Are Outlook Price Forecasts Rational?

by

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The formation of commodity price expectations is a critical problem faced by virtually all agricultural producers. In a recent survey (Smith, 1989), 80 percent of producers indicated that pricing and marketing decisions were either important or very important to the financial success of their operations.

An important purpose of outlook programs in the U.S. Department of Agriculture and State Land-Grant Colleges of Agriculture is to enable agricultural producers to develop more accurate expectations and forecasts of crop and livestock prices (Futrell, 1987). Considerable resources are devoted to these programs. For example, situation and outlook activities in the Economic Research Service of the USDA currently have a budget allocation in the range of $10 to 11 million (O'Brian, 1990).

A number of studies examine the accuracy of forecasts generated by outlook programs (Green, 1926; Stine, 1929; Baker and Paarlberg, 1952; Haidacher and Matthews, 1977; Helmers and Held, 1977; Marquardt, 1979; Just and Rausser, 1981; Moe, 1985; Aldinger, 1986). However, none of the studies test whether the price forecasts are rational. Muth (1961) defines a rational price forecast as one based on all available, relevant information, including current knowledge of future events. Thus, a rational price forecast is an unbiased estimate of subsequent actual prices and forecast errors are uncorrelated with available information.

The purpose of this study is to conduct a comprehensive evaluation of the rationality of outlook price forecasts. Specifically, hog and cattle price forecasts from the following four outlook programs are examined: University of Illinois, Iowa State University, University of Missouri, and U.S. Department of Agriculture. Hog and cattle price forecasts are selected because: (1) the forecasts are quantitative and subject to little interpretation, and (2) relatively long samples of price forecasts are available for each of the programs and commodities. The sample period for the forecasts is 1979:I through 1990:I.

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The Rational Expectations Model

The formal theory of rational expectations was introduced by Muth in 1961. He argued that information is scarce, and hence, economic agents do not waste information or make systematic errors in interpretation. More formally, an expectation is rational if it is equal to the mathematical expectation conditioned on all information relevant to forming the expectation. In terms of prices, this can be expressed as

$$FP^{i}_{t,\,t+k} = E(\, P_{t+k} \mid I^{i}_{t} \,) \tag{1}$$

where $FP^{i}_{t,\,t+k}$ is the forecast of time t+k price made by forecaster i at time t, P_{t+k} is the price at time t+k, I^{i}_{t} is the information set available to forecaster i at time t, and E is the expectation operator.

The rational expectations model implies that price forecasts are unbiased. If forecasts are biased due to systematic errors, forecasts do not equal the mathematical expectation of price based on all available information. For an individual forecaster i, unbiasedness can be tested via the following regression,

$$P_{t+k} = \alpha + \beta\, FP_{t,\,t+k} + \mu_t \tag{2}$$

where μ_t is a standard normal error term, and all other variables are defined as before. Unbiasedness requires that the intercept equals zero and the slope coefficient equals one. An F-test generally is used to test the joint hypothesis that $(\alpha,\beta) = (0,1)$.

The rational expectation model implies that forecasts are efficient. Hence, forecast errors should be uncorrelated. If forecast errors are correlated, this implies that a forecaster does not use all relevant information in making forecasts, namely, past errors. For an individual forecaster, efficiency can be tested via the following regression,

$$e_{t+k} = \alpha + \sum_{i=1}^{q} \beta_i\, e_{t+k-i} + \eta_t \tag{3}$$

where e_{t+k} is equal to P_{t+k} minus $FP_{t,\,t+k}$, and η_t is a standard normal error term. Efficiency implies that the estimated β_i coefficients equal zero. Again, an F-test is used to test the joint hypothesis.

Data

The forecast data for the study are the quarterly hog and cattle price forecasts issued by four well-known public outlook programs located at the University of Illinois, Iowa State University, University of Missouri, and the U.S. Department of Agriculture. Illinois forecasts are drawn from issues of the *Illinois Livestock Outlook*. Iowa State forecasts are drawn from issues of the *Iowa Farm Outlook*. Missouri forecasts are drawn from issues of the *Livestock Outlook Letter*. U.S. Department of Agriculture (USDA) forecasts are drawn from issues of the *Livestock Situation and Outlook Report*.

A description of the forecast data is presented in Table 1. All of the forecast series begin in 1979:I or 1979:III and end between 1988:IV and 1990:I. In all but one case at least thirty observations are available. Some observations are missing in most series.[1] However, the missing observations are randomly distributed in the series, and thus, are not expected to bias evaluations. Forecasts are entirely unavailable at some forecasting horizons, particularly for cattle. Finally, note that the forecasts are not in the form of panel data. Forecast release dates vary by program and commodity.[2]

Forecasts are reported as ranges, with the exception of Illinois' hog price forecasts, which are reported as point estimates. The forecast ranges generally are $4 or $5/cwt. Point estimates are generated as the mid-point of the reported forecast price range. This assumes that forecast prices within the reported range follow a symmetric distribution.

Econometric Issues

The first econometric issue is the potential presence of unit roots in the actual and forecast price series. Previous research suggests commodity prices generally contain unit roots (e.g. Ardeni, 1989). If unit roots are present in actual and forecast prices, the dependent and independent variables in bias regressions will be non-stationary, a violation of the underlying assumptions of OLS.

A standard unit root test is the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979). For a given variable X, ADF tests are based on the following regression:

$$\Delta X_t = \alpha_0 + \beta_0 X_{t-1} + \sum_{i=1}^{p} \beta_i \Delta X_{t-i} + \epsilon_t \tag{4}$$

The order of the lag length p is set such that the error term is white noise. The test for a unit root in the series X is whether β_0 equals zero. Since the distribution of β_0 is non-standard, tables of critical values from Fuller (1976) must be used to conduct the hypothesis test.

ADF regressions are estimated for each forecast and actual price series. Estimates of the β_0 coefficient and associated pseudo t-statistics are presented in Table 2.[3] In the case of hogs, the null hypothesis of one unit root cannot be rejected for any of the actual price or forecast price series. Mixed results are found for cattle. At a five percent level of significance, the null hypothesis is rejected in three of six cases: Iowa and Southern Minnesota cattle prices, Iowa's one-quarter ahead forecasts of Iowa and Southern Minnesota cattle prices, and USDA's two-quarter ahead forecasts of Omaha cattle prices. However, in each of these cases the null hypothesis is not rejected at the one percent level of significance.

The ADF test results indicate that actual and forecast hog and cattle prices generally contain a unit root. Hence, standard inference procedures cannot be applied to bias regressions estimated via OLS. Specifically, F-statistics calculated to test the null hypothesis of unbiasedness $[(\alpha,\beta)=(0,1)]$ are not distributed as a standard F-distribution. Fisher (1989) points out, however, that Dickey and Fuller (1981) provide the needed distributional information. Dickey and Fuller use Monte Carlo methods to generate the distribution of an 'F-statistic' to test whether $(\alpha,\beta)=(0,1)$ under the assumption that the dependent and independent variables contain unit roots. Critical values from Dickey and Fuller's Monte Carlo distributions are used to conduct tests of the unbiasedness hypothesis $[(\alpha,\beta)=(0,1)]$ for the hog and cattle price forecasts.[4]

The second econometric issue is related to the use of overlapping forecast horizons. In the case of k-step ahead forecasts made at sampling interval l, forecast horizons overlap if k is greater than l. This introduces a moving average (MA) process of order k-l into the forecast errors (Granger and Newbold, 1986, p.130). For example, forecast errors for three-quarter ahead forecasts ($k=3$) made every quarter ($l=1$) will contain an MA(2) process.

The two- and three-quarter ahead forecast data examined in this study contain overlapping horizons. Hence, moving average processes may be introduced into the error terms of bias regressions estimated using two- and three-quarter ahead forecast data. Newey and West propose an alternative variance-covariance estimator that is consistent in the presence of serial correlation in regression error terms. The Newey-West estimator is used to estimated variances and covariances for all regressions based on overlapping forecast data.[5]

Rationality Test Results

Bias Tests

Bias regression results for the hog and cattle price forecasts are presented in Table 3. The results are striking. In twelve of the fifteen cases, the null hypothesis of unbiasedness is rejected at the five percent level. Eight of eleven hog price forecast series are biased, while all four of the cattle price forecast series are biased. Hence, rationality is rejected for eighty percent of the forecast series.[6]

The form of the bias is consistent across commodity, forecast horizon, and outlook program. Specifically, intercepts are much larger than zero and slopes are much smaller than zero. This implies a more complex form of bias than a simple intercept shift. In other words, the forecasts are not consistently over or under actual prices. Instead, forecasts are too low when making "low" price forecasts and too high when making "high" price forecasts. Forecasters appear to be either overly-pessimistic or overly-optimistic when forecasting hog and cattle prices.

A graphical illustration of the phenomenon is provided in Figure 1. Here, the actual data points and estimated regression line for USDA's two-quarter ahead forecasts of hog price are plotted. Near the mean of actual prices, USDA's forecasts are relatively unbiased. But the bias is substantial for forecasts at the high or low end of the price range. For example, a USDA two-quarter ahead forecast of $60 per cwt. is biased upwards by $7.95, while a $35 per cwt. forecast is biased downward by $5.30.

The bias becomes more pronounced as the forecast horizon increases. First, two of the three cases where unbiasedness could not be rejected are associated with one-quarter ahead forecasts. Second, in every applicable case, the size of estimated intercepts increases and slope coefficients decrease as the forecast horizon increases. Third, the R^2 for the bias regressions generally drops as the forecast horizon increases. For example, the R^2 for Missouri's hog price bias equations decreases from .621 at one-quarter ahead to .234 at two-quarters ahead. This evidence suggests that forecasters' tendency to be either overly-pessimistic or overly-optimistic is directly related to the length of the forecast horizon.

Efficiency Tests

A rational forecast is unbiased and efficient. In the previous section it is shown that unbiasedness is rejected for twelve of the fifteen forecast series examined. Hence, rationality is rejected for twelve of the series without testing for efficiency. The three unbiased forecast series are: Iowa's one- and two-quarter ahead hog price forecast and Missouri's one-quarter ahead hog price forecast. Further tests are necessary to determine whether the three unbiased series also are efficient. Efficiency implies that forecast errors are uncorrelated.

In each of the three cases, four lags of forecast errors are regressed on the current period error.[7] The results of the regressions are shown in Table 4. Efficiency is rejected only in the case of Iowa's one-quarter ahead forecasts of hog prices. These forecasts exhibited a significant pattern of over- and under-forecasting, with lag one and three coefficients positive and lag two and four negative. It is interesting to note that, while not significant, a similar pattern is observed in the other two regressions.

In summary, only two forecast series are both unbiased and efficient: Iowa's two-quarter ahead forecasts of hog prices and Missouri's one-quarter ahead forecasts of hog prices. Rationality cannot be rejected for these two series.

Alternative Explanations of the Rationality Results

The results presented in the previous sections indicate that rationality is rejected for thirteen of the fifteen series of hog and cattle price forecasts. Only two forecast series are both unbiased and efficient: Missouri's one-quarter ahead forecast of hog prices and Iowa's two-quarter ahead forecast of hog prices. The most frequent reason for the rejection of rationality is bias: forecasts tend to be too low when making "low" price forecasts and too high when making "high" price forecasts.

Five potential sources of bias are identified: 1) measurement error, 2) structural change in demand, 3) feedback effects, 4) incentive problems, and 5) the psychology of prediction. Each of the different explanations is considered below.

1. Measurement Error

The first possibility is that the observed bias is due to measurement error in the forecasts. As noted earlier, the mid-point of the forecast range is used as estimate of the expected forecast price. If the mid-point is not the true expectation of prices, then forecasts are measured with error.

It is well-known (e.g. Judge, Hill, Griffiths, Lutkepohl, and Lee, 1980, p.534) that the slope coefficient in a bivariate regression is biased if the independent variable is measured with error. Assuming that price forecasts are measured with error, the asymptotic bias of the slope coefficient in equation (2) is,

$$plim\ (\hat{\beta} - \beta) = - \beta \frac{\sigma_v^2}{\sigma_{FP}^2} \qquad (5)$$

where $\hat{\beta}$ is the estimated slope coefficient, β is the true slope coefficient, σ_v^2 is the variance of the measurement error, and σ_{FP}^2 is the variance of the observed forecast. Assuming β is positive, the asymptotic bias is downward and directly proportional β. The downward bias will be small only if the variance of the measurement error is small relative to the variance of the observed forecast. Note that if the slope is downwardly biased, then the intercept is upwardly biased.

The bias caused by measurement error is similar to the bias observed for hog and cattle price forecasts. Despite the similarity, measurement error is unlikely to explain the observed bias. Take the case of USDA's two-quarter ahead hog price forecasts, where the estimated $\hat{\beta}$ is 0.47 (approximately equal to the average β reported in Table 4). If the true β is equal to one, then the ratio of the variance of the measurement error relative to the variance of the observed forecasts must be approximately equal to 0.53. However, this ratio is substantially higher than a reasonable estimate of the upper-bound of the actual ratio.

Estimation of the ratio is based on the assumption that a forecaster's true expectation is contained in the reported forecast range. Therefore, by taking the mid-point of the range, the maximum error in any period is equal to one-half of the range, and the maximum variance of the measurement error asymptotically is,

$$\sigma_{v_{max}}^2 = (R/2)^2 \qquad (6)$$

where R is the forecast range. If the forecast range is $5, then the maximum variance of the measurement error is approximately equal to 6.25. The variance of the observed (mid-point) USDA two-quarter ahead hog price forecasts is 43.98. Hence, the upper bound of the ratio of the variances is 0.14, substantially less than the ratio necessary for measurement error to account for the observed bias. Similar results are found for the other hog and cattle forecast series that exhibited significant bias.

2. Structural Change in Demand

A second possibility is that the observed pattern of bias is due to a structural change in the pork and beef markets. Some researchers (e.g. Purcell, 1989) conclude that the demand for beef and pork shifted inward in the late 1970s and early 1980s due to health concerns of consumers. The hypothesized shift in demand occurred during the sample periods examined in this study. If forecasters did not detect the shift, forecasts would be systematically biased upward.

A structural change in demand could generate a biased forecast series. But the pattern of bias resulting from an inward shift in demand is not consistent with the type of bias observed for the hog and cattle price forecasts. As noted above, if forecasters did not detect the demand shift, forecasts would be upwardly biased. The forecast series examined in this study exhibit both upward and downward bias, depending on the forecast price level. Hence, it is unlikely that structural change in the demand for pork and beef is the source of the observed bias.

3. Feedback Effects

A third possible explanation of the observed pattern of bias is related to feedback effects. Tomek and Robinson (1990) describe the feedback effect of forecasts as follows:

> Short-run public forecasting of prices, however, presents a serious dilemma. If the forecast is made sufficiently far in advance to enable producers to alter production plans, it may turn out to be inaccurate. For example, if the government forecasts a rise in hog prices over the next 18 months, prices may begin to fall before the expiration of that period because a sufficient number of producers have taken the forecast seriously and have increased production. (p. 348)

Hence, if producers react to "high" outlook price forecasts by increasing production over the forecast horizon, the realized price will be lower than the forecast. Similarly, if producers react to "low" outlook price forecasts by decreasing production over the forecast horizon, the realized price will be higher than the forecast. In this way, feedback effects could generate the pattern of bias apparent in the hog and cattle price forecasts.

There is a compelling reason to reject the argument that feedback effects generate the observed bias. As Tomek and Robinson point out, feedback effects can occur only if the forecasts are published before relevant production decisions are made. Over one- and two-quarter horizons, hog and cattle production is approximately fixed due to biological lags in production. Hog and cattle producers have little scope to adjust production over such short time horizons. Even at a three-quarter horizon it is doubtful that producers have the ability to alter production to the degree implied by the bias regressions.

4. Incentive Problems

A fourth possibility is that the observed bias reflects a lack of economic incentives. Forecasters may not have sufficient monetary incentives to produce rational forecasts. In other words, forecasters may not have anything to lose if they make bad forecasts. Keane and Runkle (1990) provide the following example of this type of problem:

> Suppose someone calls Keane and asks for his forecast of the three-month T-Bill rate for the next quarter. He is busy writing a paper for a conference - the activity for which he receives monetary reward - that is due in three days. Quickly, Keane tells the caller 8 percent. While reading the *Wall Street Journal* later in the day, Keane sees that the forward rate on three-month T-Bills is 9 percent. He does not run out to buy bonds in the expectation that rate will fall to 8 percent because, when he thinks about it, 9 percent seems reasonable. Thus, 8 percent is an erroneous measure of his true expectation because he does not act in the market as if that were his expectation. (p.715)

The validity of the incentives argument is more difficult to assess than the previous two possibilities. On one hand, the hypothesis seems plausible in that the compensation of outlook forecasters (to our knowledge) is not based on forecast accuracy. Further, forecasters in universities and the government have other responsibilities which may reduce the time available to developing forecasts.

On the other hand, forecasters are well-aware of the wide-dissemination of their forecasts and the potential adverse affects of inaccurate forecasts on producer income. Considerable effort and analysis is devoted to preparing the forecasts, as evidenced by the newsletters or reports in which the forecasts are published. In the case of the USDA, a highly-developed structure is used as the basis for generating forecasts.

5. Psychology of Prediction

A fifth possibility is that the pattern of bias is the result of psychological biases endemic to subjective prediction. A similar bias to that observed for outlook forecasters is found in a wide range of subjective predictions. Kahneman and Tversky (1982b) refer to such a bias as "non-regressive prediction," in the sense that too many extreme predictions are made. Kahneman and Tversky cite evidence of non-regressive prediction in numerous settings, including prediction of occupation, grade point average, performance of airline pilots, and scores of officer candidates for the Israeli Army. In each case, predictions of "high" outcomes were too high and predictions of "low" outcomes were too low. De Bondt (1991) reports that economists' forecasts of stock prices also are too extreme.

Kahneman and Tversky assert that non-regressive prediction is caused by the problem of "representativeness." The following passage summarizes their argument:

> People are sometimes called upon to make such numerical predictions as the future value of a stock, the demand for a commodity, or the outcome of a football game. Such predictions are often made by representativeness. For example, suppose one is given a description of a company and is asked to predict its future profit. If the description of the company is very favorable, a very high profit will appear most representative of that description; if the description is mediocre, a mediocre performance will appear most representative. The degree to which the description is favorable is unaffected by the reliability of that description or to by the degree to which it permits accurate prediction. Hence, if people predict solely in terms of the favorableness of the description, their predictions will be insensitive to the reliability of the evidence and to the expected accuracy of the prediction. (Tversky and Kahneman, 1982)

It is plausible that outlook forecasters generate predictions based on representativeness. The typical process is to observe the supply and demand situation for hogs or cattle after the release of a major USDA report (e.g. *The Hogs and Pigs Report*). A judgement regarding the favorableness of the supply and demand situation is made, and subjective forecasts are generated based on this judgement.

Forecasts made by representativeness violate the statistical theory of optimal prediction (Tversky and Kahneman, 1982). The extremeness and range of optimal predictions is controlled by the degree of predictability. This can be illustrated by first considering the cases of maximum and minimum predictability. When predictive accuracy is perfect, the variability of predictions and outcomes are equal. When predictive accuracy is non-existent, a constant value is predicted, and the variability of predictions is zero.

Now consider the more normal case of intermediate predictive ability. With intermediate predictive accuracy, the variability of predictions is intermediate, or less than the variability of outcomes. In other words, predictions are regressive with respect to outcomes.

The degree to which outlook forecasts violate optimal prediction rules is demonstrated in Table 5. Here, it can be seen that the standard deviation of forecasts (σ_F) is close to the standard deviation of actual prices (σ_A). In 12 of the 15 cases, the ratio of standard deviations is between about 0.8 and 1.2. In none of the 15 cases can a null hypothesis of equal variance be rejected (based on F-tests of the homogeneity of variances). Hence, outlook forecasters behave as if they have perfect or nearly perfect predictive ability. By contrast, the correlation between actual and forecast prices ($\rho_{A,F}$) indicates that predictive ability is of a low or intermediate level.

Summary and Implications

The purpose of this study is to determine the rationality of outlook forecasts of hog and cattle prices. A rational price forecast is an unbiased estimate of subsequent actual prices and forecast errors are uncorrelated with available information (Muth, 1961).

Rationality is rejected in 13 of the 15 series of hog and cattle price forecasts. The principal reason for the rejections is a bias which takes the form of too many extreme forecasts. That is, forecasts are too low when making "low" price forecasts and too high when making "high" price forecasts. In other words, outlook forecasters tend to be overly-pessimistic or overly-optimistic when predicting hog and cattle prices.

Five potential sources of bias are identified: 1) measurement error, 2) structural change in demand, 3) feedback effects, 4) incentive problems, and 5) the psychology of prediction. The first three sources are unlikely to be the source of bias. The fourth source, incentive problems, may have some validity in explaining the observed bias. Forecasters may not have sufficient monetary incentives to produce rational forecasts. The hypothesis is plausible in that the compensation of outlook forecasters (to our knowledge) is not based on forecast accuracy. On the other hand, forecasters are well-aware of the wide-dissemination of their forecasts and the potential adverse affects of inaccurate forecasts on producer income.

A psychological explanation also is consistent with the observed pattern of bias. A similar bias to that observed for outlook forecasters is found in a wide range of subjective predictions. Kahneman and Tversky (1982b) refer to such a bias as "non-regressive prediction," in the sense that too many extreme predictions are made. Kahneman and Tversky assert that non-regressive prediction is caused by the problem of "representativeness." That is, forecasts are made by matching prediction to impression, without proper consideration of the reliability of the evidence or to the expected accuracy of the prediction.

If the correct explanation is psychological, corrective procedures are available. Kahneman and Tversky (1982a) develop a five-step plan for de-biasing forecasts. A key part of the process is to estimate the degree of predictive ability on the part of forecasters. They argue that a good estimate, if available, is the past correlation between actual and forecast outcomes. The correlation is used to adjust forecasts towards the average outcome. In this way, sufficiently regressive forecasts are generated.

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Endnotes

1. The sample periods for Illinois and the USDA contain 45 quarters, while the Missouri and Iowa State sample periods contain 44 and 40 quarters, respectively.

2. Release dates for a given program, commodity, and quarter vary slightly from year-to-year. Release dates are quoted in the following list as the average number of calendar days before the first day of the forecast quarter:

	One-Qtr. Ahead	Two-Qtrs. Ahead	Three-Qtrs. Ahead
Hogs			
Illinois	-66	-156	-246
Iowa	0	-90	-180
Missouri	+7	-83	-173
USDA	-49	-139	
Cattle			
Iowa	-65		
Missouri	-54		
USDA	-49	-139	

An example will clarify the previous listing. In the case of Illinois, one-quarter ahead forecasts of hog prices are released on average 66 days before the first day of the forecast quarter. Since one-, two- and three-quarter ahead forecasts are released on the same day, the average release day for these forecasts is simply the one-quarter ahead release day plus 90 and 180 days, respectively. Note that in one case forecasts are released during the forecast quarter. The average release date for Missouri's one-quarter ahead forecast of hog prices is the seventh day of the forecast quarter. Given lags in publishing newsletters and reports, this should effectively approximate a beginning of quarter forecast date.

3. The lag length p in each regression is set as follows. First, as suggested by Said and Dickey (1984), the lag length is set equal to the (rounded) value of $(N)^{1/3}$, where N is the number of observations. Next, if this lag length is insufficient to generate a white noise error term, then the lag length is increased. Generally, a lag length of four is sufficient to whiten the errors.

4. Dickey and Fuller identify the test statistic as ϕ_1, which is calculated identically to an F-statistic. Critical values for ϕ_1 are found in Table IV of their 1981 paper.

5. With the use of the Newey-West estimator, the statistic calculated to test the hypothesis of unbiasedness is distributed as a Chi-Square. However, as noted previously, the Dickey and Fuller distributions apply to calculated 'F-statistics'. Thus, in order to conduct hypothesis tests, it is necessary to make use of the following asymptotic result (Judge, *et al.*, p.187),

$$F(j, n-k) \rightarrow \chi^2(j, n-k)/j$$

where j is the number of parameter restrictions, n is the number of observations, and k is the number of parameters estimated. The number of restrictions implied by the hypothesis of unbiasedness is two. Therefore, in the case of two-quarter and three-quarter ahead forecasts, calculated Chi-Square statistics are divided by two to approximate an F-statistic.

6. To check the sensitivity of the estimation, two- and three-quarter ahead bias equations are estimated using only OLS. Calculated F-statistics for the OLS versions are close to the Newey-West versions presented in Table 3. Hence, there are no changes in the results of hypothesis tests.

The sensitivity of the results to the assumption of unit roots also is examined. Calculated F-statistics for both OLS and Newey-West equations are compared to critical values from standard F-distributions. The results of hypothesis tests are unchanged with one exception: Iowa State's two-quarter ahead forecast of hog prices. For both the OLS and Newey-West equations, the critical F-value is lowered enough that the hypothesis of unbiasedness is rejected in this case. Hence, an overall conclusion that the results are not sensitive to the assumption of unit roots in the actual and forecast prices.

7. Regressions also were specified with one, two, and three, and five lags of forecast errors. The results are not sensitive to the lag length. In addition, a moving average term of order one is included in the forecast error regressions for Iowa's two-quarter ahead forecasts. The moving average term is included to capture the correlation in forecast errors induced by overlapping forecast horizons.

Table 2. Results of Augmented Dickey-Fuller Unit Root Tests.

Series	Commodity			
	Hogs		Cattle	
	β_0	t-value	β_0	t-value
Actual Price				
Omaha	-0.468	-2.261	-0.370	-2.760
Iowa & S. Minn.	-0.311	-1.639	-0.541	-3.162*
7 Mkt. Avg.	-0.389	-2.069		
Forecast Price: One-Qtr. Ahead				
Illinois	0.800	0.888		
Iowa	-0.389	-2.219	-0.398	-3.328*
Missouri	-0.417	-2.051	-0.417	-2.123
USDA	-0.428	-2.438	-0.279	-3.079*
Forecast Price: Two-Qtrs. Ahead				
Illinois	0.707	2.304		
Iowa	-0.371	-1.960		
Missouri	-0.315	-1.960		
USDA	-0.315	-1.579	-2.347	-1.354
Forecast Price: Three-Qtrs. Ahead				
Illinois	1.430	1.570		
Iowa	-1.267	-1.669		
Missouri	-0.228	-1.700		

Note: The ADF unit root test is based on the following regression:

$$\Delta X_t = \alpha_0 + \beta_0 X_{t-1} + \sum_{i=1}^{p} \beta_i \Delta X_{t-i} + \epsilon_t$$

The critical value of the t-statistic for β_0 is -2.89 (-3.51) for a 5% (1%) significance level based on Table 8.5.2 of Fuller (1976). One star (two stars) indicates a statistically significant coefficient at the 5% (1%) level. Significance implies rejection of the null hypothesis of one unit root.

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d Cattle Price Forecast Data

Forecast Series	Sample Period	Number of Observations		
		One-Qtr. Ahead	Two-Qtrs. Ahead	Three-Qtrs. Ahead
Omaha	1979:III-1990:III	38	36	34
Iowa & S. Minn.	1979:I-1988:IV	40	40	32
7 Mkt. Avg.	1979:I-1989:IV	40	40	30
7 Mkt. Avg.	1979:I-1990:I	45	29	NA
Iowa & S. Minn.	1979:I-1988:IV	40	NA	NA
Omaha	1979:I-1989:IV	39	NA	NA
Omaha	1979:I-1990:I	44	30	NA

tes forecast data unavailable

Table 3. **Bias Regression Results for Hog and Cattle Price Forecasts.**

Forecast Horizon/ Program	Hogs				Cattle			
	α^a	β^b	R^2	$F(0,1)^c$	α^a	β^b	R^2	$F(0,1)^c$
One-Qtr. Ahead								
Illinois	31.46 (5.14)	0.35 (-5.31)	0.166	14.21**				
Iowa	7.22 (1.31)	0.77 (-2.48)	0.582	1.03	52.71 (4.20)	0.19 (-4.30)	0.024	10.37**
Missouri	4.75 (0.91)	0.84 (-1.37)	0.631	0.43	41.17 (3.78)	0.36 (-3.93)	0.113	9.72**
USDA	17.63 (2.90)	0.62 (-3.02)	0.352	4.83*	31.29 (2.63)	0.50 (-2.82)	0.161	8.30**
Two-Qtr. Ahead								
Illinois	37.01 (6.24)	0.22 (-6.65)	0.103	22.99**				
Iowa	18.61 (2.51)	0.60 (-2.65)	0.295	3.75				
Missouri	20.34 (2.80)	0.56 (-3.00)	0.254	4.99*				
USDA	23.85 (2.72)	0.47 (-2.96)	0.250	5.85*	39.58 (2.34)	0.39 (-2.47)	0.082	5.41*
Three-Qtr. Ahead								
Illinois	40.80 (8.07)	0.14 (-8.20)	0.060	71.19**				
Iowa	25.94 (2.99)	0.43 (-3.12)	0.173	5.12*				
Missouri	21.55 (3.08)	0.51 (-3.48)	0.297	8.89**				

Note: For a given program and commodity, the regression is specified as follows:

$$P_{t+k} = \alpha + \beta \ FP_{t,\ t+k} + \mu_t$$

where P_{t+k} is the actual price at time t+k and $FP_{t,t+k}$ is the forecast of time t+k price made at t.

[a]The t-values in parentheses are calculated for the null hypothesis that $\alpha = 0$.
[b]The t-values in parentheses are calculated for the null hypothesis that $\beta = 1$.
[c]F-statistics are calculated for the null hypothesis that $(\alpha,\beta) = (0,1)$. The critical value is 4.71 (6.70) for a 5% (1%) significance level based on Table IV of Dickey and Fuller (1981). One star (two stars) indicates significance at the 5% (1%) level.

Table 4. Efficiency Test Results for Hog Price Forecasts.

Forecast Horizon/ Program	α	β_1	β_2	β_3	β_4	R^2	F^1
One-Qtr. Ahead							
Iowa	-0.19 (-0.31)	0.46 (2.85)*	-0.51 (-3.27)*	0.45 (2.83)	-0.27 (-1.77)*	0.227	3.87*
Missouri	0.22 (0.32)	0.21 (1.09)	-0.24 (-1.24)	0.16 (0.82)	-0.10 (-0.56)	0.081	0.68
Two-Qtr. Ahead							
Iowa	-0.54 (-0.56)	0.58 (1.23)	-0.46 (-1.89)	0.29 (1.36)	-0.22 (-1.36)	0.230	0.99

Note: Estimated regressions are of the following form:

$$e_{t+k} = \alpha + \sum_{i=1}^{4} \beta_i \, e_{t+k-i} + \eta_t$$

The figures in parentheses are t-statistics. One star (two stars) indicates significance at the 5% (1%) level.

[1]The F-statistic is calculated to test the null hypothesis that the estimated coefficients are jointly equal to zero.

Table 5. **Prediction Statistics for Hog and Cattle Price Forecasts**

Forecast Horizon/ Program	Hogs				Cattle			
	σ_A	σ_F	σ_F/σ_A	$\rho_{A,F}$	σ_A	σ_F	σ_F/σ_A	$\rho_{A,F}$
One-Qtr. Ahead								
Illinois	7.328	8.911	1.216	.412				
Iowa	6.696	6.070	0.906	.762	4.726	3.993	0.845	.141
Missouri	6.517	5.761	0.884	.794	4.901	4.628	0.944	.300
USDA	6.456	6.221	0.963	.592	5.404	4.326	0.801	.400
Two-Qtr. Ahead								
Illinois	6.598	9.805	1.486	.316				
Iowa	6.696	6.090	0.909	.538				
Missouri	6.814	6.122	0.898	.504				
USDA	6.197	6.632	1.070	.500	5.668	4.158	0.733	.224
Three-Qtr. Ahead								
Illinois	6.478	11.369	1.755	.245				
Iowa	6.409	6.130	0.957	.412				
Missouri	6.224	6.689	1.075	.548				

Note:

σ_A = standard deviation of actual price ($/cwt.),

σ_F = standard deviation of forecast price ($/cwt.),

$\rho_{A,F}$ = correlation coefficient between the actual price and forecast price.

Figure 1. USDA Two-Qtr. Ahead Hog Price Forecast vs. Actual Price, 1979I-1990I