fill the gap in the literature on agricultural price forecasting by evaluating the accuracy of publicly available USDA agricultural price forecasts for beef, hogs, and broilers.

Accurate forecasts are central to the successful implementation of policy. USDA price forecasting provides producers and market participants with extensive information on the current market situation and future cash prices (Colino et al., 2011). Previous research compared USDA price forecasts using a variety of time-series and econometric models. Although results of price forecast accuracy have been mixed, USDA forecasts have been shown to produce valuable information (Colino et al., 2011). The current study supported the argument that USDA price forecasts are reliable with room for improvement.

Recent innovations in forecasting techniques and tools have allowed livestock price forecasting to improve the accuracy of USDA price forecasts. Overall, USDA price forecasting is accurate and unbiased for hogs and broilers. However, the USDA could improve their forecasting by removing reported bias and inefficiencies in cattle price forecasts. Nevertheless, less efforts were made to evaluate the accuracy of public price forecasts.

Negative implications of the efficient market hypothesis and mixed results generated by previous modeling have reduced the resources devoted to the development and testing of price forecasting models (Colino et al., 2011). Therefore, innovative forecasting methods are integral to market efficiency (Timmermann and Granger, 2004). Since producers utilize public forecasts to make wise production and marketing decisions, improved efficiency and accuracy in public forecasts may result in less livestock price fluctuations and subsequent increased welfare of agricultural producers.

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