A Sequential Rationality and Efficiency Test of U.S. Department of Agriculture Program Crop Price Estimates: Rice, Wheat, and Soybeans

Sung Chul No (contact person)

Associate Professor
W.E. Bill Tucker Endowed Professorship

321 T.T. Allain Hall
Depart. of Econ. and Fin.
College of Business,
Southern University and A&M College
Baton Rouge, LA, 70813
Phone: 225-771-2992
E-mail: sung_no@subr.edu

Michael E. Salassi

J. Nelson Fairbanks Professor

Depart. of Ag. Econ. and Agribus.
Louisiana State University
Baton Rouge, LA 70803
Phone: 225-578-2713
E-mail: msalassi@agcenter.lsu.edu

Selected Paper prepared for presentation at the Southern Agricultural Economics Association Annual Meeting, Dallas, TX, February 2-6, 2008

A Sequential Rationality and Efficiency Test of U.S. Department of Agriculture Program Crop Price Estimates: Rice, Wheat, and Soybeans

Sung C. No and Michael E. Salassi

I. Introduction

Commodity price forecasts generated by the USDA provide pivotal information for both policy makers in government and people involved in making decisions about marketing and investing. Unbiased and efficient forecasting information was demonstrated to maximize social welfare and assure efficient allocation of resources (p. 223, Stein, 1981).

A number of researchers have closely scrutinized USDA price forecasts in terms of absolute accuracy (Elam and Holder, 1985; Kastents, Schroeder, and Plain, 1998), bias and efficiency issues (Sanders and Manfredo, 2005), or directional accuracy (No, 2007). While these academic researchers have used different forecasting methods, a common approach to evaluating USDA price forecast includes a comparison of one step ahead USDA forecast, $E(P_{t+1}|\Omega_t)$ with their own forecast $E(P_{t+1}|X_t)$, where Ω_t is a quantitative and qualitative information set (p.10, Vogel and Bange, 1999) available time *t* and X_t is a vector of price related time series as well as actual price available time *t*.

In an earlier study, Elam and Holder (1985) found that USDA rice forecasts had lower mean square forecast errors than random walk model forecasts. Not all researchers and investigators were in favor of the USDA model. Kastens, Schroder, and Plain (1998) reported that extension forecasts are more accurate than USDA forecasts for livestock. In contrast, Sanders and Manfredo (2005) found that USDA forecasts are statistically more accurate than competing times series forecasts for fluid milk. No (2007), however, found that USDA hog price forecasts have lower accurate forecast ratio and higher worst forecast ratio than the forecasts of time-series model, suggesting weaker directional accuracy in USDA model. In addition, Sanders and Manfredo (2007) documented that USDA price forecasts for hogs, turkeys, eggs and milk are biased and improperly scaled, and forecast errors tend to be repeated. This may be due to unforeseen future random price shocks which are difficult to capture even with a system of comprehensive USDA forecasting models.

The research from these investigators has focused on commodity price forecasts. However, the USDA also provides a commodity price estimate. For instance, the USDA's monthly *Rice Outlook* on July 13, 2007 released an estimated rice price for the previous month (mid June), as opposed to a forecasted mean production for the fourth calendar quarter (October, November, and December) released on July 12, 2007 from the USDA's monthly *World Agricultural Supply and Demand Estimate* (WASDE) report. The estimated rice price, $E(P_{t-1}|\Omega_t)$ in its monthly outlook reports is essentially an ex post "forecast" in that a rice price of the previous month, P_{t-1} is estimated using information available time t, Ω_t. Presumably, the estimated rice price reflects all information embodied in the past actual prices. Therefore, it is likely that USDA price estimates, $E(P_{t-1}|\Omega_t)$ are more close to actual prices than its forecasts, $E(P_{t+1}|\Omega_t)$. To date, this line of research to evaluate USDA program crop price estimates has not been published.

The paper has two objectives. First, it is to evaluate U.S. Department of Agriculture program crop price estimates: Rice, wheat, and soybeans, using a sequential evaluation procedure. Secondly, it investigates whether spot commodity prices reflect price information embodied in USDA estimates. The plan of the paper is as follows. The next section gives the description of the data followed by a methodology. Next, an empirical analysis of the paper is presented. The final section includes a review of findings and conclusions.

II. Data

Several agencies within USDA are responsible for estimating program crop prices. USDA program crops consist of twelve field crops. Peanut price estimates are, for instance, reported only October through February during the marketing year. Missing data for several program crops results in a complete monthly data set of only rice, soybeans, and wheat for the current research. The monthly sample spans December 1997 and April 2007.

Rice prices ($/cwt) are average rough rice price received by farmers. The monthly price data are obtained from various issues of *Rice: Situation and Outlook Yearbook* (ERS/USDA). Soybeans prices ($/bushel) are average price received by farmers obtained from various issues of *Oil Crops Situation and Outlook Yearbook* (ERS/USDA). Wheat prices ($/bushel) are weighted average of hard red winter, hard red spring, soft red winter, white, and durum. The price series are obtained from various issues of *Wheat Situation and Outlook Yearbook* (ERS/USDA).

The USDA publishes mid-month estimates for rice between the 10th and 16th of each month. The monthly estimates are collected from various *Rice Outlook* reports. Soybeans estimates are reported between the 9th and 16th of each month obtained from various *Oil Crops Outlook* reports. For wheat, projected monthly prices are published in various *Wheat Outlook* reports between the 10th and 17th of each month and are obtained from the outlook reports. All price series are transformed in natural logarithm to reduce heteroskedasticity in the data.

III. Methodology

Numerous studies have examined the predictability of USDA's forecasting models based on several parametric and nonparametric evaluation criteria. Moreover, a recent advance in time-series analysis adds complexity to a good understanding of empirical literature pertaining to

USDA forecasts. However, a recent paper by Sanders and Manfredo (2007) provides a unified guideline to forecasting practitioners and extension service agents who often find forecasting literature intriguing and yet intricate.

This paper closely draws on the recent unified methodological guideline to conduct a sequential rationality and optimality test of USDA program crop price estimates: Rice, wheat, and soybeans. Conventionally, forecasting performance is examined using some variations of a linear regression equation as follows:

(1) $A_t = b_0 + b_1 P_t + e_t$,

where A_t is actual price at time t and P_t is the price estimate for t. For an unbiased estimate, the estimated parameter, b_0 should be zero; for an optimal estimate, the estimated parameter, b_1 should be one, indicating a long run unitary elasticity of estimates. With the joint hypothesis of $b_0 = 0$ and $b_1 = 1$ being failed to reject, an independent identically distributed error, e_t indicates that a rational estimate does not consistently under- or over- estimate the actual value and estimate errors are uncorrelated. Thus, prerequisites for a rational price estimate are unbiasedness, optimality, and uncorrelated estimate errors (Cheung and Chinn, 1998; Sanders and Manfredo, 2007).

In accordance with Stein (1981), social welfare loss resulted from rational forecasts decreases as R^2 in Equation (1) increases. However, modern contemporary time series literature demonstrates several statistical issues regarding proper estimation of b_0, b_1, and hence R^2 in Equation (1): First, A_t and P_t are not integrated of the same order, a unbalanced regression results in estimation errors (p. 190, Benerjee, 1993). Secondly, differencing I(1) or I(2) in Equation (1) may result in unnecessary restrictions on the short-and long-run dynamics between the forecasts and realized prices.

However, time-series econometricians have offered some remedies for these spurious regression models. Engle and Granger representation theorem showed that if A_t and P_t are I(1) and cointegrated and then Equation (1) can be expressed in an error correction form to show the short and long run dynamics between the two series (Engle and Granger, 1987; Johansen and Juselius, 1990) as follows:

(2) $\Delta A_t = \gamma + \lambda e_{t-1} + \beta_0 \Delta P_t + \sum_{j=1}^{J} (\alpha_j \Delta A_{t-j} + \beta_j \Delta P_{t-j}) + v_t,$

where e_{t-1} equals the error-correction term from Equation (1), $e_{t-1} = A_{t-1} - b_0 - b_1 P_{t-1}$.

McKenzie et al. (2002) showed that Equation (2) reduces to Equation (1). By substituting $e_{t-1} = A_{t-1} - b_0 - b_1 P_{t-1}$ into Equation (2), the specification can be written as follows:

(3) $A_t = \gamma - \lambda b_0 + (1+\lambda) A_{t-1} + \beta_0 P_t - (\lambda b_1 + \beta_0) P_{t-1} + \sum_{j=1}^{J} (\alpha_j \Delta A_{t-j} + \beta_j \Delta P_{t-j}) + \varepsilon_t,$

Holding parameters b_0 and b_1 equal to zero and one, respectively in Equation (1) implies that $\lambda = -1$, $\beta_0 = 1$, and $\gamma = 0$ in Equations (2) and (3). Further assuming that the estimates are orthogonal to past estimates and realization ($\alpha_j = \beta_j = 0, \forall_j$), Equation (3) reduces to Equation (1). Therefore, in the ECM shown in Equation (2), $\lambda = -1$, $\beta_0 = 1$, and $\gamma = 0$ represent the null hypothesis of short-run rationality, where the change in price, ΔA_t should equal the change in the estimate, ΔP_t adjusted for the estimate error in levels from the previous period, e_{t-1}.

A sequential rationality and efficiency test of USDA program crop price estimates can be summarized in orderly steps below:

Step 1: Test if A_t and P_t are the same order of integrations. If A_t and P_t does not share the same order of integration, proceed no further and conclude that P_t is not rational. If both series are stationary in levels, estimate Equation (1), test the null of $b_0 = 0$, $b_1 = 1$, and $e_t \sim i.i.d.$, and conclude P_t is a rational estimate of A_t only if failed to reject the null. Otherwise, conclude that P_t is not rational.

Step 2: If A_t and P_t are both stationary in first differences, proceed to test if both series are

cointegrated. Retest the null of $b_0 = 0$, $b_1 = 1$, and $e_t \sim i.i.d.$ and conclude P_t is rational in the long run only if failed to reject the hypotheses. If two series are not cointegrated, conclude that P_t is not rational, indicating that the two series drift apart through time with no long-run relationship holding them together.

Step 3: If A_t and P_t are indeed cointegrated, an additional condition for price estimate to be rational should be met. In other words, test the null of $\gamma = 0$, $\beta_0 = 1$ and $\lambda = -1$ in the error-correction model in Equation 2. Conclude that P_t is rational in short run as well as in long run only if failed to reject the null. Otherwise, the nonstationary price estimate is not rational both in the short and long run.

Step 4: For an informational efficiency, test the null of $\beta_j = 0$, $\forall_j$. If failed to reject, conclude that actual price reflects all past information embodied in USDA price estimates. Conduct forecast error variance decomposition as additional confirmation.

IV. Empirical Results

Visual inspection of the time-series in Figure 1 suggests that actual values and USDA estimates for rice, soybeans, and wheat display trends or smooth patterns with big swings, a characteristic of time series with unit roots. To formally characterize time-series properties of actual values and estimates for the selected commodities, the unit root tests of the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) are used.

The ADF test statistics in Table 1 are 2.05, 1.86, 2.06, 2.49, 1.20, and 1.64 in absolute value for rice estimate and actual, soybeans estimate and actual, and wheat estimate and actual in levels, respectively. Given a MacKinnon 90 percent critical value of 2.57, this study fails to reject the null hypothesis of a unit root for all the time series. Each series was then first differenced and the ADF regressions were re-estimated. In each case, the ADF test statistics rose considerably, indicating that all the time-series are integrated of order one I(1). The PP results were supportive of the nonstationarity of all the variables.

This suffices to proceed to the second step described above: A cointegration test. A typical Johansen maximum-likelihood cointegration test (pp. 80-84, 1995) invokes two-step identification: Identification of optimal leg length and appropriate specification of cointegration equation. The guiding principal for lag length selection is that the lag length must be sufficiently large so that a vector of the error terms is white noise. AIC and SBC (Enders, 2004) choose lag lengths, 5, 3, and 4 as an optimal for the bivariate models of rice, soybeans, and wheat, respectively.

Johansen and Juselius (1990) Johansen (1995) identify five specifications[1] so as to appropriately model deterministic trends in cointegration equation. Each of the specifications was estimated using EViews and CATS in RATS. The sequential results in details below are reported only for rice due to space limitations.

The lambda max test (Johansen and Juselius, 1990; Johansen, 1992) in Table 2 indicates that there exists one co-integrating equation in the system based on Models 2, 3 and 5, but no co-integrating equation based on Model 1. In practice, Model 1 is rarely used because of an implausible assumption that the level data have no deterministic trends and the co-integrating equations do not have an intercept. The lambda trace test result is consistent with the result for the max test except Model 4. Therefore, the paper concludes that actual rice price and USDA price estimate are indeed cointegrated. Similarly, the study found cointegrating vector for soybeans and wheat (not reported here).

Confirming a cointegration after a battery of tests, the paper estimates a long-run relationship between actual price and USDA estimate. The results are listed in Table 3. The null hypothesis

---

[1] Model 1 specifies that the level data have no deterministic trends and the co-integrating equations do not have an intercept; Model 2 specifies that the level data have no deterministic trends and the co-integrating equations have an intercept; Model 3 indicates that the level data have linear trends but the co-integrating equations have only intercepts; Model 4 assumes that the level data and co-integrating equations include linear trends; lastly Model 5 assumes that the level data have quadratic trends and the co-integrating equations have linear trends.

that b_1= 1 is rejected for each commodity, indicating that USDA price estimates are not optimal in long run. Looking first at rice, the long-run elasticity is statistically less than unity at 0.96. This suggests that the USDA estimates are consistently overpredicting actual rice prices. This result is implied by a descriptive statistic in Table 4, showing that average mean absolute percentage error for rice is 3.75 with mean positive and negative percentage error (error = A_t – P_t) being 3.62 and -4.01, respectively (pp. 143-45, Ferris, 1997). The negative percentage error dominates positive percentage error. Table 3 also shows that the USDA rice estimates are biased upward with the intercept statistically greater than zero at the 1% level. Comparisons of monthly mean absolute percentage errors (MAPE) in Figure 2 provide an interesting observation that USDA estimate error is distinctive in September and declines as the harvesting season progresses. This result is not surprising because price uncertainty reduces as rice production become more accurate.

The results for soybeans have some similarities to those of rice, but there are also important differences. The long-run elasticity is statistically less than unity at 0.97 and the null hypothesis on b_0 is rejected. Thus, the unbiasedness and long-run optimality for USDA soybeans estimates are rejected. Average MAPE is much smaller than that of rice, and errors are asymmetric with the negative percentage error and the positive percentage error, -1.80 and 1.48, respectively. The USDA estimate error in September is the greatest, seemingly contradictory to an early study[2] (Egelkraut et al. 2003) reported that the USDA's September production forecast is most accurate. Table 3 also shows that the USDA soybean estimates are biased upward in the long run.

Regarding wheat, the test results in Table 5 indicate that the USDA estimate is neither unbiased nor optimal in the long run. Although the joint hypothesis of b_0 = 0 and b_1 = 1 is failed

[2] Although comparison of USDA soybean production forecast and soybean price estimate is not direct, USDA soybean price estimate is most accurate in February and USDA soybean production forecast error is the smallest in September (Egelkraut et al. 2003).

to reject at the conventional significance level, the parameters, b_0 and b_1 are significantly different from zero and one, respectively, suggesting that USDA wheat price estimates need to be adjusted downward, especially in September (in Figure 2).

Following Sanders and Manfredo (2007), the paper proceeds to examine whether or not the forecasts are rational in the short run. The estimates of Equation (2) are summarized in Table 5. Looking first at rice, the short-run elasticity (β_0) is significantly different from one and the error correction term (λ) is significantly different from negative one. Surprisingly, given a long-run biasedness, the ECM shows that USDA rice estimates are not biased (γ=0) in the short run. Qualitatively similar results for soybeans and wheat are confirmed. In other words, the USDA soybeans and wheat price estimates are unbiased, but are not optimal ($\beta_0 \neq 1$) in the short run.

Lastly, it is interesting to see if actual price reflects the information embodied in USDA past price estimates ($\beta_j = 0$). Rejection of the null hypothesis indicates that actual prices do not incorporate all of the information in past USDA estimates. Both rice and wheat actual price marginally incorporate the information embodied in USDA past price estimates.

Interestingly, soybeans actual price by no means incorporate the past USDA estimates. This observation becomes apparent by looking into forecast error variance decompositions (FEVD) generated by the ECM model in Equation (3). Notice that the FEVD tells us the proportion of the actual price changes in a sequence due to its own shock and shock to USDA price estimate or vice versa (p.64, Lutkepohl, 2005).

The proportions of forecast error variances of soybeans price accounted for by own innovations are 99.06% and 98.72%, at six and twenty-four months ahead, whereas the proportions of forecast error of actual soybeans explained by USDA estimates are minimal for the entire time horizon. In contrast, forecast error variances of USDA estimates are almost entirely explained by actual soybean price shock at twenty-four months ahead, suggesting that soybean price is a leading variable and USDA soybean price estimate is a lagging variable, not the other around. On the contrary, the proportions of forecast error variances of rice price accounted for by shocks to USDA estimates minimally increase as time horizon gets longer. For wheat, qualitatively similar observations are obtained in Table 6.

V. Summary and Conclusions

Along with an advance in time-series analysis, researchers have examined forecasting performance of the USDA model by offering their own forecasting models for crop prices. Their focus on USDA price forecasts may preclude a scrutiny into another important service of USDA: Providing monthly estimates. Hence, this paper extends a unified forecasting evaluation technique of Sanders and Manfredo to evaluate USDA price estimates of rice, soybeans, and wheat. Specifically, the paper tests a rationality of the price estimate. Rationality requires unbiasedness, optimality, and uncorrelated estimate errors in USDA price estimates.

A battery of testing procedures is implemented. In the first sequence of tests that focuses on determining the order of integration of the estimates and actual prices, the paper finds that rice, soybeans, and wheat prices and estimates are integrated order of one. Thus, the long-run cointegrating relationship and error-correction mechanism must be estimated to provide valid statistical tests. The estimated and actual prices for rice, soybeans, and wheat are indeed cointegrated.

Traditional regression (i.e., super-consistent estimator with cointegrated variables, Enders, 2004) of actual prices on USDA estimates indicates that rice, soybeans, wheat estimates are neither unbiased nor rational in the long run. Error correction models show that USDA soybean estimates are neither unbiased nor optimal in the short run. Interestingly enough, rice and wheat are unbiased in the short run, although they are not optimal in the short run. To sum, monthly USDA estimates of rice, soybeans, and wheat are failed to meet a rationality condition, suggesting that USDA price estimates tend to be biased and overpredicted, especially in the long run.

Despite comparative advantage in informational contexts, USDA price estimates exhibit qualitatively similar performance to USDA crop forecasts. Thus, several points emerge from this research. Market participants are advised to adjust these USDA price estimates correctly for bias and scale, especially for long-run projections. At the same time, the USDA may want to review its estimation method for improvements.

Nevertheless, the USDA rice, soybeans, and wheat price estimates still have economic value to market participants because many of them lack the expertise or resources to generate their own estimates and because the estimates significantly reduce price uncertainty prevailing in making decisions about marketing and investing.

References

Banerjee, Anindya, Juan J. Dolado, John W. Galbraith, and David F. Hendry. *Co-Integration, Error Correction, and the Econometric Analysis of Non-Stationary Data*. Oxford: Oxford University Press, 1993.

Cheung, Yin-Wong and Menzie D. Chinn. " Integration, Cointegration, and the Forecast Consistency of Structural Exchange Rate Models." *Journal of International Money and Finance*, 17 (1998): 813-830.

Elam, Emmett W. and Shelby H. Holder. "An Evaluation of the Rice Outlook and Situation Price Forecasts." *Southern Journal of Agricultural Economics*, 27(1985): 155-161.

Enders, Walter. *Applied Econometric Time Series*. Hoboken: John Wiley & Sons, Inc., 2004.

Engle, Robert E. and Clive W. J. Granger. "Cointegration and Error-Correction: Representation, Estimation, and Testing." *Econometrica* 55(1987): 251-76.

Ferris, John N. *Agricultural Prices and Commodity Market Analysis*. New York: McGraw-Hill, 1997.

Frederic A. Vogel and Gerald A. Bange. "Understanding USDA Crop Forecasts." Miscellaneous Publication No. 1554, NASS/WAOB, USDA, 1999.

Johansen, Soren and Katerina Juselius. "Maximum Likelihood Estimation and Inferences on Cointegration with Application to the Demand for Money." *Oxford Bulletin of Economics and Statistics* 52(1990): 169-209.

Johansen, Soren. "Testing Structural Hypotheses in a Multivariate Cointegration Analysis of PPP and the UIP for UK." *Journal of Econometrics* 53(1992): 211-44.

Johansen, Soren. *Likelihood-based Inferences in Cointegrated Vector Autoregressive Models*, Oxford: Oxford University Press, 1995.

Kastens, Terry L., Ted C. Schroeder, and Ron Plain. "Evaluation of Extension and USDA Price and Production Forecasts." *Journal of Agricultural and Resource Economics* 23(1998):244-261.

Lutkepohl, Helmut. *New Introduction to Multiple Time Series Analysis*. Berlin: Springer, 2005.

No, Sung Chul. "Parametric and Nonparametric Evaluation of USDA Hog Price Forecast." *The Journal of American Academy of Business, Cambridge* 10(2007): 107-113.

Sanders, Dwight R. and Mark R. Manfredo. "Forecast Encompassing as the Necessary Condition to Reject Futures Market Efficiency: Fluid Milk Futures." *American Journal of Agricultural Economics* 87(2005): 610-620.

Sanders, Dwight R. and Mark R. Manfredo. "Rationality of U.S. Department of Agriculture Livestock Price Forecasts: A Unified Approach." *Journal of Agricultural and Applied Economics* 39(2007):75-85.

Sanders, Dwight R. and Mark R. Manfredo. "USDA Production Forecasts for Pork, Beef, and Broilers: An Evaluation." *Journal of Agricultural and Resource Economics* 27(1998):114-127.

Stein, Jerome L. "Speculative Price: Economic Welfare and the Idiot of Chance." *The Review of Economics and Statistics* 63(1981): 223-32.

Egelkraut Thorsten M., Philip Garcia, Scott H. Irwin, and Darrel L. Good. "An Evaluation of Crop Forecast Accuracy for Corn and Soybeans: USDA and Private Information Agencies." *Journal of Agricultural and Applied Economics* 35(2003):79-95.

TABLE 1

Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) Unit Root Tests

Time Series (Annual)	Test (ADF) Statistic τ	Test (PP) Statistic τ	Critical Values 90%
Level Data (in log)			
Rice Forecast (RP_t)	-2.05	-0.66	-2.57
Rice Actual (RA_t)	-1.86	-0.81	-3.13
Soybeans Forecast (SP_t)	-2.06	-1.90	-2.57
Soybeans Actual (SA_t)	-2.49	-1.73	-3.13
Wheat Forecast (WP_t)	-1.20	-1.36	-2.57
Wheat Actual (WA_t)	-1.64	-1.24	-3.13
First Differences (in log)			
Rice Forecast (ΔRP_t)	-43.69^{*}	-40.90^{*}	-2.57
Rice Actual (ΔRA_t)	-43.19^{*}	-37.77^{*}	-3.13
Soybeans Forecast (ΔSP_t)	-29.41^{*}	-28.17^{*}	-2.57
Soybeans Actual (ΔSA_t)	-34.69^{*}	-29.77^{*}	-3.13
Wheat Forecast (ΔWP_t)	-25.40^{*}	-24.28^{*}	-2.57
Wheat Actual (ΔWA_t)	-27.79^{*}	-25.22^{*}	-2.57

Note: the asterisk, * indicates the null hypothesis of a unit root is rejected at the 10 percent.

TABLE 2
Summary of Johansen Cointegration Tests and Number of Co-integration Relations Based on λ_{trace} and λ_{max}.

Model Assumption	Model 1	Model 2	Model 3	Model 4	Model 5
No Trend in Data	No	No	Linear	Linear	Quadratic
Intercept in CE[a]	No	Yes	Yes	Yes	Yes
Trend in CE[a]	No	No	No	Yes	Yes
The Number of Co-integrating Relations					
λ_{trace} Test	0	1	1	0	1
λ_{max} Test	0	1	1	1	1

Note: CE[a] stands for co-integrating equation.

TABLE 3

Long-run Rationality Tests for I(1) Estimate Series: $A_t = b_0 + b_1P_t + e_t$

	Coefficient Estimates		Tested Restriction P-values		
	b_0	b_1	$b_0 = 0, b_1 = 1$	$b_0 = 0$	$b_1 = 1$
Rice	0.096 (3.10)[a]	0.960 (61.05)[a]	10.359[b] (0.000)[c]	3.095[b] (0.002)[c]	-2.56[b] (.011)[c]
Soybeans	0.055 (3.04)	0.970 (94.94)	5.539 (0.005)	3.041 (0.003)	-2.87 (.005)
Wheat	0.026 (2.15)	0.978 (100.3)	2.537 (0.083)	4.617 (0.033)	4.98 (.027)

Note: [a] denotes t-statistics in parenthesis.
[b] denotes F-statistics.
[c] denotes p-values in parenthesis.

TABLE 4
Root Mean Square Error, Mean Absolute Percent Error, Mean Negative Percent Error, and Mean Positive Percent Error: 1997:12 – 2007:04

	Rice	Soybeans	Wheat
Root Mean Square Error	0.40	0.16	0.09
Mean Absolute Percent Error	3.75	1.61	1.72
Mean Negative Percent Error	-4.01	-1.80	-2.13
Mean Positive Percent Error	3.62	1.48	1.40

TABLE 5

Long – and Short Run Rationality and Efficiency Tests for I(1) Forecast Series, Error-Correction Model: $\Delta A_t = \gamma + \lambda e_{t-1} + \beta_0 \Delta P_t + \sum_{j=1}^{J} (\alpha_j \Delta A_{t-j} + \beta_j \Delta P_{t-j}) + \nu_t$

	Coefficient Estimates			Tested Restriction P-values			
						$\lambda = -1$	
	γ	λ	β_0	$\lambda = -1$	$\beta_0 = 1$	$\beta_0 = 1$	$\beta_j = 0$
Rice	-0.000	-0.287	0.583	45.32[b]	19.45[b]	26.21[b]	2.53[b]
	(-0.15)[a]	(-2.71)[a]	(6.17)[a]	(0.00)[c]	(0.00)[c]	(0.00)[c]	(0.04)[c]
Soybeans	0.000	-0.652	0.692	10.56	105.9	54.71	0.02
	(0.22)	(-6.08)	(23.11)	(0.00)	(0.00)	(0.00)	(0.98)
Wheat	0.000	-0.476	0.835	18.25	18.22	16.67	2.99
	(0.11)	(-3.88)	(21.65)	(0.00)	(0.00)	(0.00)	(0.03)

Note: [a] denotes t-statistics in parenthesis.
[b] denotes F-statistics.
[c] denotes p-values in parenthesis.

TABLE 6

Decompositions of Forecast Error Variance Generated by ECM Model

	Period	Rice A_t	Rice P_t	Soybeans A_t	Soybeans P_t	Wheat A_t	Wheat P_t
		% of Forecast Error Explained by					
A_t	1	100.0	0.00	100.0	0.00	100.0	0.00
	6	97.44	2.56	99.06	0.94	98.79	1.21
	12	95.21	4.79	98.82	1.18	97.91	2.09
	18	93.45	6.55	98.75	1.25	97.49	2.51
	24	92.34	7.66	98.72	1.28	97.26	2.74
P_t	1	23.32	76.68	47.53	20.44	77.52	22.48
	6	90.21	9.78	56.83	3.03	95.30	4.70
	12	92.39	7.61	62.57	2.16	95.92	4.08
	18	91.82	8.18	68.23	1.89	96.14	3.86
	24	91.17	8.83	72.48	1.76	96.25	3.75

FIGURE 1
Selected Commodity Prices and USDA Estimates: 1997:12 – 2007:04

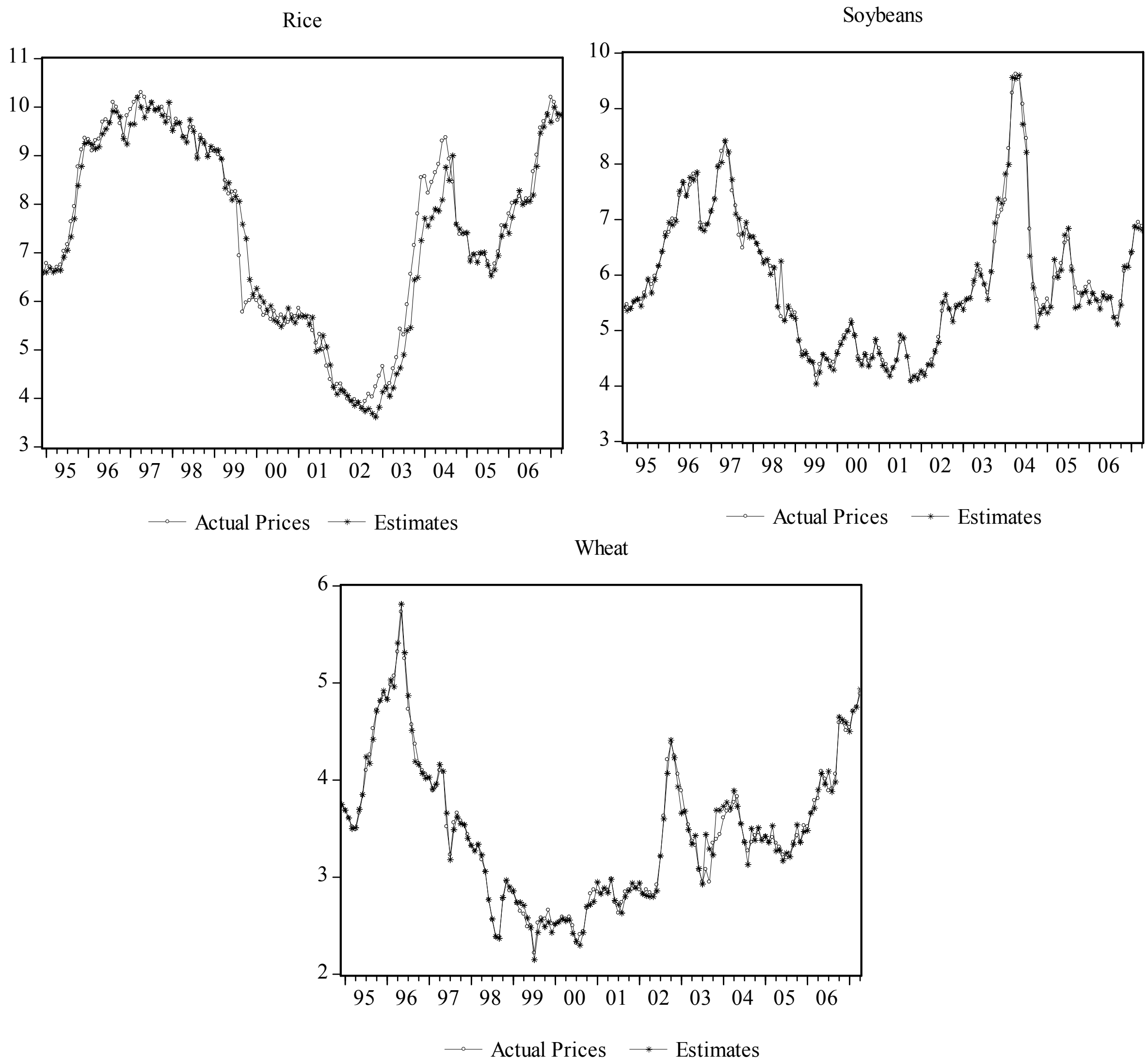

FIGURE 2
USDA Mean Absolute Percentage Errors in Month: 1997-2007