Rationality of U.S. Department of Agriculture Livestock Price Forecasts: A Unified Approach

Dwight R. Sanders and Mark R. Manfredo

This research presents a systematic and unified approach to evaluating forecast rationality that considers the potential of nonstationarity in forecasts and realized values. The approach is applied to one-quarter ahead U.S. Department of Agriculture livestock price forecasts from 1982 through 2004. Results show that forecasts and realized prices are integrated of the same order, and those that are nonstationary are cointegrated. However, the stationary price forecasts for hogs, turkeys, eggs, and milk are biased and improperly scaled, and forecast errors tend to be repeated. Similarly, nonstationary forecasts for cattle and broilers are also biased and irrational in the long run, but short-run dynamics are rational.

Key Words: forecast evaluation, livestock prices, rationality

JEL Classifications: C53, Q13

A barrage of tests exists for evaluating price forecasts. The majority of forecast evaluation procedures focus on absolute accuracy (Kastens, Schroeder, and Plain), bias and efficiency issues (Elam and Holder), encompassing and composite forecasts (Sanders and Manfredo), or directional accuracy (Pons 2001). These evaluation procedures are important for comparing alternative forecasting methods, and ultimately determining the value of forecasts. The concept of forecast rationality is a major tenet of this line of research, and it is often evaluated using some variation of the following regression (Granger and Newbold, p. 281):

$$(1) \quad P_t = a + bF_t + e_t$$

Dwight R. Sanders is associate professor, Department of Agribusiness Economics, Southern Illinois University, Carbondale, IL. Mark R. Manfredo is associate professor, Morrison School of Agribusiness and Resource Management, Arizona State University, Mesa, AZ.

where P_t equals the actual price level for a particular time period t and F_t equals the one step ahead price forecast for t. A rational and optimal forecast is tested under the null hypothesis that $a = 0$, $b = 1$, and e_t is an independent identically distributed error. That is, a rational and optimal forecast is unbiased in that it does not consistently under- or overestimate the actual value, it is properly scaled, and forecast errors are uncorrelated.

Researchers often encounter statistical issues in estimating Equation (1), especially when there is a lack of stationarity in either the actual price or forecast data. For instance, if P_t and F_t are not integrated of the same order, it may result in estimation errors (Zivot). As well, nonstationary data series may generate spurious results (Zulauf et al.). To remedy the problem of nonstationarity, researchers often rely on examining forecasts in first differences or in terms of forecasted price changes. However, differencing may place potentially unnecessary restrictions on the short- and long-run dynamics between the forecasts and realized prices (McKenzie et al.).

Indeed, there are a number of statistical pitfalls along the path of forecast evaluation. Therefore, it is important to develop a unified roadmap for testing forecast rationality that considers both the long-run and short-run dynamics between the forecasted and actual price series (Cheung and Chinn).

In evaluating the forecast performance of structural exchange rate models, Cheung and Chinn develop the notion of forecast consistency, which is premised on the time series properties of the forecasts and actual values. Not to be confused with the common statistical concept of consistency, Cheung and Chinn (p. 814) specifically propose that forecasts are consistent if they meet the following three criteria: the forecasted and actual series must (1) share the same order of integration, (2) be cointegrated, and (3) have a cointegrating vector that is consistent with long-run unitary elasticity. Ideally, a consistent forecast should have a one-to-one long-run relationship with the underlying variable, and the two series should not drift too far apart over time. Interestingly, this evaluation structure is closely related to procedures used to test for market efficiency in agricultural futures markets (McKenzie and Holt) and forward exchange rates (Wang and Jones; Zivot). For instance, McKenzie and Holt show that if spot and futures prices are nonstationary, a necessary condition for short-run market efficiency and unbiasedness is that the two price series are cointegrated. Researchers have also used cointegration techniques for examining forecast rationality (Aggarwal, Mohanty, and Song; Grant and Thomas), but the applications have generally fallen short of presenting a unified approach to forecast evaluation. Here, we pull together the existing literature to provide a comprehensive approach to forecast evaluation.

The overall objective of this research is to present a unified and comprehensive approach to evaluating forecast rationality. In doing this, we include the definition of consistency proposed by Cheung and Chinn and extend their tests using the cointegration and error-correction methods proposed in market efficiency studies (e.g., McKenzie and Holt) while also elaborating on the form of the error-correction mechanism under rational expectations (e.g., Grant and Thomas). Indeed, this process involves the amalgamation of similar yet disparate lines of literature, drawing heavily from forecasting and market efficiency studies in agricultural economics, economics, and finance.

This research expands the existing literature by providing a comprehensive, unified, and sequential approach to testing forecast rationality—one that is especially well suited for testing rationality in potentially nonstationary series. While cointegration techniques have been used to examine efficiency in commodity futures markets (Dequan and Holt; McKenzie and Holt; McKenzie et al.; Yang and Leatham; Zivot), they have not been used to evaluate commodity price forecasts per se. In demonstrating this new approach to evaluating forecast rationality, U.S. Department of Agriculture (USDA) livestock price forecasts are examined. Applying the proposed evaluation procedure to these forecasts provides additional insight and confirmation as to the performance of USDA forecasting procedures for livestock-related commodities (Sanders and Manfredo). Thus, forecast users, as well as the USDA, can gain additional insight into the performance of USDA forecasts for this important commodity group. Even more importantly, practitioners will gain an understanding of the interaction between long-run consistency in forecasts and short-run dynamics displayed by the forecasts.

Method

Traditionally, forecast rationality is examined using Equation (1), where a rational and optimal forecast is unbiased ($a = 0$) and weakly efficient with $b = 1$ and e_t is an i.i.d. error. Researchers have used variations of equation (1) to evaluate forecasts, but the variations are primarily intended to circumvent statistical issues associated with nonstationary data and hypothesis testing (Pons 2000) and fail to represent a general approach to testing rationality. While differencing is a common practice, the focus on differenced data disregards information about the long-

run relationship between the two series (Pindyck and Rubinfeld, p. 513). Conversely, estimating Equation (1) in levels may produce spurious regression results with nonstationary data that are not cointegrated (Zulauf et al.). Or, if P_t and F_t are not integrated of the same order—say from a misspecified forecasting model—it may result in estimation errors due to an unbalanced regression (Zivot). So, proper estimation and testing of the standard forecast efficiency hypothesis requires a unified approach that includes tests for stationarity and cointegration (Cheung and Chinn).

This unified approach is inspired by the market efficiency literature (e.g., Zivot) as well as forecast evaluation studies (e.g., Aggarwal, Mohanty, and Song). The methodology initially relies on a sequence of tests proposed by Chueng and Chinn and then proceeds to test rationality in the framework proposed by McKenzie et al. The result is an ordered testing approach that lends itself to fully incorporating and understanding the long- and short-term dynamics of the forecasts. The test moves along the following sequence, which is illustrated in Figure 1. First, P_t and F_t must have the same order of integration; if not, the forecast is inconsistent (Chueng and Chinn). If P_t and F_t are stationary in levels with a fixed mean and variance, I(0), then Equation (1) can be estimated in levels and the standard statistical tests are valid. Now, assuming that P_t and F_t are both stationary in first differences, I(1), then Chueng and Chinn's definition of consistency requires that P_t and F_t be cointegrated. Furthermore, P_t and F_t must have a cointegrating vector that is consistent with long-run unitary elasticity of expectations ($a = 0$, $b = 1$ in Equation 1). Finally, for cointegrated P_t and F_t, short-run efficiency is tested with restrictions on the error-correction mechanism.

In the event of stationary series, I(0), there is no explicit distinction between short- and long-run rationality in a time series econometric sense. Further, in the case that both P_t and F_t are stationary around some fixed mean, F_t will provide consistent forecasts in the sense that P_t and F_t share the same order of integration. However, the forecasts still may

not be rational in that $a \neq 0$ or $b \neq 1$ in Equation (1). In contrast, consider the case where P_t is I(1) but F_t is I(0). Then, actual prices can drift randomly, while the forecasts will remain fixed about some mean. In this case, F_t is inconsistent and clearly not rational (Chueng and Chinn). Similarly, if P_t and F_t are both I(1), then they must be cointegrated; otherwise, they can drift apart through time with no long-run relationship holding them together. If the two series are not cointegrated, then F_t is providing an inconsistent and irrational forecast. Even if P_t and F_t are both I(1) and cointegrated, then long-run rationality requires unitary long-run elasticity to be consistent with the traditional rationality test in Equation (1). Moreover, short-run dynamics are restricted within an error-correction framework (see McKenzie et al.).

Assuming that P_t and F_t are, in fact, cointegrated in levels, then the standard error-correction mechanism (ECM) can be written as

$$(2) \quad \Delta P_t = \lambda + \rho e_{t-1} + \beta \Delta F_t + \sum_{i=1}^{m} \beta_i \Delta F_{t-i} + \sum_{j=1}^{k} \theta_j \Delta P_{t-j} + \upsilon_t,$$

where e_{t-1} equals the error-correction term from Equation (1), $e_{t-1} = P_{t-1} - a - bF_{t-1}$. Substituting $e_{t-1} = P_{t-1} - a - bF_{t-1}$ into Equation (2) and simplifying results in Equation (3)

$$(3) \quad P_t = \lambda - \rho a + (1 + \rho)P_{t-1} + \beta F_t - (\rho b + \beta)F_{t-1} + \sum_{i=1}^{m} \beta_i \Delta F_{t-i} + \sum_{j=1}^{k} \theta_j \Delta P_{t-j} + \varepsilon_t.$$

Long-run rationality in Equation (1) requires that $a = 0$ and $b = 1$, which implies that $\rho = -1$, $\beta = 1$, and $\lambda = 0$ in the short-run error-correction models shown in Equations (2) and (3). That is, setting $\rho = -1$, $\beta = 1$, and $\lambda = 0$ causes Equation (3) to reduce to Equation (1), assuming the forecasts
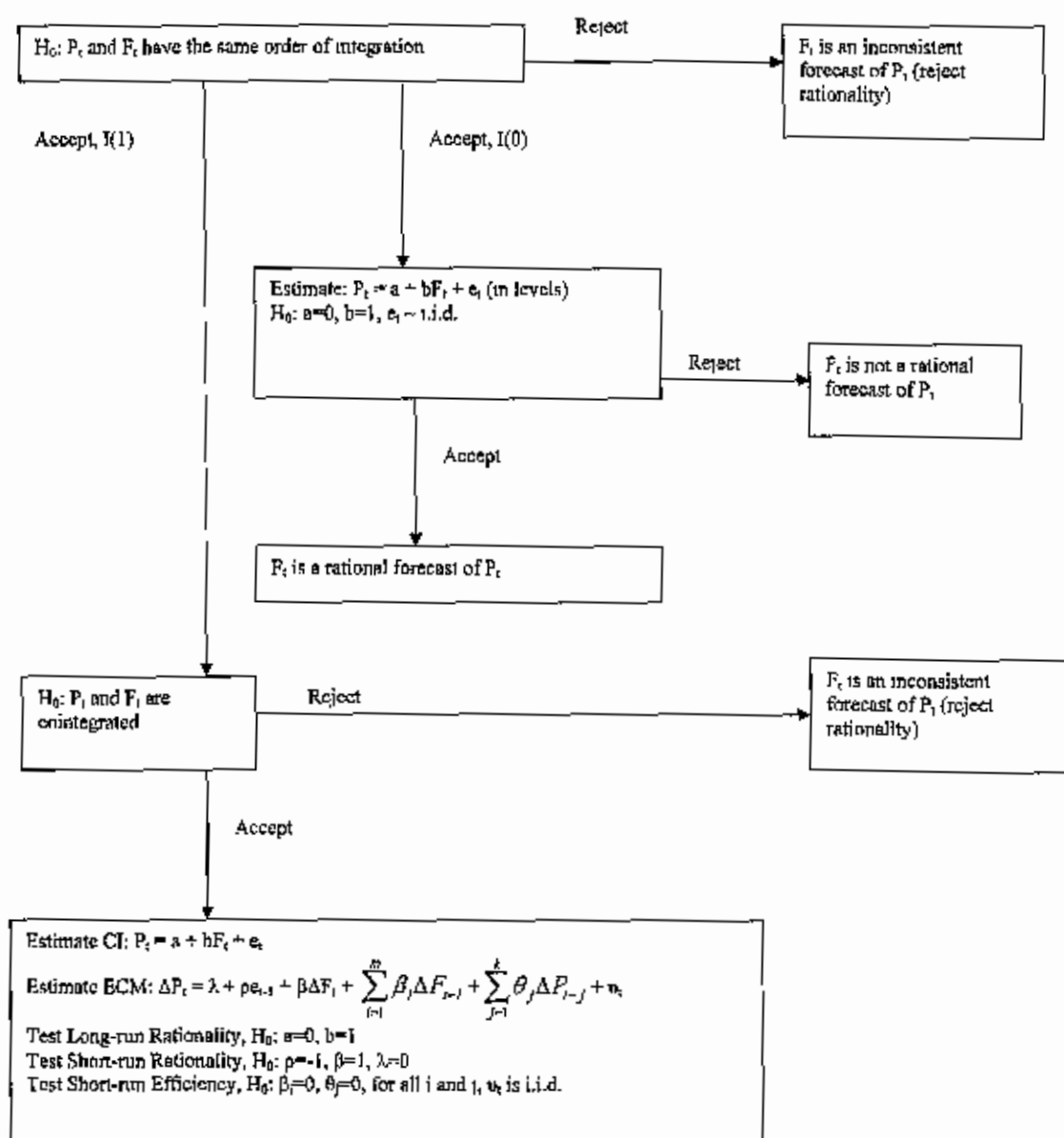
Figure 1.   Sequential Testing Procedure for Forecast Rationality

are orthogonal to past forecasts and realizations ($\beta_i = \theta_j = 0, \forall_{i,j}$). Therefore, in the ECM shown in Equation (2), $\rho = -1$, $\beta = 1$, and $\lambda = 0$ represent the null hypothesis of short-run rationality, where the change in price, ΔP_t, should equal the change in the forecast, ΔF_t, adjusted for the forecast error (in levels) from the previous period, e_{t-1}.

The sequential testing procedure outlined above and illustrated in Figure 1 provides a general approach to testing forecast rationality. Importantly, it considers both long-run

and short-run dynamics within the forecast and actual series. In the following section we use this method to test the rationality of USDA livestock price forecasts.

Data and Empirical Results

Data

Forecast rationality is tested using six USDA livestock price forecast series: cattle (Nebraska, direct, 1100–1300 pound slaughter cattle);

hogs (national base, live equivalent, 51–52% lean hogs); broilers (wholesale. 12-city broilers); turkeys (grade A, large, New York turkeys); eggs (grade A, large, New York); and milk (farm level, all milk). Specifically, one-quarter ahead price forecasts are collected from the *World Agriculture Supply and Demand Estimates* (*WASDE*). The forecasts are issued between the 8th and 14th of the first month of each quarter (January, April, July, and October). Over the sample period, the USDA occasionally changed their cash market definitions, such as market location and animal weights, so the realized or actual prices are also collected from the *WASDE* reports to assure the correspondence between the forecasts and actual prices. The one-quarter ahead forecasts (F_t) and realizations (P_t) are collected from 1982.3 through 2004.3, resulting in 103 observations. The prices are converted to log levels, using the natural logarithm operator, to reduce heteroskedasticity in the series.

The USDA's World Agricultural Outlook Board employs what might be best described as a mixed or composite forecasting method in making the *WASDE* livestock price forecasts (Green, personal communication). That is, they rely on production estimates and other supply data provided by the Economic Research Service to gauge potential supply and formulate annual supply and usage balance sheets. Then, they often apply empirically estimated flexibilities to make price adjustments. The price forecasts are then further modified using the board's expert opinion in regard to seasonality, demand, trade, and supplies of competing products. Personnel at the World Agricultural Outlook Board indicated that this forecasting process has been in place for a number of years.

Unit Root Tests

Keeping with the testing sequence presented in Figure 1, the first step is to test for stationarity in F_t and P_t. Following the work of Rapach, we use the augmented Dickey-Fuller (ADF) test, which has a null hypothesis of nonstationarity (unit root), as well as the test proposed

by Kwiatkowski, Phillips, Schmidt, and Shin (KPSS), which has a null hypothesis of stationarity or no unit. As suggested by Rapach, incorporating unit root tests with a different null hypothesis helps to serve as a cross-check on the results, especially given controversy and ongoing research related to the power of unit root tests and use of deterministic regressors in their specification (Enders).

The results for both the ADF and KPSS tests are presented in Table 1. Following Figure 1, the unit root tests address two important questions. First, are the forecasts consistent as defined by Cheung and Chinn? That is, do F_t and P_t have the same order of integration? Second, what is the order of integration? In price levels (Table 1, Panel A), the ADF test provides conflicting stationarity results only for turkeys, where the existence of a unit root is rejected in P_t, but not in F_t. In contrast, the KPSS test shows that for turkeys both P_t and F_t contain a unit root. The only conflicting result in the KPSS tests is with cattle, where the null hypothesis of no unit root is rejected for P_t but not F_t. However, there is no set of forecasts for which the ADF and KPSS tests both show different orders of integration for P_t and F_t. Therefore, the forecasts appear consistent in the sense that they share the same order of integration.

It is more difficult to draw conclusions concerning the order of integration for each market. In Table 1, Panel A, the results clearly indicate that turkey, egg, and milk prices (and forecasts) are stationary in levels, I(0). Likewise, it is clear that cattle prices are nonstationary in levels, but stationary in first differences, I(1). However, the results for broilers and hogs are in conflict. For instance, with hogs, the ADF test shows that the forecast and actual price series are stationary in levels, whereas the KPSS test rejects stationarity. To examine this further, we test the null hypothesis of no unit root using Johansen's procedure on broilers and hogs (results not presented). The Johhansen test fails to reject a unit root in broilers (*P*-value = 0.3514) but not in hogs (*P*-value = 0.0446). As shown in Panel B of Table 1, both the ADF

Table 1. Unit Root Test Results

| Panel A: Price Levels | ADF test[a] | ADF test | KPSS test[b] | KPSS test |
	Actual P_t	Forecast F_t	Actual P_t	Forecast F_t
Cattle	−2.76	−1.81	0.379*	0.295
Hogs	−4.81***	−4.61***	0.468***	0.609**
Broilers	−3.24**	−2.69*	0.982***	1.072***
Turkeys	−2.93**	−2.16	0.086	0.207
Eggs	−4.75***	−3.26**	0.104	0.134
Milk	−5.07***	−5.55***	0.287	0.269

| Panel B: First Differences | ADF test | ADF test | KPSS test | KPSS test |
	Actual P_t	Forecast F_t	Actual P_t	Forecast F_t
Cattle	−9.75***	−10.85***	0.065	0.174
Hogs	−6.19***	−4.86***	0.114	0.191
Broilers	−6.74***	−8.23***	0.178	0.247
Turkeys	−6.31***	−7.16***	0.125	0.124
Eggs	−9.46***	−10.16***	0.284	0.230
Milk	−7.71***	−7.68***	0.041	0.191

[a] Augmented Dickey-Fuller (ADF) test with a null hypothesis of nonstationarity (unit root). The reported t-statistics have critical values of −2.58 (10% level), −2.89 (5% level), and −3.51 (1% level).

[b] Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test with a null hypothesis of stationarity (no unit root). The reported LM statistics have critical values of 0.347 (10% level), 0.463 (5% level), and 0.739 (1% level).

***Rejects null hypothesis at the 1% significance level.

**Rejects null hypothesis at the 5% significance level.

*Rejects null hypothesis at the 10% significance level.

and KPSS tests indicate that the series are stationary in first differences.

Based on these results, we conclude that all of the forecasts are consistent in that they share the same order of integration with the actual price series. Furthermore, the hog, turkey, egg, and milk data are stationary in levels; therefore, Equation (1) can be estimated directly in levels. Conversely, the broiler and cattle series are nonstationary in levels. Hence, these two series require testing for cointegration and estimation of the error-correction mechanism in Equation (2).

Rationality in I(0) Series

For those actual and forecast series that are stationary, I(0), in levels, the next step is to estimate Equation (1) and test for rationality: $a = 0$, $b = 1$, and e_t is i.i.d. (see Figure 1). Equation (1) is first estimated with ordinary least squares (OLS). Then the residuals are tested for heteroskedasticity using White's

test. If the errors are heteroskedastic, then the equation is reestimated using White's heteroskedastic consistent covariance estimator. Next, the residuals are tested for serial correlation using the Lagrange multiplier test (results reported in the final column of Table 2). If the null of no serial correlation in the residuals is rejected, the equation is again reestimated using the Newey-West estimator. The final parameter estimates and hypothesis tests are presented in Table 2.

The null hypothesis of rationality in the forecasts states that $a = 0$, $b = 1$, and e_t is i.i.d. A joint test of the parameter restrictions, $a = 0$ and $b = 1$, is rejected for both turkeys and milk at the 5% level and near the 10% level for hogs and eggs. This suggests that these forecasts are not fully rational. Looking more closely at the individual parameter estimates reveals that the forecasts for hogs, turkeys, and milk are downward biased with $a > 0$ at the 5% level. Furthermore, the estimated slope coefficients are statistically less than one at the

Table 2. Efficiency Tests for I(0) Forecast Series: $P_t = a + bF_t + e_t$

	Coefficient Estimates		Tested Restriction P-Values			
	a	b	$a = 0, b = 1$	$a = 0$	$b = 1$	e_t is i.i.d.
Hogs	0.490 (0.235)[a]	0.873 (0.061)	0.110[b]	0.040[c]	0.039[c]	0.000[d]
Turkeys	0.736 (0.246)	0.827 (0.059)	0.001	0.004	0.004	0.381
Eggs	0.321 (0.352)	0.929 (0.083)	0.101	0.364	0.400	0.000
Milk	0.329 (0.116)	0.877 (0.045)	0.000	0.006	0.008	0.025

[a] Standard errors in parentheses.
[b] P-value from F-test on stated restriction
[c] P-value from t-test (two-tailed) on stated restriction.
[d] P-value from LM test for serial correlation in e_t.

5% level for hogs, turkeys, and milk, indicating that the USDA forecasts for these commodities are too extreme and need to be rescaled to provide a rational forecast. Notable in Table 2, the USDA egg forecasts appear to be the most rational in terms of bias ($a = 0$) and optimality ($b = 1$). However, the egg forecasts, along with hogs and milk, are inefficient in that the error term is serially correlated.

These results are consistent with the findings of Sanders and Manfredo, who also document extreme USDA livestock price forecasts and positive serial correlation in forecasting errors. For these markets (hogs, turkeys, eggs, and milk) practitioners are advised to appropriately scale USDA forecasts. For instance, in the case of the I(0) milk forecasts, if the USDA is forecasting a milk price of $12.00, then the natural logarithm is scaled by 0.877 and bias adjusted by 0.329 for a forecast of 2.508 ($0.877 \times \ln(12) + 0.329$). In this case, the conversion to antilogs requires an adjustment, $\exp[2.508 + 0.50(\sigma^2)]$, where σ^2 is the sample variance of the mean logarithm milk price (0.00924), which yields a forecast of $12.34 (SHAZAM, p. 124). Likewise, the forecast user should be aware that the USDA repeats errors: overestimates are followed by overestimates as evidenced by the positive serial correlation in the errors. An understanding of these issues can help the practitioner make better use of the USDA forecasts that are stationary in levels. However, the issues of cointegration and error correction must be addressed to understand the rationality of nonstationary price forecasts.

Rationality in I(1) Series

The nonstationary series, cattle and broilers, must meet three requirements for rationality. First, they must be cointegrated. If they are not cointegrated, then F_t is considered an inconsistent forecast of P_t and therefore the forecast is irrational. Second, for cases when F_t and P_t are indeed cointegrated, the long-run cointegrating parameters must be $a = 0$ and $b = 1$ in Equation (1) for rationality to hold. Third, the error-correction mechanism (Equation 2) must have parameters that are consistent with short-run rationality ($\rho = -1$, $\beta = 1$, $\lambda = 0$) and short-run efficiency ($\beta_i = \theta_j = 0$).

Following McKenzie et al., cointegration is tested using Johansen's procedure. The unrestricted cointegration rank test fails to reject that the maximum eigenvalue is one (Table 3). Therefore, for both cattle and broilers, it appears that P_t and F_t are linked in the long run and do not drift apart. However, the cointegrating regressions do not show a long-run unitary elasticity between P_t and F_t. That is, the null hypothesis that $a = 0$ and $b = 1$ is rejected. For cattle, the long-run elasticity is statistically greater than unity at 1.227. This indicates that the forecasts are not too extreme, rather they are too conservative. Visually, this is confirmed in Figure 2, where the cattle price forecasts are too high at price cycle lows (e.g., 1985) and too low at price cycle highs (e.g., 2003). Moreover, the cattle forecasts are biased upward with the intercept statistically less than zero at the 5% level. In contrast, the USDA broiler forecast must be scaled down ($b < 1$) and it is biased downward

Table 3. Efficiency Tests for I(1) Forecast Series: $P_t = a + bF_t + e_t$

	Coefficient Estimates		Tested Restriction P-Values				
	a	b	$a = 0, b = 1$	$a = 0$	$b = 1$	e_t is i.i.d.	max $k = 1$
Cattle	−0.959 (0.190)[a]	1.227 (0.045)	0.000[b]	0.000[c]	0.000[c]	0.254[d]	0.4609[e]
Broilers	0.639 (0.222)	0.846 (0.055)	0.000	0.010	0.013	0.010	0.3514

[a] Standard errors in parentheses.
[b] P-value from F-test on stated restriction.
[c] P-value from a t-test (two-tailed) on stated restriction.
[d] P-value from LM test for serial correlation in e_t.
[e] P-value from the null hypothesis that the maximum eigenenvalue is one (unrestricted cointegration rank test).

($a > 0$). So for both broilers and cattle, the forecasts meet Cheung and Chinn's consistency criteria in the sense that they are cointegrated with the actual series, but they ultimately do not meet the conditions of long-run rationality since the long-run elasticities are not unitary.

The error-correction mechanism in Equation (2) involves stationary data; therefore, it is estimated using OLS (McKenzie et al.). The parameter estimates from Equation (2) are provided in Table 4. Surprisingly, given the long-run cointegration results, the short-run forecast dynamics are mostly rational. Looking first at cattle, the short-run elasticity (β) is not statistically different from one, the error-correction parameter (ρ) is not statistically different from negative one, and there is no bias ($\lambda = 0$). This suggests that the USDA cattle forecasts behave rationally in the short term; however, rejection of the null hypothesis of $\beta_t = \theta_j = 0$ suggests that the forecasts are not efficient. They do not incorporate all of

the information in past price changes ($\theta_j \neq 0$) and past forecasts ($\beta_i \neq 0$). That is, cattle forecasts are not efficient in the short run. Broiler forecasts are rational and efficient in the short run by all counts ($\rho = -1$, $\beta = 1$, and $\beta_i = \theta_j = 0$). Collectively these results indicate that the USDA forecasts and actual prices, which are nonstationary, are quite rational in the short term ($\beta = 1$, $\rho = -1$). That is, they adjust to recent price changes and deviations from the long-run cointegrating relationship, but the long-run relationship itself is not rational ($a \neq 0$, $b \neq 1$).

Incorporation of the sequential forecast evaluation procedure discussed and illustrated here and in Figure 1 affords forecasters, as well as users of forecasts, the opportunity to examine multiple facets of forecast rationality. In particular, it allows for a better understanding of both long- and short-run dynamics between forecasts and realized values, as well as the efficiency of the forecasts. Indeed, the insights gained from the examination of USDA livestock forecasts illustrate the practicality of the procedure and the type of information conveyed to forecast practitioners.

Figure 2. Live Cattle Prices and Forecasts, 1983.3–2004.3

Summary and Conclusions

Most forecast evaluations focus on forecasted price changes either in first or seasonal differences. However, that focus may exclude some important information contained in the forecasted price levels. In this research, we propose a sequential testing procedure for forecast rationality that provides forecasters
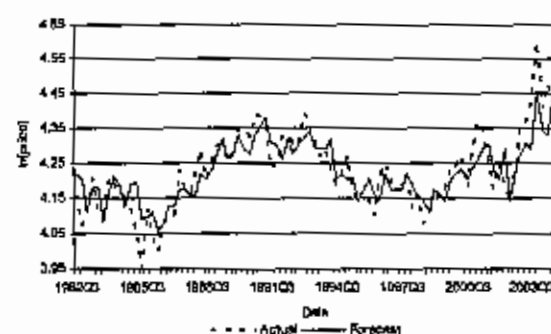
Table 4. Efficiency Tests for I(1) Forecast Series, Error-Correction Model: $\Delta P_t = \lambda + \rho e_{t-1} + \beta \Delta F_t + \sum_{i=1}^{m} \beta_i \Delta F_{t-i} + \Sigma_{j=1}^{k} \theta_j \Delta P_{t-j} + \upsilon_t$

	Coefficient Estimates			Tested Restriction P-Values				
	λ	ρ	β	$\rho = -1$	$\beta = 1$	$\rho = -1$, $\beta = 1$	$\beta_i = 0$, $\theta_j = 0$	υ_t is i.i.d.
Cattle	0.001 (0.005)[a]	−1.434 (0.305)	1.064 (0.171)	0.159[b]	0.709[b]	0.352[c]	0.010[c]	0.717[d]
Broilers	0.003 (0.006)	−0.883 (0.164)	1.008 (0.099)	0.475	0.937	0.709	0.589	0.937

[a] Standard errors in parentheses.
[b] P-value from a t-test (two-tailed) on stated restriction
[c] P-value from F-test on stated restriction
[d] P-value from LM test for serial correlation in e_t

with greater insight into the long-run and short-run dynamics of forecasts otherwise lost through differencing. Specifically, the proposed methodology combines the concept of forecast consistency developed by Cheung and Chinn with the rationality and efficiency tests commonly applied to evaluation of futures markets and foreign exchange markets. Collectively, the methodology provides a comprehensive and systematic approach to evaluating forecast rationality. Thus, it provides an additional forecast evaluation tool for use by both academic researchers and practitioners who use forecasts in making business decisions.

The testing procedure is applied to one-quarter ahead USDA livestock price forecasts for cattle, hogs, broilers, turkeys, eggs, and milk. In the first sequence of tests that focuses on determining the order of integration of the forecasts and actual prices, we find that hog, turkey, egg, and milk prices and forecasts are indeed stationary in levels, thus sharing the same order of integration, I(0). Hence, for these commodities, the traditional regression approach to testing rationality using forecast and price levels is statistically valid. Conversely, cattle and broiler forecasts and actual prices are nonstationary in levels, I(1); thus, the long-run cointegrating relationship and error-correction mechanism must be estimated to provide valid statistical tests. The forecasted and actual prices for both cattle and broilers are indeed cointegrated. Given this, the forecasts

generally meet Cheung and Chinn's first two requirements for consistency. That is, the forecasts and actual prices are integrated of the same order, and those that are non-stationary are cointegrated.

However, except for eggs, the stationary price forecasts generally are not rational in the sense that they are both biased and not correctly scaled, and forecast errors tend to be repeated. The nonstationary price forecasts, cattle and broilers, are also not rational because they are inconsistent (long-run elasticities are different from one), and they are biased. Interestingly, in the short run, USDA forecasts quickly reflect recent price changes and adjust to deviations from the long-run relationship. However, cattle price forecasts are not efficient, failing to incorporate the information contained in past prices and forecasts.

The forecast evaluation procedure presented here provides a new and comprehensive way of thinking about forecast rationality. While it is limited to a linear specification, the procedure provides critical insight and information into the long- and short-term dynamics of forecasts—information that may be lost when differencing to ensure stationarity, a common practice with many forecast evaluation procedures.[1] The evalua-

---

[1] As suggested by a reviewer, the threshold cointegration methods proposed by Balke and Fomby may be incorporated if the relationship between the forecasts and actual values are found to be nonlinear.

tion of USDA livestock price forecasts not only illustrates to forecasters and forecast users the information that can be garnered from the use of this procedure but also provides a greater understanding of the performance of these important forecasts. Indeed, insight into the performance of USDA livestock price forecasts is important for both the USDA and users of this publicly available information.

Moreover, the results presented in this research corroborate with studies that have used other methods of evaluation in assessing USDA livestock price forecasts. In particular, other researchers have also reported a tendency for USDA price forecasts to be incorrectly scaled and to repeat errors (Sanders and Manfredo). Given this, practitioners are advised to adjust these USDA price forecasts correctly for bias and scale. As well, the USDA may want to consider remedies to improve their forecasting, such as correcting for repetition of forecasting errors in hogs, eggs, and milk. Still, both making and using forecasts can be difficult tasks. However, the methods presented here allow forecasters and their intended audience to better understand the short- and long-run dynamics associated with the process.

References

Aggarwal, R., S. Mohanty, and F. Song. "Are Survey Forecasts of Macroeconomic Variables Rational?" *Journal of Business* 68(1995): 99–119.

Balke, N.S., and B. Fomby. "Threshold Cointegration." *International Economic Review* 38(1997): 627–45.

Cheung, Y.W., and M.D. Chinn. "Integration, Cointegration and the Forecast Consistency of Structural Exchange Rate Models." *Journal of International Money and Finance* 17(1998):813–30.

Dequan, H., and M. Holt. "Efficiency of Forest Commodity Futures." Paper presented at the American Agricultural Economics Association Annual Meeting, Denver, Colorado, August 1–4, 2004.

Elam, E.W., and S.H. Holder. "An Evaluation of the Rice Outlook and Situation Price Forecasts." *Southern Journal of Agricultural Economics* 17(1985):155–61.

Enders, W. *Applied Econometric Time Series*. New York: John Wiley & Sons, 1995.

Granger, C.W.J., and P. Newbold. *Forecasting Economic Time Series*. New York: Academic Press, 1986.

Grant, A.P., and L.B. Thomas. "Inflationary Expectations and Rationality Revisited." *Economics Letters* 62(1999):331–38

Green, J. Personal Communication, Livestock, Dairy, and Poultry Analyst, World Agricultural Outlook Board, USDA, March 2006.

Kastens, T.L., T.C. Schroeder, and R. Plain. "Evaluation of Extension and USDA Price and Production Forecasts." *Journal of Agricultural and Resource Economics* 23(1998): 244–61.

Kwiatkowski, D., P.C. Phillips, P. Schmidt, and Y. Shin. "Testing the Null Hypothesis of Stationarity against the Alternative of a Unit Root." *Journal of Econometrics* 54(1992):159–78.

McKenzie, A.M., and M.T. Holt. "Market Efficiency in Agricultural Futures Markets." *Applied Economics* 34(2002):1519–32.

McKenzie, A.M., B. Jiang, H. Djundaidi, L. Hoffman, and E. Wailes. "Unbiasedness and Market Efficiency Tests of the U.S. Rice Futures Market." *Review of Agricultural Economics* 24(2002):474–93.

Pindyck, R.S., and D.L. Rubinfeld. *Econometric Models and Economic Forecasts*. New York: Irwin/McGraw-Hill, 1998.

Pons, J. "The Accuracy of IMF and OECD Forecasts for G7 Countries." *Journal of Forecasting* 19(2000):53–63.

———."The Rationality of Price Forecasts: A Directional Analysis." *Applied Financial Economics* 11(2001):287–90.

Rapach, D.E. "The Long-Run Relationship between Inflation and Real Stock Prices." *Journal of Macroeconomics* 24(2002):331–51.

Sanders, D.R., and M.R. Manfredo. "USDA Livestock Price Forecasts: A Comprehensive Evaluation." *Journal of Agricultural and Resource Economics* 28(2003):316–34.

SHAZAM. *User's Reference Manual Version 7.0*. New York: McGraw-Hill, 1993.

Wang, P., and T. Jones. "Testing for Efficiency and Rationality in Foreign Exchange Markets—A Review of the Literature and Research on Foreign Exchange Market Efficiency and Rationality with Comments." *Journal of International Money and Finance* 21(2002):223–39.

Yang, J., and D.J Leatham. "Market Efficiency of U.S. Grain Markets: Application of Cointegra-

tion Tests." *Agribusiness: An International Journal* 14(1998):107–12.

Zivot, E. "Cointegration and Forward and Spot Exchange Rate Regressions." *Journal of International Money and Finance* 19(2000):785–812.

Zulauf, C.R., S.H. Irwin, J.E. Ropp, and A.J. Sberna. "A Reappraisal of the Forecasting Performance of Corn and Soybean New Crop Futures." *Journal of Futures Markets* 19(1999): 603–18.