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**USDA Production Forecasts for Pork, Beef, and Broilers:  
A Further Evaluation**

**Dwight R. Sanders**

**and**

**Mark R. Manfredo<sup>\*</sup>**

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<sup>\*</sup>Dwight R. Sanders (DwightS@siu.edu) is an Assistant Professor of Agribusiness Economics at Southern Illinois University, Carbondale, Illinois. Mark R. Manfredo (manfredo@asu.edu) is an Assistant Professor of Agribusiness in the Morrison School of Agribusiness and Resource Management at Arizona State University.

# USDA Production Forecasts for Pork, Beef, and Broilers: A Further Evaluation

## Practitioner's Abstract

*This paper examines USDA one-step ahead forecasts of quarterly beef, pork, and poultry production. The forecasts are evaluated based on traditional criteria for optimality—efficiency and unbiasedness—as well as their performance versus an univariate time series model. The results suggest that the USDA forecasts are unbiased; however, they are generally not efficient. That is, they do not fully incorporate the information contained in past forecasts. Moreover, the USDA predictions do not encompass all the information contained in forecasts generated by simple time series models.*

**Keywords:** forecast evaluation, forecast efficiency, USDA forecasts

## Introduction

Information supplied by the United States Department of Agriculture (USDA) has been closely scrutinized in terms of accuracy (e.g., Garcia, Irwin, Leuthold, and Yang), information content (e.g., Carter and Galopin), and market impact (e.g., Sumner and Mueller). These issues are important since government supplied information is costly, thus its production should be justified. Accurate public information can result in improved decision making by private forecasters while also reducing market price variation (Smyth). Therefore, it is important to understand which government supplied information is useful and which is not. If this is known, informed decisions can be made as to whether the production of the data should be continued, improved, or perhaps even discontinued.

Most academic research examining production forecasts (as opposed to the release of survey data) has focused on the crop production forecasts issued in the USDA's *Crop Production* publication. However, the USDA also provides meat production estimates in the monthly publication of *World Agricultural Supply and Demand Estimates* (WASDE). These forecasts have not been closely evaluated outside of the work done by Bailey and Brorsen. Specifically, they examine the accuracy of the USDA's monthly forecasts for annual beef and pork production. Bailey and Brorsen report that over the entire 1982-1996 sample period the USDA forecasts are biased predictors, and furthermore, do not meet the optimality conditions set forth by Diebold and Lopez. However, in the latter years of their sample, the forecasts appear to be optimal. In fact, the authors find that the percentage forecast error declines over the sample period; hence, they conclude that the information contained in the USDA's forecasts improved over the respective time period.

It is our observation that industry participants neither widely anticipate the release of USDA meat production forecasts nor do they rely heavily upon them for price analysis (personal contacts). Thus, the following research questions are posed. First, do private forecasters have reason to ignore the USDA's meat production forecasts? Second, 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 some insight into these questions, this

research expands on their work to provide a more comprehensive evaluation of the USDA's meat production forecasts.

This research differs from that of Bailey and Brorsen in three key aspects. First, Bailey and Brorsen examined monthly forecasts for annual production. Here, we collect and analyze the USDA's production forecasts for a given quarter. That is, we use a quarterly time series of forecasted and realized production levels, providing a greater number of independent time series forecasts. But, more importantly, quarterly data closely reflect the aggregation level used by livestock market analysts. Second, three major meat categories are examined: beef, pork, and chicken. This allows a direct comparison among industries with distinctly different production cycles. Third, 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.

The research results are important because they assess the accuracy 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 or analysis. If the forecasts provide no incremental value over a naïve model, then the USDA may want to review their current forecasting procedures for the meat complex. The results may also provide an explanation as to why the trade does not heavily rely on these forecasts. Finally, the research provides some information as to the relative forecastability of production across beef, pork, and poultry—three important protein categories in the food sector.

## Data

This study focuses on the one-step (one quarter) ahead forecasts for beef, pork, and broiler production taken from the USDA's *World Agricultural Supply and Demand Estimates* (WASDE). The forecasts are for total commercial production during the calendar quarter for beef and pork. The broiler forecast is for federally inspected production on a ready-to-cook basis.

The WASDE is released between the 8<sup>th</sup> and 14<sup>th</sup> of each month. The forecasted level of meat production is collected from the January, April, July, and October WASDE reports for the quarter.<sup>1</sup> 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, since the forecast for a particular quarter occurs eight to fourteen days into the quarter, the forecast intervals do not overlap and the proceeding quarter's realized production is known.<sup>2</sup> This collection process eliminates the potential

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<sup>1</sup>The USDA actually updates the quarterly forecasts with each monthly release of the WASDE.

<sup>2</sup> The forecasts certainly do not overlap and 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 level of certainty. Production estimates are released each week and revised with a two-week delay. So, by the 8<sup>th</sup> or 14<sup>th</sup> of (say) April, the actual production levels for January and February are known and weekly revised estimates for March are available. Therefore, the

econometric problems identified by Brown and Maital and discussed by Clements and Hendry (p. 57). Final (actual) 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) to 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 (beef, pork, and broilers) demonstrates strong seasonality and trends. Therefore, to assure stationarity in the variables, the analysis focuses on seasonal differences. Furthermore, the data are converted to log-levels such that the seasonal differences represent percent changes from the prior year. This is consistent with how the trade and most analysts utilize the data. For example, let  $A_t$  equal actual quarter  $t$  production and  $F_t$  equal the one-step ahead forecasted production for quarter  $t$ . The variables of interest are thus defined as the actual change in 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 percent change in quarterly meat production from the prior year.<sup>3</sup>

## 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 poultry. The other 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 case, that alternative is an AR(4) model applied to the seasonally differenced data. A series of one-step ahead forecasts are made from modeling  $AP_t$  as an AR(4) process. The data used in estimating the forecasting models begin with the first quarter of 1975 (1975.1). For example, the forecast for 1982.3 is made with the time series model estimated with observations of  $AP_t$  from 1975.1 through 1982.2, and the forecast for 1998.4 is made with an AR(4) model estimated from 1975.1 through 1998.3. Throughout the analysis, equivalent statistical tests are performed on both the USDA and the time series alternative.

### Summary Statistics and Forecast Accuracy

The summary statistics for each series are presented in Table 1. The data shows that from the third quarter of 1982 (1982.3) through the fourth quarter 2000 (2000.4), beef production grew at an annual rate 1.05% with a standard deviation of 3.00%. 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 series (beef, pork, and broilers), both the USDA and the time series forecasts have the optimal property of being less volatile than the series being forecast (Granger and Newbold, p. 283).

Various summary measures of forecasting accuracy with respect to the actual value ( $AP_t$ ) are presented in Table 2. The summary statistics include root mean squared error (RMSE), mean

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forecast error should not demonstrate autocorrelation due to a lack of knowledge about prior forecast errors (see Clements and Hendry, p. 57).

<sup>3</sup> The seasonally differenced production data,  $AP_t = \ln(A_t/A_{t-4})$ , and forecasts,  $FP_t = \ln(F_t/A_{t-4})$ , are stationary series (augmented Dickey-Fuller tests).

absolute error (MAE), and Theil's U. Because the underlying variables of interest show markedly different levels of volatility, comparisons across markets must be made cautiously.

Comparing the USDA forecasts with the time series alternative, we see that for all the markets, the USDA forecasts are more accurate by all three measures. The lone exception is the time series model produces a lower MAE for beef than the USDA. Generally speaking, it appears that the USDA forecasts provide the least improvement in accuracy measures in the beef sector.

### Forecast Optimality

Optimal forecasts are both unbiased and efficient. Usually, forecasts are evaluated for optimality by regressing actual values against the forecasts,

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

and then testing the joint null,  $\alpha=0$  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 show that the joint null is a sufficient, but not necessary, condition for unbiasedness. Thus, a rejection of the null does not lead to clear alternatives.

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,  $e_t = AP_t - FP_t$ . Following Pons, a test for unbiasedness is conducted in the following OLS regression framework such that,

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

The null hypothesis of an unbiased forecast,  $\gamma = 0$ , is tested with a t-test. The results are presented in Table 3.<sup>4</sup> Notably, the USDA forecasts underestimate production 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.

Forecasts are efficient if the forecast errors,  $e_t$ , are orthogonal to *all* of the information available to the forecaster at the time the forecasts are made. Here, we test for efficiency only with respect to the history of  $AP_t$  ("weak" efficiency, see Nordhaus) with the following regressions:

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

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

A condition for efficiency is that  $\beta=0$  in (3) and  $\rho=0$  in (4). If  $\beta \neq 0$ , then the forecast is inefficient in the sense that it is not the minimum variance forecast—that is, the forecasts do not

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<sup>4</sup> In this and all subsequent regression models, heteroskedasticity is tested for using White's test and serial correlation using the Lagrange multiplier test. Heteroskedasticity is corrected for using White's heteroskedastic consistent covariance estimator and serial correlation using the covariance estimator of Newey and West.

include all available information when they are made.<sup>5</sup> If  $\rho \neq 0$ , then the forecasts are inefficient because past errors are repeated, and the forecasts can be improved by adjusting them by  $\rho$ .<sup>6</sup>

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 suggests that forecasts are too extreme. That is, positive (negative) forecasts tend to be associated with negative (positive) errors. The time series model shows a similar pattern of negative coefficient estimates, and the null efficiency hypothesis is rejected for beef at the 5% level. The fact that this inefficiency characterizes forecasts by both models may suggest an underlying structural change that is difficult to capture with formal modeling procedures.

Table 5 shows the results of estimating equation (4). Again, there is some consistency across the three meat sectors. The estimated  $\rho$  is positive for all three meat production forecast series, and it is statistically significant (5% level) for beef and broilers. So, past forecast errors have a tendency to be repeated. Not surprisingly, this inefficiency is evident in the time series models that rely on serial correlation to generate forecasts.

### Forecast Encompassing

A preferred forecast is said to encompass another if there is no linear combination of the forecasts that would produce a smaller mean squared error than those attached to the preferred (see Harvey and Newbold; Mills and Pepper). This is tested through the following regression model,

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

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 that you cannot construct a composite forecast with the two series that 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).

The OLS estimates of equation (5) are present in Table 6.<sup>7</sup> The null hypothesis that the USDA forecast (the preferred forecast) encompasses the time series forecast (competing) is rejected at the 5% level for beef, pork, and broilers. This would suggest that the accuracy of the USDA forecasts can be improved upon by combining them with time series forecasts from a relatively simple AR(4) model. Likewise, as shown in the lower panel of Table 6, the time series forecasts do not encompass all of the information contained in the USDA forecasts ( $\lambda = 0$  is rejected). Each set of forecasts contains some unique information.

<sup>5</sup> This is equivalent to testing that  $\beta_0 = 1$  in equation 1 (Clements and Hendry, p. 58).

<sup>6</sup> This is equivalent to testing for first order serial correlation in (1) under the null hypothesis that  $\alpha=0$  and  $\beta=1$ .

<sup>7</sup> Harvey, Leybourne, and Newbold show that the traditional F-test is oversized in small samples when forecast errors are non-normal. However, our forecast errors do not demonstrate a statistical deviation from normality (Jarque-Bera test) and the sample size is relatively large (74 observations).

## Forecast Improvement

Bailey and Brorsen find that the information provided by annual USDA beef and pork production forecasts improved over their sample period. To test for improvement in the USDA quarterly forecasts, the bias, efficiency, and encompassing tests (equations 2,3,4, and 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). Thus, these data do not suggest that the USDA forecasts became more efficient after 1991.1 as suggested by Bailey and Brorsen.

The second test is a more general test where the absolute value of the forecast errors are regressed against a time trend:

$$|e_t| = \theta_1 + \theta_2 \text{Trend}_t + \mu_t. \quad (6)$$

The null hypothesis of no systematic reduction in the absolute value of the error through time,  $\theta_2=0$ , is tested with a t-test. The results are presented in Table 7. Although the coefficient estimates are negative across the three meat sectors—indicating that the absolute forecast errors have gotten smaller—the null hypothesis can not be rejected at the 5% level for any of the USDA forecasts. In contrast, 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 is likely 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 evidence that the USDA forecasts examined in this study have improved through time. This is a surprising result given the findings of Bailey and Brorsen.

## Summary and Conclusions

This research examines the performance of the USDA's quarterly forecasts for beef, pork, and poultry production found in the WASDE reports. Specifically, this research attempts to determine whether these forecasts exhibit the properties of forecast optimality, namely that they are unbiased and efficient. In addition, encompassing tests are conducted to determine if the forecasts could potentially be improved upon by incorporating information inherent in an alternative forecast. The alternative forecast used in the encompassing tests is that of a simple AR(4) forecasting model. Tests are also conducted to determine if these quarterly meat production forecasts have improved over time as suggested by Bailey and Brorsen.

The findings suggest that the forecasts are unbiased, but inefficient. Specifically, in the case of beef and pork, forecasts do not incorporate all available information at the time that they are made. Furthermore, with beef and poultry, errors are found to be correlated over time, suggesting that errors are repeated. For the most part, summary measures of forecast accuracy (RMSE, MAE, and Theil's U) suggest improved forecast accuracy of the USDA forecasts relative to the AR(4) model. However, none of the meat forecast series encompass the information contained in the simple AR(4) forecasting model. Finally, the results do not suggest that the USDA's forecasts have improved through time. The results do not strongly suggest that



one sector is “easier” to forecast than another. The beef forecasts violate optimality conditions more frequently than either pork or poultry, which may suggest that its relatively long production cycle makes forecasting difficult (see Bailey and Brorsen).

These results suggest that the USDA may want to review their methods for producing quarterly meat production forecasts. In particular, the results of the encompassing tests suggest that there is valuable information contained in alternative forecasts that may be used to improve existing meat production forecasts. This research does not attempt to make specific recommendations for improving the USDA’s meat production forecasts, but potentially creating composite forecasts between their current methodology and simple time series models, such as the AR(4) used here, can improve forecasting accuracy. While it appears that the USDA can take steps to improve their forecasts, practitioners should not ignore them. Rather, the results show practitioners how to adjust the biases in these forecasts such that they can be used more effectively. Furthermore, even though the USDA’s meat production forecasts are not optimal, they do contain information that may be useful for improving private models.

## References

- Baily, D.V. and B.W. Brorsen. “Trends in the Accuracy of USDA Production Forecasts for Beef and Pork.” *NCR Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management*, pp. 205-211, 1998.
- Brown, B.W. and S. Maital. “What do Economists Know? An Empirical Study of Experts’ Expectations.” *Econometrica*. 49(1981):491-504.
- Carter, C.A. and C.A. Galopin. “Informational Content of Government Hogs and Pigs Reports.” *American Journal of Agricultural Economics*, 75(1993):711-718.
- Clements, M.P. and D.F. Hendry. *Forecasting Economic Time Series*. Cambridge University Press, 1998.
- Diebold, F.X. and J.A. Lopez. “Forecast Evaluation and Combination.” *Handbook of Statistics 14: Statistical Methods in Finance*, G.S. Maddala and C.R. Rao, eds., Amsterdam: North-Holland, 1998.
- Garcia, P., S.H. Irwin, R.M. Leuthold and L. Yang. “The Value of Public Information in Commodity Futures Markets.” *Journal of Economic Behavior and Organization*. 32(1997):559-570.
- Granger, C.W.J. “Can We Improve the Perceived Quality of Economic Forecasts?” *Journal of Applied Econometrics*. 11(1996):455-473.
- Granger, C.W.J. and P. Newbold. *Forecasting Economic Time Series*. Second Edition. Academic Press, New York, 1986.
- Harvey, D.I., S.J. Leybourne, and P. Newbold. “Tests for Forecast Encompassing.” *Journal of Business and Economic Statistics*. 16(1998):254-259.
- Harvey, D. and P. Newbold. “Tests for Multiple Forecast Encompassing.” *Journal of Applied Econometrics*. 15(2000):471-482.
- Hansen, L.P. and R.J. Hodrick. “Forward Exchange Rates as Optimal Predictors of Future Spot Rates: An Econometric Analysis.” *Journal of Political Economy*. 88(1980):829-853.
- Holden, K. and D.A. Peel. “On Testing for Unbiasedness and Efficiency of Forecasts.” *The Manchester School* (1990): 120-127.

- Jones, V.D., S. Bretschneider, and W.L. Gorr. "Organizational Pressures on Forecast Evaluation: Managerial, Political and Procedural Influences." *Journal of Forecasting*. 16(1997):241-254.
- Lawrence, D.B. "Models for the Assessment of the Value of Forecast Information." *Journal of Forecasting*. 10(1991):425-443.
- Mills, T.C. and G.T. Pepper. "Assessing the Forecasters: An Analysis of the Forecasting Records of the Treasury, the London Business School and the National Institute." *International Journal of Forecasting*. 15(1999):247-257.
- Nordhaus, W.D. "Forecasting Efficiency: Concepts and Applications." *The Review of Economics and Statistics*. 69(1987):667-674
- Pons, J. "The Accuracy of IMF and OECD Forecasts for G7 Countries." *Journal of Forecasting*. 19(2000):53-63.
- Smyth, D.J. "Effect of Public Price Forecasts on Market Price Variation: A Stochastic Cobweb Example." *American Journal of Agricultural Economics*. 55(1973):83-88.
- Sumner, D.A. and R.A.E. Mueller. "Are Harvest Forecasts News? USDA Announcements and Futures Market Reactions." *American Journal of Agricultural Economics*. 71(1989):1-8.

Table 1. Summary Statistics, 1982.3-2000.4

	Beef	Actual Production	
		Pork	Broilers
Mean	0.0105	0.0126	0.0506
Standard Deviation	0.0300	0.0618	0.0264
	Beef	USDA Forecasts	
		Pork	Broilers
Mean	0.0049	0.0082	0.0483
Standard Deviation	0.0293	0.0616	0.0222
	Beef	Time Series Forecasts	
		Pork	Broilers
Mean	0.0066	0.0166	0.0525
Standard Deviation	0.0248	0.0501	0.0189

Table 2. Forecast Accuracy Measures, 1982.3-2000.4

	USDA Forecasts		
	Beef	Pork	Broilers
RMSE*	0.0262	0.0299	0.0186
MAE	0.0220	0.0222	0.0154
Theil's U	0.8294	0.4776	0.3269

  

	Time Series Forecasts		
	Beef	Pork	Broilers
RMSE	0.0266	0.0399	0.0230
MAE	0.0203	0.0310	0.0190
Theil's U	0.8439	0.6363	0.4033

\* Note: RMSE is the root mean squared error and MAE is the mean absolute error.

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

	USDA Forecasts		
	Beef	Pork	Broilers
Estimated $\gamma$ (t-statistic)	0.0057 (1.44) <sup>†</sup>	0.0044 (1.27)	0.0023 (0.87) <sup>†</sup>

  

	Time Series Forecasts		
	Beef	Pork	Broilers
Estimated $\gamma$ (t-statistic)	0.0040 (1.29)	-0.0040 (-0.87)	-0.0019 (-0.72)

<sup>†</sup> Newey-West covariance estimator.

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

	USDA Forecasts		
	Beef	Pork	Broilers
Estimated $\beta$ (t-statistic)	-0.3632 (-3.50) <sup>†</sup>	-0.1142 (-2.06)	-0.1454 (-1.50) <sup>†</sup>

  

	Time Series Forecasts		
	Beef	Pork	Broilers
Estimated $\beta$ (t-statistic)	-0.3420 (-2.86)	-0.0582 (-0.622)	-0.2708 (-1.92)

<sup>†</sup> Newey-West covariance estimator.

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

	USDA Forecasts		
	Beef	Pork	Broilers
Estimated $\rho$ (t-statistic)	0.3156 (2.80)	0.1515 (1.30)	0.2504 (2.18)
	Time Series Forecasts		
	Beef	Pork	Broilers
Estimated $\rho$ (t-statistic)	-0.1285 (-1.12)	-0.0226 (-0.20)	0.0358 (0.30)

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

	USDA encompass Time Series		
	Beef	Pork	Broilers
Estimated $\lambda$ (t-statistic)	0.4776 (5.78) <sup>†</sup>	0.2885 (3.66) <sup>†</sup>	0.2509 (2.29) <sup>†</sup>
	Time Series encompass USDA		
	Beef	Pork	Broilers
Estimated $\lambda$ (t-statistic)	0.5224 (6.32)	0.7115 (9.01)	0.7491 (6.83)

<sup>†</sup>Newey-West covariance estimator

Table 7. Time Improvement Test,  $|e_t| = \theta_1 + \theta_2 \text{Trend}_t + \mu_t$ , 1982.3-2000.4

	USDA		
	Beef	Pork	Broilers
Estimated $\theta_2 \times 10^{-2}$ (t-statistic)	-0.0134 (-1.60) <sup>†</sup>	-0.0152 (-1.40)	-0.0001 (-0.02)
	Time Series		
	Beef	Pork	Broilers
Estimated $\theta_2 \times 10^{-2}$ (t-statistic)	-0.0219 (-2.39)	-0.0386 (-2.78)	-0.0005 (-0.68)

<sup>†</sup>Newey-West covariance estimator