USDA Production Forecasts for Pork, Beef, and Broilers: An Evaluation

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One-step-ahead forecasts of quarterly beef, pork, and poultry production are examined and evaluated based on traditional criteria for optimality—efficiency and unbiasedness—as well as their performance versus a univariate time-series model. However, traditional regression methodology for evaluating forecasts is avoided due to interpretive issues. Instead, an empirical framework focusing on forecast errors is employed. Results suggest USDA forecasts are unbiased, but generally not efficient. That is, they do not fully incorporate the information contained in past forecasts. Moreover, USDA's predictions do not encompass all the information contained in forecasts generated by simple time-series models. Thus, practitioners who use the USDA forecasts may want to supplement them with time-series forecasts.

Key words: forecast efficiency, forecast evaluation, USDA forecasts

Introduction

Farmers and ranchers rely on NASS reports in making all sorts of production and marketing decisions ... such as how much corn to plant, how many cattle to raise, and when to sell. NASS estimates and forecasts are greatly relied upon by the transportation sector, warehouse and storage companies, banks and other lending institutions, commodity traders, and food processors. Those in agribusiness who provide farmers with seeds, equipment, chemicals, and other goods and services study the reports when planning their marketing strategies (U.S. Department of Agriculture/National Agricultural Statistics Service, online, 2001).

By their own assertion, the estimates and forecasts developed by the U.S. Department of Agriculture (USDA) and its agencies—such as the National Agricultural Statistics Service (NASS)—provide important information for decision makers throughout the entire agribusiness sector. Therefore, it is critical this information be unbiased and efficient to maximize social welfare and assure efficient allocation of resources.

Researchers have closely scrutinized USDA estimates in terms of accuracy (Kastens, Schroeder, and Plain; Garcia et al.), information content (Carter and Galopin), and market impact (Sumner and Mueller). These issues are germane because government-supplied information is costly. Accurate public information can result in improved decision making by private forecasters while also reducing variation in market price (Smyth).

Recognizing which government-supplied information is useful and which is not is important. With this knowledge, informed decisions can then be made as to whether the production of these forecasts should be improved, or perhaps even discontinued.

Most academic research examining production forecasts, as opposed to the release of survey data (Schaefer and Myers), has focused on the crop production forecasts issued in the USDA's *Crop Production* publication (Irwin, Good, and Gomez). However, the USDA also provides meat production estimates in its monthly publication, *World Agricultural Supply and Demand Estimates* (*WASDE*). Despite 1998 farm-level receipts for beef, pork, and poultry totaling nearly $60 billion (50% larger than those for corn, soybeans, and wheat combined),[1] production forecasts for livestock have not been closely evaluated except by Bailey and Brorsen. Specifically, Bailey and Brorsen examined the accuracy of the USDA's monthly forecasts for annual beef and pork production over the period 1982–1996. They found that over the entire 15-year sample period, the USDA forecasts were biased predictors, and furthermore, did not meet the optimality conditions set forth by Diebold and Lopez.

The following analysis shares a similar objective with Bailey and Brorsen, but uses a distinctly different methodology. The principal goal of this research is to provide insight into the performance of government-supplied forecasts for beef, pork, and poultry production. Based on personal contacts with various industry analysts,[2] it is our observation that industry participants and traders do not widely anticipate the release of USDA meat production forecasts, nor do they rely heavily upon them for price analysis. Thus, the following two-part research question is posed. Are the USDA's forecasts optimal? And if so, do they provide information beyond that of a relatively simple or naïve forecasting model?

While Bailey and Brorsen provide important insight into this question, this study extends their work in three key respects. First, Bailey and Brorsen examine monthly forecasts for annual production in a fixed-event framework. A fixed-event framework looks at the properties of a forecast for a given event made at a variety of times leading up to the event. For instance, monthly forecasts for, say, 1995 annual beef production may begin in May of 1994 with the final forecast being made in December of 1995, resulting in a series of 20 monthly forecasts of annual production. Here, we pursue a different approach and analyze the USDA's production forecasts for a given quarter in a rolling-event framework where each forecast is a distinctly different event. For example, in the first quarter of 1995, there is a forecast made for second-quarter production, and in the second quarter there is a forecast made for third-quarter production, and so forth.[3] To incorporate the rolling-event framework, we use quarterly time series of one-step-ahead forecasted and realized production levels, providing a greater number of independent time-series observations. But, more importantly, quarterly data closely reflect the aggregation level used by livestock market analysts (e.g., Mintert; Hurt).

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[1] These figures are based on 1998 farm-level receipts provided by the USDA/Economic Research Service (ERS), online at http://usda.mannlib.cornell.edu/.

[2] At the request of the analysts interviewed, their names and employers are not revealed. Their statements are verified, however, by a search of various newswires (Bloomberg and Futures World News) the day before and after the October 12, 2001 *WASDE* report. These searches revealed pre- and post-report analysis of the crop production estimates, but no mention of the USDA forecasts for meat production.

[3] See Clements and Hendry (pp. 59–60) for further discussion on fixed versus rolling-event forecasting.

Second, this research expands on Bailey and Brorsen's analysis by examining three major meat categories: beef, pork, and chicken. This combination allows a direct comparison among industries with distinctly different production cycles. Third, as recommended by Granger, the out-of-sample performance of the USDA forecasts is compared to that of a simple time-series model. This comparison is not intended to be a search for a "better model." Rather, we are looking for a possible explanation as to why trade participants do not focus on the USDA's forecasts, and if the forecasts can be improved with standard time-series techniques.

Traditionally, forecast efficiency is evaluated in a simple regression framework (Mincer and Zarnowitz). However, this methodology can be fraught with econometric problems and interpretive issues (Granger and Newbold, p. 281). In this study, we follow the advice of Granger and Newbold, and the example of Pons, and focus on the forecast error series. This approach allows us to test the USDA's forecasts for the traditional optimality conditions—unbiasedness and efficiency—while also utilizing a set of nontraditional tests. The framework is useful because it provides a clear and comprehensive approach to forecast evaluation.

The results of this research are important because they assess the accuracy and efficiency of the USDA's quarterly meat production forecasts. If the forecasts are suboptimal (e.g., biased), then the results will tell practitioners how to correct the forecasts for use in their private models. Furthermore, the USDA may want to review its current forecasting procedures for the meat complex. Our findings may also provide an explanation as to why the trade does not appear to rely heavily on these forecasts. Additionally, the results of this study will give policy- and decision makers knowledge of the errors inherent in this type of forecasting (Aaron). Finally, this research provides some information as to the relative forecastability of production across beef, pork, and poultry. Given the size of these industries, accurate and efficient forecasts can have a large dollar impact on the food marketing chain.

Data

This study focuses on the one-quarter-ahead forecasts for beef, pork, and broiler production taken from the USDA's monthly *WASDE* reports. For beef and pork, the forecasts are for total commercial production during the calendar quarter. The broiler forecast is for federally inspected production on a ready-to-cook basis for the calendar quarter.

The *WASDE* is released between the 8th and 14th of each month. Thus, the forecasted level of meat production is collected from the January, April, July, and October *WASDE* reports for each calendar quarter.[4] For instance, from the January issue, the forecasted meat production for the first calendar quarter (January, February, and March) is collected. This collection process results in a series of rolling-event forecasts. Furthermore, because the forecast for a particular quarter occurs 8 to 14 days into the quarter, the forecast intervals do not overlap, and the preceding quarter's realized production is known. This collection process eliminates the problem of inconsistent ordinary least squares (OLS) estimates of standard errors associated with overlapping forecasts (Brown

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[4] The USDA actually updates the quarterly forecasts with each monthly release of the *WASDE*.

and Maital; Clements and Hendry, p. 57).[5] Actual or final production levels are collected as reported in the USDA's *Livestock, Dairy, and Poultry* reports. The data span from the third quarter of 1982 (1982.3) through the fourth quarter of 2000 (2000.4), resulting in 74 quarterly observations of one-step-ahead production forecasts and actual values.

Not surprisingly, the absolute level of meat production demonstrates strong seasonality and trends. Therefore, to assure stationarity in the variables, the analysis focuses on seasonal differences defined as the change in production from the same quarter of the prior year. Furthermore, the data are converted to log levels, where the seasonal differences represent percentage changes from the same quarter of the prior year.

For example, let A_t equal the level of production in quarter t, and F_t equal the one-step-ahead forecast of production for quarter t. The variables of interest are thus defined as the change in actual production, $AP_t = \ln(A_t/A_{t-4})$, and the forecasted change in production, $FP_t = \ln(F_t/A_{t-4})$, such that the change represents the percentage change in quarterly meat production from the prior year.[6] Organizing the data in this manner provides time series consistent with those used by the trade and most industry analysts (e.g., Hurt; Kastens, Schroeder, and Plain), and are well suited for the evaluation methods presented below.

Methodology and Results

One objective of this research is to compare and contrast the USDA's forecasts across the three primary meats: beef, pork, and broilers. Another is to compare the USDA's forecasts to that of a relatively naïve alternative. Granger suggests simple univariate models as worthy standards of comparison. In this vein, we generate forecasts from a simple autoregressive model to serve as a standard of comparison for the USDA's forecasts. Summary statistics and measures of forecast accuracy of the USDA forecasts and simple time-series forecasts are examined. Procedures for testing bias, efficiency, information content (encompassing tests), forecast improvement, and their results are then presented.

The Time-Series Alternative

The alternative used in this analysis is an AR(4) model applied to the seasonally differenced data. A series of one-step-ahead forecasts are made by modeling AP_t as an AR(4) process. This is not meant to be a forecasting competition; rather, the specification is meant to represent a simple time-series alternative to the USDA's forecasts. The data used to estimate the forecasting models begin with the first quarter of 1975 (1975.1). The models are reestimated as additional data become available; however, they are not respecified. For example, the forecast for 1982.3 is made with an AR(4) model estimated

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[5] The forecast horizons do not overlap, and they are truly one-step-ahead forecasts. Therefore, they will not have an inherent moving-average process as identified by Granger and Newbold (p. 282). Also, the prior quarter's actual production, and hence forecast error, is known within a reasonable certainty level. Production estimates are released each week and revised with a two-week delay. So, by the 8th or 14th of (say) April, the actual production levels for January and February are known, and weekly revised estimates for March are available. Therefore, the actual forecast error is known, and it should not demonstrate autocorrelation due to a lack of knowledge about prior forecast errors (Clements and Hendry, p. 57).

[6] The seasonally differenced actual production, $AP_t = \ln(A_t/A_{t-4})$, and forecasts, $FP_t = \ln(F_t/A_{t-4})$, are stationary series (augmented Dickey-Fuller tests).

with 30 observations of AP_t from 1975.1 through 1982.2, and the forecast for 1998.4 is made with an AR(4) model estimated with 95 observations from 1975.1 through 1998.3. The result is a series of 74 one-quarter-ahead forecasts for AP_t from 1982.3 through 2000.4.

Throughout the analysis, this forecast series is used as a standard of comparison against the USDA forecasts. Equivalent statistical tests are performed on both the USDA forecasts and the time-series alternative. When appropriate, direct comparisons are made and conclusions about the USDA's forecasting procedures are drawn. The analysis begins by examining the summary statistics and comparing traditional measures of forecast accuracy.

Summary Statistics and Forecast Accuracy

The summary statistics for each series are presented in table 1. Given that the variable(s) of interest represent the percentage change in quarterly meat production from the prior year, the summary statistics presented are the mean and standard deviation of the percentage growth rate over the sample period. For example, beef production grew at an annual rate of 1.05% with a standard deviation of 3.00% from the third quarter of 1982 (1982.3) through the fourth quarter 2000 (2000.4). It is worth noting that broilers demonstrated the fastest growth (over 5% per year), while pork production was the most volatile with a standard deviation of over 6%. For all of the markets, both the USDA and the time-series forecasts have the optimal property of being less volatile than the actual series being forecasted (Granger and Newbold, p. 283).

Various summary measures of forecasting accuracy with respect to actual production (AP_t) are presented in table 2. The summary statistics include root mean squared error (RMSE), mean absolute error (MAE), and Theil's U.[7] Because the underlying variables of interest show markedly different volatility levels, accuracy comparisons among beef, pork, and broilers must be made cautiously. Comparing the USDA forecasts with the time-series alternative, the USDA forecasts are more accurate by all measures across the three sectors. As observed from table 2, the lone exception is the time-series model which produces a lower MAE for beef compared to the USDA forecast. Generally speaking, it appears the USDA forecasts provide the least improvement in accuracy measures in the beef sector.

Accuracy is an important criterion by which to measure forecast performance. However, if the forecasts are not optimal (unbiased and efficient), then they are not the most accurate forecasts possible (in a mean-squared error framework) using the available information set. The following section looks at the optimality of the USDA forecasts.

The Traditional Test for Optimality

Traditionally, forecasts are evaluated for optimality by regressing actual values against the forecasts:

(1) $$AP_t = \alpha_0 + \beta_0 FP_t + \omega_t,$$

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[7] For n observations, the RMSE $= (\Sigma e^2/n)^{0.5}$, MAE $= \Sigma |e|/n$, and Theil's $U = (\Sigma e^2/n)^{0.5}/(\Sigma AP^2)^{0.5}$.

Table 1. Summary Statistics: Beef, Pork, and Broilers, 1982.3–2000.4

Statistical Measure	Actual Production		
	Beef	Pork	Broilers
Mean	0.0105	0.0126	0.0506
Standard Deviation	0.0300	0.0618	0.0264

Statistical Measure	USDA Forecasts			Time-Series Forecasts		
	Beef	Pork	Broilers	Beef	Pork	Broilers
Mean	0.0049	0.0082	0.0483	0.0066	0.0166	0.0525
Standard Deviation	0.0293	0.0616	0.0222	0.0248	0.0501	0.0189

Note: Numbers in the table are interpreted as percentages; e.g., the mean growth rate for beef production is 1.05% with a standard deviation of 3.00%.

Table 2. Forecast Accuracy Measures, 1982.3–2000.4

Accuracy Measure [a]	USDA Forecasts			Time-Series Forecasts		
	Beef	Pork	Broilers	Beef	Pork	Broilers
RMSE	0.0262	0.0299	0.0186	0.0266	0.0399	0.0230
MAE	0.0220	0.0222	0.0154	0.0203	0.0310	0.0190
Theil's U	0.8294	0.4776	0.3269	0.8439	0.6363	0.4033

[a] RMSE is the root mean squared error, and MAE is the mean absolute error.

and then testing the joint null, $\alpha_0 = 0$ and $\beta_0 = 1$. However, Granger and Newbold (p. 282) are careful to point out that this is only a necessary condition for efficiency. Furthermore, Holden and Peel demonstrate the joint null is a sufficient, but not necessary, condition for unbiasedness. Thus, a rejection of the null does not lead to clear alternative statements about the forecasts' properties.

Given these interpretive problems with the traditional test, we follow the suggestion of Granger and Newbold (p. 286), and Holden and Peel, and focus strictly on the forecast errors, $e_t = AP_t - FP_t$. The first step in this framework is to evaluate the forecasts for a systematic bias.

A Test for Bias

Following Pons, a test for forecast bias is conducted in the following OLS regression framework:

$$(2) \qquad e_t = (AP_t - FP_t) = \gamma + \mu_t.$$

The null hypothesis of an unbiased forecast, $\gamma = 0$, is tested with a t-test.[8] Optimal forecast errors should have a zero mean (Diebold and Lopez). If the null hypothesis cannot be rejected, then on average the forecasted growth rates equal the actual $(AP_t = FP_t)$. The appropriate two-tailed alternative hypothesis is that the forecasts systematically over- $(\gamma < 0)$ or underestimate $(\gamma > 0)$ actual production.

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[8] This is equivalent to testing that $\alpha_0 = 0$, under the restriction that $\beta_0 = 1$, in equation (1).

Table 3. Forecast Bias Test ($e_t = \gamma + \mu_t$), 1982.3–2000.4

Description	USDA Forecasts			Time-Series Forecasts		
	Beef	Pork	Broilers	Beef	Pork	Broilers
Estimated γ	0.0057	0.0044	0.0023	0.0040	−0.0040	−0.0019
(*t*-Statistic)	(1.44)[a]	(1.27)	(0.87)[a]	(1.29)	(−0.87)	(−0.72)

[a] Newey-West covariance estimator.

The estimation results for (2) are presented in table 3.[9] Consistent with the findings of Bailey and Brorsen, the USDA forecasts underestimate production ($\gamma > 0$) for beef, pork, and broilers. However, none of estimated biases are statistically different from zero at the 5% level. Likewise, the time-series forecasts do not exhibit a statistically significant bias. These results suggest the USDA's forecasts are not biased—i.e., they cannot be statistically improved by simply adding or subtracting a constant to the forecast. The next section tests for forecast efficiency.

Tests for Efficiency

Forecasts are strongly efficient if the forecast errors, e_t, are orthogonal to *all* information at the time the forecasts are made, whereas they are weakly efficient if e_t is orthogonal to all past forecasts and forecast errors (Nordhaus). Here, we test for weak efficiency with the following regressions:

$$(3) \qquad\qquad\qquad e_t = \alpha_1 + \beta FP_t + \mu_t;$$

$$(4) \qquad\qquad\qquad e_t = \alpha_2 + \rho e_{t-1} + \mu_t.$$

A condition for efficiency is that $\beta = 0$ in (3) and $\rho = 0$ in (4).[10]

In equation (3), if $\beta \neq 0$, then the forecast is inefficient in the sense it is not a minimum variance forecast. The intuition behind this test lies in the fact that FP_t is formed with some information set, Ω_{t-1}, which is available when the forecasts are made at time $t-1$.[11] Forecast errors, e_t, should be orthogonal to that information set ($\beta = 0$). If they are not ($\beta \neq 0$), then the information is not being efficiently or optimally incorporated into the forecast, FP_t. For example, assume Ω_{t-1} exclusively contains the number of cattle on feed at time $t-1$, and the forecaster uses an elasticity of 0.5% between the number of cattle on feed at time $t-1$ and beef production at time t. However, say the true elasticity is 1%; then, although the forecaster is using this piece of information, he or she is doing so inefficiently. In this example, the β in equation (3) would equal one. Since the β is greater than zero, then the forecasts are systematically too conservative. The actual forecasts can be improved by scaling them by a factor of two ($1 + \beta = 2$).

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[9] In this and all subsequent regression models, heteroskedasticity is tested using White's test, and serial correlation using the Lagrange multiplier test. Heteroskedasticity is corrected using White's heteroskedastic consistent covariance estimator and serial correlation using the covariance estimator of Newey and West (Hamilton, p. 218).

[10] Equation (3) is equivalent to testing that $\beta_0 = 1$ in equation (1), and equation (4) is equivalent to testing for first-order serial correlation in (1) under the restriction that $\alpha_0 = 0$ and $\beta_0 = 1$ (Clements and Hendry, p. 58).

[11] Strong efficiency would question whether or not Ω_{t-1} contains all available information.

Table 4. Beta Efficiency Test ($e_t = \alpha_1 + \beta FP_t + \mu_t$), 1982.3–2000.4

Description	USDA Forecasts			Time-Series Forecasts		
	Beef	Pork	Broilers	Beef	Pork	Broilers
Estimated β	-0.3632*	-0.1142*	-0.1454	-0.3420*	-0.0582	-0.2708
(t-Statistic)	(-3.50)[a]	(-2.06)	(-1.50)[a]	(-2.86)	(-0.622)	(-1.92)

Note: An asterisk (*) denotes significance at the 5% level.
[a] Newey-West covariance estimator.

The results of estimating (3) are presented in table 4. Looking at the USDA forecasts, the null hypothesis of efficiency ($\beta = 0$) is rejected at the 5% level (two-tailed t-test) for both beef and pork, but not broilers. The estimated beta coefficients are negative, which indicates the forecasts are too extreme, resulting in positive (negative) forecasts associated with negative (positive) errors. For instance, the estimated β for beef is -0.3632. So, the USDA forecast needs to be scaled down by a factor of 0.6368 ($1 + \beta$). The time-series forecasts show a similar pattern of negative coefficient estimates, and the null hypothesis of efficiency is rejected for beef at the 5% level. The fact that this inefficiency characterizes forecasts by both the USDA and the time-series models may suggest an underlying structural change which is difficult to capture with formal modeling procedures. This could result from rapid technological advances such as improved information flow in the supply chain.

Equation (4) tests if forecast errors are systematically linked to past forecast errors. If $\rho \neq 0$, then the forecasts are inefficient because current forecast errors are related to past errors, and the forecasts can be improved by adjusting them by ρ. If $\rho > 0$, then past errors tend to be repeated: overestimates followed by overestimates. Likewise, if $\rho < 0$, then overestimates are followed by underestimates.

Table 5 shows the results of estimating equation (4). Again, there is some consistency across the three meat sectors. The estimated ρ is positive for all three USDA meat production forecast series, and it is statistically significant (5% level) for beef and broilers. So, past forecast errors have some tendency to be repeated. For instance, the estimated ρ for beef is 0.3156. So, if the previous quarter's forecast error is 2%, then the current quarter's forecast should be adjusted by subtracting 0.6312% ($0.3156 \times 0.02 = 0.006312$). Positive serial correlation ($\rho > 0$) in the errors could be due to a slow recognition of technical change or regime shifts which are difficult to capture in structural econometric models. This inefficiency is not evident in the time-series models relying on serial correlation to generate forecasts.

Our results suggest the USDA's forecasts are not capturing some relevant time-series information. This could stem from a forecasting method that relies entirely on structural equations and ignores time-series properties. In such a case, a composite of the USDA's forecast and the time-series forecast may be an improvement. We formally demonstrate this technique in the following section with a test of forecast encompassing.

Forecast Encompassing

A preferred forecast is said to encompass an alternative if there is no linear combination of the forecasts which would produce a smaller mean squared error than that of the preferred (Mills and Pepper). Put another way, if a composite predictor formed from the

Table 5. Rho Efficiency Test ($e_t = \alpha_2 + \rho e_{t-1} + \mu_t$), 1982.3–2000.4

Description	USDA Forecasts			Time-Series Forecasts		
	Beef	Pork	Broilers	Beef	Pork	Broilers
Estimated ρ	0.3156*	0.1515	0.2504*	−0.1285	−0.0226	0.0358
(t-Statistic)	(2.80)	(1.30)	(2.18)	(−1.12)	(−0.20)	(0.30)

Note: An asterisk (*) denotes significance at the 5% level.

weighted average of two individual forecasts is considered, then the preferred forecast
is said to encompass the alternative if the alternative forecast's optimal weight (λ) in the
composite is zero.[12] The inferior forecast then contains no useful information not found
in the preferred forecast (Harvey and Newbold). Forecast encompassing is tested with
the following regression model:

$$(5) \qquad\qquad e_{1t} = \alpha_3 + \lambda(e_{1t} - e_{2t}) + \varepsilon_t,$$

where e_{1t} is the forecast error series of the preferred forecasts, and e_{2t} is the forecast
error series of the competing forecasts. A test of the null hypothesis, $\lambda = 0$, is a test that
the covariance between e_{1t} and $(e_{1t} - e_{2t})$ is zero. Accepting the null hypothesis implies a
composite forecast cannot be constructed from the two series which would result in a
smaller expected squared error than using the preferred forecasts by themselves. Thus,
the preferred forecast "encompasses" or is "conditionally efficient" with respect to the
competitor (Harvey, Leybourne, and Newbold).

To gain some intuition into this test, consider some extreme examples. First, consider
the case where the preferred and competing forecasts are identical. Thus, the forecast
errors are identical ($e_{1t} = e_{2t}$). In this case, the competing forecast clearly provides no
marginal information to the preferred, and the optimal weight in a composite forecast
is trivially zero ($\lambda = 0$). Now, consider the case where the alternative forecast produces
an error, e_{2t}, of equal size but opposite sign of the preferred forecast error, e_{1t}. Then, the
estimated λ in equation (5) would be 0.5, and the optimal composite predictor would be
an equally weighted average of the preferred and alternative forecasts.

Here, we test for forecast encompassing using both the USDA and the time-series
forecasts as the preferred models. The OLS estimates of equation (5) are presented in
table 6.[13] The null hypothesis that the USDA forecast (the preferred forecast) encom-
passes the time-series forecast (competing) is rejected at the 5% level for beef, pork, and
broilers (columns A, table 6). These findings indicate the accuracy of the USDA forecasts
could be improved by combining them with time-series forecasts from a relatively simple
AR(4) model. Furthermore, the optimal weight (λ) received by the competing time-series
forecasts is relatively large at 0.2509, 0.2885, and 0.4776 for the broilers, pork, and beef
forecasts, respectively, showing time-series behavior is a relatively large component of
the optimal composite forecast.

To verify these results, equation (5) is reestimated with the time-series forecasts as
the preferred and the USDA forecasts as the competing. The results are reported in

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[12] In this study, λ is the weight on the competing or alternative forecast, and $1 - \lambda$ is the weight on the preferred forecast.

[13] Harvey, Leybourne, and Newbold show the traditional F-test is oversized in small samples when forecast errors are
nonnormal. However, our forecast errors do not demonstrate a statistical deviation from normality (Jarque-Bera test) and
mple size is relatively large (74 observations).

Table 6. Forecast Encompassing Test [$e_{1t} = \alpha_3 + \lambda(e_{1t} - e_{2t}) + \varepsilon_t$], 1982.3–2000.4

Description	[A] USDA Encompass Time-Series Forecasts			[B] Time-Series Encompass USDA Forecasts		
	Beef	Pork	Broilers	Beef	Pork	Broilers
Estimated λ	0.4776*	0.2885*	0.2509*	0.5224*	0.7115*	0.7491*
(*t*-Statistic)	(5.78)[a]	(3.66)[a]	(2.29)[a]	(6.32)	(9.01)	(6.83)

Note: An asterisk (*) denotes significance at the 5% level.
[a] Newey-West covariance estimator.

columns B of table 6. As expected, the time-series forecasts do not encompass all of the information contained in the USDA forecasts ($\lambda = 0$ is rejected at the 5% level in all cases). Of course, the estimated coefficient for each market equals one minus the estimated λ from columns A of table 6. Each set of forecasts contains some unique information, and a composite forecast consisting of the USDA and time-series models would have provided a statistically lower MSE than either series alone over the sample interval.

It is clear the USDA forecasts for meat production were not optimal over the entire sample period. This result is consistent with the findings of Bailey and Brorsen. However, Bailey and Brorsen also found the USDA's forecasts improved through time, with most of the improvement in the early or initial monthly forecasts for annual production. Although they observed much more modest improvements in forecasts made near the end of the production year, their findings still raise the possibility that our results could be driven by some particularly poor forecasting in the early part of the sample. Consequently, it is important to test if the USDA's performance changed through the sample period. A change in performance could have occurred if the USDA's methodologies were altered or if the underlying data-generating process became more or less noisy. In either case, the potential for changes in forecast performance is investigated in the following section.

Forecast Improvement

Bailey and Brorsen found the information provided by annual USDA beef and pork production forecasts improved from 1982 to 1996, with most of the improvement in the long-horizon forecasts. To test for improvement or worsening in USDA quarterly forecasts, the bias, efficiency, and encompassing tests [equations (2)–(5)] are first tested for stability using the Chow break-point test. The first quarter of 1991 is used as the break point. This roughly splits the data in half, with 34 observations from 1982.3 through 1990.4, and 40 observations from 1991.1 through 2000.4.

The null hypothesis of no change in the parameter estimates between the two samples cannot be rejected for any of the tests or markets (results not shown). For example, the estimated ρ from equation (4) for the USDA's beef forecasts is 0.235 (*t*-ratio = 1.32) in the early subsample, and 0.357 (*t*-ratio = 2.38) in the second subsample. In this example, the F-statistic generated by the Chow break-point test is not statistically significant at conventional levels. Collectively, the Chow tests suggest the behavior of the USDA forecast errors did not change after 1991.1.

The second test resembles the methodology used by Bailey and Brorsen. The absolute values of the forecast errors are regressed against a time trend:

Table 7. Time Improvement Test ($|e_t| = \theta_1 + \theta_2 Trend_t + \mu_t$), 1982.3–2000.4

Description	USDA Forecasts			Time-Series Forecasts		
	Beef	Pork	Broilers	Beef	Pork	Broilers
Estimated $\theta_2 \times 10^2$	−0.0134	−0.0152	−0.0001	−0.0219*	−0.0386*	−0.0005
(*t*-Statistic)	(−1.60)[a]	(−1.40)	(−0.02)	(−2.39)	(−2.78)	(−0.68)

Note: An asterisk (*) denotes significance at the 5% level.
[a] White's covariance estimator.

$$(6) \qquad\qquad\qquad |e_t| = \theta_1 + \theta_2 Trend_t + \mu_t.$$

The null hypothesis ($\theta_2 = 0$) of no systematic reduction or increase in the absolute value of the forecast error, $|e_t|$, through time is tested with a two-tailed *t*-test. The results are presented in table 7.

Although the coefficient estimates are negative across the three meat sectors—indicating the absolute forecast errors have become smaller—the null hypothesis cannot be rejected at the 5% level for any of the USDA forecasts. A Chow break-point test, with 1991.1 serving as the break, was also administered for equation (6). Again, there was not a statistically significant difference in the estimated parameters before and after 1991.1. Because it is also possible $|e_t|$ has a seasonal component, equation (6) was estimated with quarterly intercept shifters to test for systematically higher or lower $|e_t|$ in particular quarters and with slope shifters on the trend variable to test for changes in forecasting accuracy in particular quarters. The null hypothesis of equal parameter estimates for θ_1 and θ_2 across quarters could not be rejected with a standard *F*-test (5% level). There is no evidence to suggest forecasting is more or less difficult in a particular quarter, or that $|e_t|$ increased or decreased through time in a particular quarter. Therefore, combining the quarters—as presented in equation (6) and table 7—is an accurate representation.

Figure 1 visually supports this conclusion, where the time-series plots of $|e_t|$ do not appear to demonstrate any patterns. In contrast to USDA forecasts, the time-series forecasts for beef and pork demonstrate a statistically significant (5% level) decrease in the absolute forecast error over the sample interval. This result is potentially due to more precise coefficient estimates of the AR(4) process as the sample grew through time. In summary, these tests do not provide any convincing evidence to indicate the USDA forecast accuracy examined in this study has statistically changed through time. Our findings appear to be consistent with those of Bailey and Brorsen who found only a modest reduction in forecast errors near the end of the year being forecasted.

Summary and Conclusions

This study examines the performance of the USDA's quarterly forecasts for beef, pork, and poultry production as reported in its monthly publication, *World Agricultural Supply and Demand Estimates* (*WASDE*). Specifically, this research attempts to establish if these forecasts exhibit the properties of forecast optimality—namely that they are unbiased and efficient. In addition, encompassing tests are conducted to assess whether the USDA forecasts can potentially be improved upon by incorporating information from an alternative forecast. The alternative forecast used in the encompassing tests is estimated with a simple AR(4) model. Tests are also conducted to determine if forecast performance changed over time.

Panel A: Beef
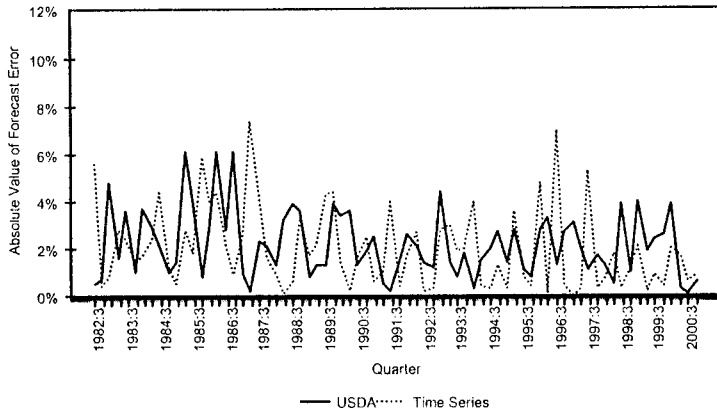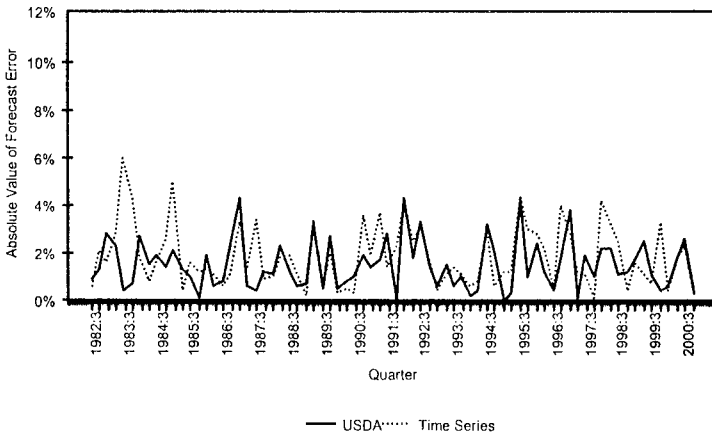

Panel B: Pork
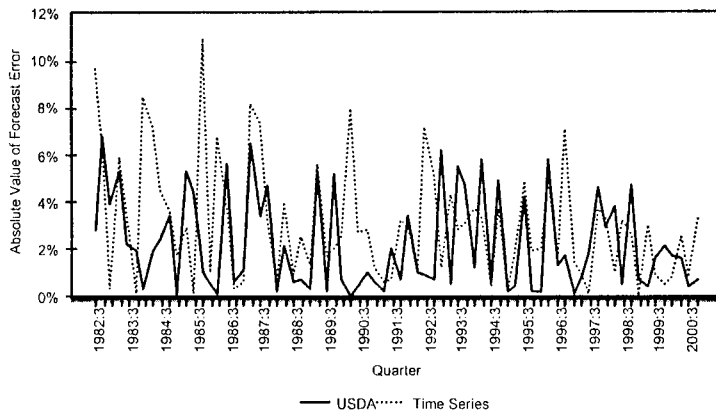
Panel C: Broilers

Figure 1. Absolute value of forecast errors, $|e_t|$, 1982.3–2000.4

The findings suggest USDA forecasts are unbiased, but inefficient. Specifically, in the cases of beef and pork, forecasts do not efficiently incorporate the information available at the time they are made. The USDA forecasts are too extreme. Furthermore, with beef and poultry, forecast errors display positive serial correlation, revealing errors are repeated. Summary measures of forecast accuracy (RMSE, MAE, and Theil's U) suggest the USDA forecasts are more accurate than those produced by the AR(4) model. However, none of the USDA forecasts encompass the information contained in the simple AR(4) forecasting model.

Consistent with Bailey and Brorsen's results for short horizons, there is little evidence to show the USDA's forecasts have improved through time. Finally, the results do not strongly suggest one sector is "easier" to forecast than another. The beef forecasts violate optimality conditions more frequently than either pork or poultry, which may indicate relatively long production cycles make forecasting more difficult. Alternatively, structural changes or productivity changes (e.g., increasing carcass weights) in the beef sector may be difficult to capture in formal models. Finally, beef production, unlike confinement pork and poultry operations, is still largely susceptible to the vagaries of weather, a factor which contributes to random shocks in production.

Based on the results of this analysis, the USDA may want to review its methods for producing quarterly meat production forecasts.[14] In particular, the encompassing tests suggest there is valuable information contained in alternative forecasts that may be used to improve existing meat production forecasts. Although this research does not attempt to make specific recommendations for improving the USDA's forecasting procedures, creating composite forecasts between its current methodology and simple time-series models [such as the AR(4) used here] can improve forecasting accuracy. Improved accuracy would undoubtedly raise the trade's reliance on, and anticipation of, these forecasts.

While the USDA can take steps to improve its forecasts, practitioners should not completely ignore these forecasts. The results presented here demonstrate how to construct composite forecasts that are more efficient. Furthermore, even though the USDA's meat production forecasts are not optimal, they do contain information not found in simple time-series models. Such information may be useful in improving existing private forecasts. Although our findings indicate USDA forecasts are inefficient, they may still provide value to those market participants who lack the expertise or resources to generate their own forecasts. Thus, these results do not suggest the USDA should discontinue this service.

Finally, decision makers—whether private or public—need to recognize the potential errors in meat production forecasts (Aaron). These errors appear to be most pronounced in beef. This may be due to the relatively long production cycle, a higher susceptibility to random weather shocks, and perhaps rapid technological advances which are difficult to capture in formal models. It is also likely that forecasting accuracy deteriorates rapidly as the forecast horizon lengthens. This issue, however, is left for future research.

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[14] In personal interviews with USDA analysts, they indicated they rely on structural econometric models to produce longer-term forecasts, whereas quarterly forecasts rely more heavily on subjective inputs such as seasonal adjustments, current slaughter weights, and potential weather impacts.

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