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by

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Cross-Commodity Relationships:
Cointegration and Price Forecasting in Selected Cash Markets

D. Demcey Johnson and Seung-Ryong Yang*

Numerous commodity prices are determined in thinly-traded cash markets. Durum wheat, barley, and sunflowers are examples of commodities for which there is no possibility of direct arbitrage between the cash market and futures. Durum is not deliverable against any of the wheat futures contracts, and there are currently no futures contracts on U.S. exchanges for barley or sunflowers. In the absence of parallel futures contracts, producers and trading companies must make use of other information in developing their price expectations. Cross-commodity relationships are of interest in this context.

Previous studies have examined opportunities for cross-hedging (e.g., Wilson; Miller; Witt, Schroeder, and Hayenga). In contrast, this paper focuses on cross-commodity price relationships in the cash market. Three different pairs of commodities are analyzed--corn and barley; dark northern spring wheat and durum wheat; and soybeans and sunflowers--each characterized by a high degree of substitutability in supply or demand. The analysis addresses two questions: 1) Can price relationships between these commodities be characterized in terms of a long-term equilibrium?; and 2) What is the significance of estimated "long-term" relationships for applied price forecasts?

Our analytical approach is suggested by recent literature on cointegrated time series. In particular, we use cointegration tests to establish the existence of long-term, equilibrium relationships between pairs of prices. We then estimate forecasting models that incorporate the parameter restrictions implied by cointegration, and evaluate their out-of-sample forecast performance.

The organization of the paper is as follows. The data and methodology are described in the next section. The third section contains results of cointegration tests, and the fourth section describes our forecast simulation. The paper concludes with a summary of the results and their implications.

Data and Methodology

All price data are drawn from Grain Market News, a weekly publication of the U.S.D.A. Agricultural Marketing Service. Ten years of weekly quotes, extending from June 1980 through February

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1991, are included in the data set; these represent cash market prices, delivered Minneapolis (or a nearby location) on the day of issue. Three pairs of prices were selected for analysis. (See time plots in Figures 1-3).

The first price pair consists of Dark Northern Spring (DNS) wheat and Hard Amber Durum (HAD). The DNS wheat price applies to 14% protein wheat, and the durum price is for terminal-quality durum. DNS wheat and durum are partially substitutable in pasta production; moreover, they compete for acreage in the Northern Plains. Durum typically trades at a premium to DNS wheat. Indeed, a premium is generally necessary to induce durum plantings, because DNS has higher average yields in the main durum growing areas.

The second pair consists of No. 2 Yellow Corn, delivered Minneapolis, and Feed Barley, delivered Duluth. Barley and corn are close substitutes in animal feed, and as such their price movements should be closely related. However, barley and corn are harvested in different periods and grown in different areas, so they may exhibit different seasonal patterns.

The third pair consists of No. 1 Soybeans, delivered Minneapolis, and Sunflower Seed, delivered Duluth.[1] The products derived from soybeans and sunflowers (oil and meal) are substitutable, and consequently prices of the raw commodities tend to move together. The harvest periods for the two crops approximately coincide.

In each case, we seek to establish whether long-term equilibrium conditions apply to the cash prices. To that end, we apply tests of cointegration to the different price pairs. Cointegration is a property of some sets of nonstationary time series variables whose behavior is governed by equilibrium or arbitrage conditions (Engle and Granger).

Let X and Y denote two variables that are individually *integrated*, so that they require differencing to induce stationarity. If there is a linear combination of X and Y that is stationary without differencing, the two series are said to be *cointegrated*. The tests for cointegration start with a regression of the form:

$$X_t = a + b\ Y_t + Z_t \tag{1}$$

where a and b are parameters, and Z is a residual. In the absence of cointegration, the residual Z is nonstationary. Conversely, when X and Y are cointegrated (i.e., exhibit a stable long-term relationship), Z is stationary and can be interpreted as an estimated deviation from equilibrium.

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[1]Beginning in October, 1988, sunflower prices are for delivery in Red Wing Minnesota.

A second regression is used to determine whether Z is stationary. This can have alternate forms, depending on the treatment of lags. The Dickey-Fuller (DF) test is based on the regression:

$$\Delta Z_t = \alpha_0 \; Z_{t-1} \qquad (2)$$

where Δ denotes a first difference. The DF test involves the t-statistic associated with α_0; this has a nonstandard distribution under the null hypothesis, which holds that Z is nonstationary. If the calculated test statistic exceeds the critical value in absolute terms, cointegration is inferred. The Augmented Dickey-Fuller (ADF) test is based on the comparable t-statistic from:

$$\Delta Z_t = \alpha_0 \; Z_{t-1} + \; \Sigma_i \; \alpha_i \; \Delta Z_{t-i} \qquad (3)$$

The inclusion of lagged changes makes this a more general specification, allowing for more complicated dynamics. When ΔZ is autocorrelated, equation (2) is misspecified and the ADF test is more powerful. Critical values for both tests are reproduced in Engle and Yoo.[2]

In the present context, the variables X and Y represent the logarithms of two commodity prices. Because the choice of dependent variable in (1) is arbitrary, the cointegration tests are repeated for both possible normalizations. The tests are also conducted within different subsamples to gauge the sensitivity of results to choice of time period and number of observations.

If the variables X and Y are cointegrated, they may be represented in terms of an *error-correction model* (Engle and Granger). This is essentially a vector-autoregression (VAR) in differences of the data, augmented to include Z_{t-1} as an additional explanatory variable:

$$\Delta X_t = \beta_0 + \Sigma \; \beta_i \; \Delta X_{t-i} + \Sigma \; \zeta_i \; \Delta Y_{t-i} \; + \gamma_1 \; Z_{t-1}$$

$$(4)$$

$$\Delta Y_t = \theta_0 + \Sigma \; \phi_i \; \Delta X_{t-i} + \Sigma \; \theta_i \; \Delta Y_{t-i} \; + \gamma_2 \; Z_{t-1}$$

The coefficients γ_1 and γ_2 indicate the responses of ΔX_t and ΔY_t to deviations from equilibrium. Engle and Granger suggest a two-step procedure for estimating the model: the cointegrating regression (1) is estimated by OLS; then the error-correction model (4) is estimated using the Z residuals. OLS estimation of (4) is fully efficient when the same explanatory variables enter

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[2]Critical values for various sample sizes are also available in the TSP program.

each equation; otherwise SURE estimation is appropriate.

An alternative representation of (4) would be a VAR in levels of the data, with a set of cross-equation restrictions implied by cointegration. An argument in favor of either formulation is that, if the (estimated) restrictions implied by (1) are true, there are potential efficiency gains from imposing them. Engle and Yoo make this point with a Monte Carlo simulation: they compare the forecasting performance of 2-step error-correction model to that of an unconstrained VAR in levels. The unconstrained VAR performs well over short forecast horizons, but the error-correction model has lower forecast errors for longer horizons. That reflects the tendency of cointegrated variables to "hang together" through time, owing to long-term equilibrium conditions.

In order to assess the practical significance of cointegration for price forecasts, we conduct simulations with actual data. The central issue is whether (given evidence of cointegration) an error-correction model yields better forecasts than an unconstrained model. Hence the relevant comparison, as in Engle and Yoo, is between an error-correction model (EC) and an unconstrained vector-autoregression (UVAR) in levels. We begin by identifying an optimal lag length for the UVAR using the Akaike Information Criterion; the EC model is estimated with one less lag, because it is estimated in differences of the data. Given the importance of seasonal patterns in the prices considered here, we also include a set of seasonal variables in each model, defined:

$$SEAS1 = \text{sine}(2\pi\ t/52); \quad SEAS2 = \text{cosine}(2\pi\ t/52);$$
$$SEAS3 = \text{sine}(2\pi\ t/26); \quad SEAS4 = \text{cosine}(2\pi\ t/26)$$

where t is a time index, and the denominators specify the cycle length in weeks. These variables provide a flexible representation of seasonal patterns in the individual price series.

In the forecast simulation, the models are initially estimated with nine years of weekly price data. Parameters are updated, and out-of-sample forecasts are computed, with each successive observation until the sample is exhausted. This replicates the kind of learning process that forecasters would experience in practice. Comparisons of performance are made on the basis of mean squared forecasting errors over various time horizons, for different model specifications.

Tests of Cointegration

Preliminary tests, due to Dickey and Fuller, confirmed that the individual data series were integrated, but were stationary after taking first-differences. For the cointegration tests it is appropriate to identify the lag structure of ΔZ. However, for simplicity we used four lags in the ADF test.

The results of the cointegration tests are shown in Table 1. For each pair of commodities, the tests were conducted over different time intervals. The shortest intervals are for individual marketing years; the longest interval extends over 10 marketing years, and includes more than 500 weekly observations.[3] Test results are shown for each normalization of the cointegrating regression. Thus, the first entry in the table reports the DF statistic for a test of corn and barley, with the log corn price treated as the dependent variable in the cointegrating regression, and the sample drawn from the 1980/81 marketing year.

There is little evidence of cointegration between soybean and sunflower prices. In fact, there is only one rejection of the null of non-cointegration among all the subsamples tested.

On the other hand, the results for the other price pairs do provide evidence of cointegration. Two features of these results should be noted. First, the test inference can vary according to the choice of normalization. For example, consider the results for dark northern spring (DNS) wheat and durum (HAD) in the 80/81 marketing year. When the cointegrating regression is normalized on DNS, the DF test indicates rejection of the null at 5 percent. The same test with the alternative (HAD) normalization does not indicate rejection.

Second, the results appear to be highly sensitive to the choice of time period. The tests for corn and barley provide an interesting example. Based on the 4-year 1986-90 sample, the null is rejected at 1 percent, strongly indicating cointegration; with the inclusion of one year of additional data (ie, the 5-year 1985-90 sample) cointegration is not indicated. Generally, there is evidence of cointegration in the corn-barley and DNS-HAD samples spanning longer time intervals. The DF tests suggest cointegration in all eight, nine, and ten-year samples for these price pairs, for each normalization.

Forecast Models and Simulation Results

The cointegration test results suggest that there are long-run equilibrium relationships between corn and barley prices, and between DNS wheat and durum wheat prices. In this section we assess the practical significance of these relationships for price forecasts. Cointegration implies that the data can be represented by an error-correction model. We estimate error-

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[3]For the corn/barley pair we use the barley marketing year, which begins in June. The marketing year for wheat also begins in June. For soybeans and sunflowers, the marketing year begins in September.

correction models (ECM) for both price pairs, and compare their out-of sample forecasts to those of models which do not incorporate the long-run relationships.

For each price pair, two specifications of the error-correction model are presented, corresponding to different normalizations of the cointegrating regression. Estimating both forms allows us to investigate the practical significance of the choice of normalization for price forecasts.

We begin by identifying the lag structure of the unconstrained model using the AIC; the error-correction models are specified with the same lags for comparability. A set of seasonal variables are included in each equation, according to the results of a Wald test. We increased the size of this test (to .20) for ad hoc reasons, in the belief that exclusion of seasonal variables could reduce forecast accuracy.

The estimated models for corn and barley are shown in Table 2. These are based on an initial 9-year sample, extending from June 1980 through May 1989. In the unconstrained model, the coefficients on the lagged price levels are significant in most cases. The error-correction models, estimated with different normalizations, provide an interesting comparison. The response of the barley price to "disequilibrium" (as measured by Z) is highly significant in one model, and not significant in the other. Thus, the choice of normalization can lead to different conclusions regarding price dynamics.

The estimated models for DNS wheat and durum are shown in Table 3. The Wald test supports inclusion of seasonal variables in the DNS equations, but not in the durum equations. This suggests a lack of seasonality in durum, or (more likely) the transmission of seasonal patterns through price interactions with DNS wheat. The unconstrained model is specified with three lags, indicating a longer memory than in the case of corn and barley. The error-correction models indicate that DNS wheat responds significantly to disequilibrium. However, the results are more ambiguous for durum prices, since (as in the case of barley) the significance of error-correction depends on the choice of normalization.

In the simulation exercise, we use each model to develop multi-step price forecasts. Initial parameter estimates are based on data from nine marketing years, ending in May 1989; these estimates are updated with each successive observation until the entire sample is exhausted. The updating of parameters--which for error-correction models includes re-estimation of cointegrating regressions--is meant to replicate a forecaster's learning process. The simulation period (extending through February 1991) allows us to evaluate the accuracy of 90 one-step ahead forecasts; for each additional step, the available observations are reduced by one.

Figure 4 provides a comparison of forecasting accuracy for the corn/barley models. The trace of the forecast covariance matrix is displayed for each model, for different forecast horizons. The unconstrained model from Table 2 is equivalent to a VAR in levels of the data, and provides the same price forecasts. Interestingly, this simple model is more accurate (in terms of mean squared error) than the error-correction models for all forecast horizons.

On the other hand, the error-correction models appear to improve forecast accuracy in the case of DNS wheat and durum. As shown in Figure 5, the differences between models are relatively minor for short horizons, but the error-correction models perform markedly better than the VAR for longer horizons (in excess of 15 steps), as suggested by Engle and Yoo. The forecasts are sensitive to the choice of normalization, with the HAD normalization performing best in this sample.

Despite the apparent gains from imposing cointegration restrictions on the DNS and durum prices, the errors may be too large for these forecasts to be practically useful. Table 5 displays mean absolute forecast errors from the "best" models, converted into cents per bushel. The errors for DNS and durum seem fairly substantial for 1-step forecasts (approximately 6 cents), and increase dramatically with the forecast horizon. Increases in forecast errors are more moderate in the cases of corn and barley.

Conclusion

This paper has investigated the existence of long-term equilibrium relationships for pairs of cash prices and their significance for forecasts. Using tests of cointegration, we confirmed the existence of such relationships between corn and barley prices, and DNS and durum wheat prices. We found little evidence of cointegration between soybean and sunflower prices, despite their apparent tendency to move together through time.

We then developed forecasting models that utilized estimates of long-run relationships, and compared their out-of-sample forecasts to those of unconstrained models. In the case of corn and barley, the imposition of cointegration restrictions did not improve forecast accuracy, even in the long-run. This was contrary to expectations, based on the findings of Engle and Yoo. The poor performance of the error-correction models for corn and barley may be due to a variety of factors, including instability in the estimated cointegration relationships. The cointegration test results for different subsamples are suggestive of such instability; if estimated long-run relationships do not hold in the forecast period, bias is introduced in the forecasts.

In the case of DNS and durum, forecasts from the error-correction models were more accurate than those from an unconstrained model. However, given the size of forecast errors, we are doubtful of the practical usefulness of the models in their present form.

Our results illustrate some of the practical consequences of alternative normalizations of the cointegrating regression. Standard tests of cointegration, based on regression residuals, can lead to different inferences depending on the choice of dependent variable. In addition, forecasts from error-correction models are sensitive to the normalization chosen. This may be important in small samples, or when the cointegration between variables is not particularly strong.

The study was motivated by an interest in thinly-traded commodities, and price discovery in the absence of futures markets. The analysis was restricted to cash price relationships between pairs of commodities; however, a natural extension would be the incorporation of futures prices (i.e., for corn and wheat) in forecasting models for barley and durum.

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Table 1:
Tests of Cointegration over Different Time Periods with Different Normalizations

	DF		ADF		DF		ADF		DF		ADF	
period	corn	bly	corn	bly	DNS	HAD	DNS	HAD	soyb	sunf	soyb	sunf
1 year												
80-81	2.39	1.83	1.56	1.33	3.83*	2.49	1.49	1.36	1.85	2.32	1.29	2.14
81-82	1.94	3.21	2.39	4.37**	5.03**	5.41**	2.59	3.77*	2.21	1.56	1.59	1.43
82-83	2.00	3.41*	1.16	2.78	3.13	2.49	2.24	1.06	1.80	1.36	2.66	1.94
83-84	2.30	2.10	1.24	1.74	2.25	2.49	1.56	1.56	2.18	0.15	1.36	0.02
84-85	2.65	4.80**	2.25	3.43	2.42	2.13	2.97	2.80	2.11	1.67	1.18	1.03
85-86	2.87	3.17	0.79	1.67	1.77	2.67	2.43	1.73	1.91	2.05	0.61	2.11
86-87	1.62	0.74	0.99	1.19	2.89	2.02	1.62	1.82	3.34	3.60	1.12	1.27
87-88	2.09	2.12	1.90	2.36	2.23	2.25	1.57	2.57	2.53	2.31	2.33	1.94
88-89	3.73*	2.01	2,86	2.51	3.98*	1.28	2.81	1.34	1.29	2.26	1.61	2.20
89-90	1.76	2.77	1.96	1.82	1.88	2.98	1.93	3.19	3.72*	2.96	2.96	1.77
2 years												
80-82	2.18	2.67	1.65	2.45	4.19**	4.12**	2.11	2.94	1.45	2.45	0.75	2.80
81-83	1.50	1.59	1.81	1.22	5.53**	5.19**	3.13	3.00	0.12	1.40	0.13	1.40
82-84	2.34	2.37	1.63	1.62	3.88*	3.56*	2.97	2.48	1.44	0.77	1.68	0.96
83-85	2.53	2.76	2.32	2.53	2.92	3.22	2.83	2.22	1.70	0.95	0.98	0.60
84-86	2.95	3.17	1.96	1.91	1.66	1.34	2.52	1.63	3.31	3.27	1.96	1.60
85-87	1.57	2.44	1.03	2.77	1.93	1.67	1.81	2.20	3.28	3.32	1.56	2.21
86-88	2.96	1.96	1.96	2.13	3.23	2.63	1.86	2.36	3.30	2.98	1.98	1.88
87-89	3.02	3.15	3.16	3.57*	1.27	1.63	1.26	2.17	1.52	1.36	1.04	0.82
88-90	2.82	2.98	2.67	3.63*	2.27	1.74	1.01	1.98	0.78	0.62	0.64	0.78
3 years												
80-83	2.09	1.97	1.47	1.58	4.93**	4.94**	2.82	3.30	2.08	1.79	1.43	1.73
81-84	2.01	2.18	1.79	1.87	5.32**	4.41**	3.20	2.35	1.94	1.21	1.50	0.95
82-85	2.89	3.00	2.21	2.28	3.47*	3.32	3.13	2.83	1.49	0.88	1.16	0.79
83-86	3.67*	3.71*	2.52	2.49	1.86	2.18	2.78	2.19	2.70	2.31	1.53	1.18
84-87	2.18	3.11	1.45	2.68	2.50	2.15	2.52	2.46	3.98*	3.71*	2.06	1.50
85-88	1.91	2.07	1.54	2.42	2.15	1.78	1.73	2.36	2.94	3.17	2.26	1.59
86-89	4.44**	4.71**	3.56*	4.57**	1.68	1.83	1.47	2.29	2.31	2.35	1.35	1.28
87-90	3.61*	3.74*	3.78*	4.16**	2.15	2.37	1.84	2.44	0.79	0.59	0.32	0.32
4 years												
80-84	2.48	2.55	1.90	2.21	5.54**	5.55**	3.21	3.70*	2.32	0.96	1.71	0.89
81-85	2.41	2.65	2.15	2.28	4.41**	3.93*	3.04	2.66	2.11	1.43	1.41	1.10
82-86	3.54*	3.71*	2.29	2.36	2.53	2.76	3.12	2.68	2.39	2.10	1.59	1.32
83-87	2.78	2.94	1.89	2.49	3.04	2.84	2.96	2.63	3.13	2.76	1.65	1.26
84-88	2.27	3.18	1.65	2.87	2.52	2.25	2.23	2.60	1.15	2.06	0.33	1.40
85-89	2.53	2.29	1.89	2.14	2.35	2.33	2.60	2.48	3.02	3.14	2.15	2.29
86-90	5.14**	5.47**	4.31**	5.39**	2.60	2.47	2.29	2.72	1.00	0.79	0.32	0.14

Table 1:
Tests of Cointegration over Different Time Periods with Different Normalizations
(continued)

period	DF corn	DF bly	ADF corn	ADF bly	DF DNS	DF HAD	ADF DNS	ADF HAD	DF soyb	DF sunf	ADF soyb	ADF sunf
5 years												
80-85	2.82	2.86	2.27	2.49	5.03**	5.27**	3.04	3.65*	2.40	1.16	1.68	1.23
81-86	2.80	2.83	2.10	1.83	3.28	3.46*	3.03	2.83	2.90	2.57	1.79	1.60
82-87	2.91	3.36	1.94	2.79	3.47*	3.23	3.46*	3.13	2.82	2.59	1.73	1.50
83-88	2.85	2.98	2.04	2.67	2.93	2.85	2.59	2.70	1.80	1.55	0.81	0.70
84-89	2.70	2.93	2.12	2.58	2.75	2.64	2.44	2.81	1.85	2.28	1.02	1.58
85-90	2.93	2.64	2.27	2.44	2.97	2.79	2.58	2.82	1.63	1.48	0.70	0.47
6 years												
80-86	3.24	3.12	2.28	2.22	3.96**	4.58**	2.80	3.35	2.99	2.24	1.96	1.54
81-87	3.09	3.40*	2.27	2.92	3.95**	3.80*	3.53*	3.45*	3.27	3.01	1.88	1.69
82-88	2.78	3.28	1.93	2.86	3.26	3.15	3.00	3.11	1.98	1.78	1.27	1.07
83-89	3.21	3.24	2.43	2.90	3.14	3.09	2.75	2.98	1.94	1.54	1.02	0.83
84-90	2.95	3.00	2.37	2.63	3.32	3.10	2.93	3.12	1.65	1.77	0.72	0.97
7 years												
80-87	3.24	3.56*	2.31	3.20	3.94**	4.24**	2.77	3.40*	3.32	2.74	2.07	1.65
81-88	3.07	3.42*	2.34	3.04	3.61*	3.64*	3.03	3.42*	2.20	2.04	1.25	1.19
82-89	3.07	3.37*	2.27	2.95	3.48*	3.40*	3.16	3.40*	2.19	1.77	1.52	1.13
83-90	3.39*	3.38*	2.59	3.02	3.66*	3.54*	3.20	3.29	1.94	1.34	0.89	0.51
8 years												
80-88	3.21	3.58*	2.35	3.31	3.72*	4.06**	2.60	3.27	2.72	2.26	1.61	1.37
81-89	3.40*	3.58*	2.72	3.33	3.81*	3.78*	3.20	3.60*	2.39	2.00	1.53	1.29
82-90	3.15	3.39*	2.35	2.98	3.96**	3.81*	3.55*	3.66*	2.09	1.50	1.27	0.75
9 years												
80-89	3.55*	3.80*	2.71	3.50*	3.95**	4.22**	2.82	3.40*	2.81	2.24	1.75	1.41
81-90	3.50*	3.64*	2.83	3.29	4.26**	4.19**	3.59*	3.88*	2.34	1.79	1.35	0.98
10 years												
80-90	3.65*	3.88*	2.79	3.57*	4.35**	4.59**	3.29	3.84*	2.73	1.98	1.58	1.11

*Signifies rejection of the null hypothesis (non-conintegration) at a 5 percent significance level; ** signifies rejection at a 1 percent level.

Periods are identified with marketing years for barley, wheat, and sunflowers.

Table 2
Forecast Models for Corn and Barley

	Unconstrained Model		E-C Model with Corn Normalization		E-C Model with Barley Normalization	
Dep. Var:	ΔC	ΔB	ΔC	ΔB	ΔC	ΔB
Const.	.00537 (.048)	.11754* (.056)	.00042 (.002)	−.00002 (.002)	.00035 (.002)	.00017 (.002)
C(−1)	−.03161** (.010)	.01617 (.012)				
B(−1)	.03188* (.012)	−.03896** (.014)				
Z(−1)			−.03139** (.010)	.01519 (.012)	.03138* (.013)	−.03918** (.014)
ΔC(−1)	−.12400* (.048)	.04623 (.056)	−.12291* (.048)	.04148 (.056)	−.12891** (.048)	.04413 (.056)
ΔB(−1)	.03819 (.044)	.04881 (.050)	.04113 (.043)	.03599 (.050)	.04177 (.044)	.05034 (.050)
SEAS1	−.00949** (.003)	−.00157 (.003)	−.00969** (.003)	−.00070 (.003)	−.00954** (.003)	−.00159 (.003)
SEAS2	.00363 (.003)	−.00114 (.003)	.00371 (.003)	−.00148 (.003)	.00264 (.003)	−.00157 (.003)
SEAS3	−.00179 (.003)	−.00640* (.003)	−.00184 (.003)	−.00620* (.003)	−.00216 (.003)	−.00656* (.003)
SEAS4	.00312 (.003)	−.00291 (.003)	.00322 (.003)	−.00335 (.003)	.00319 (.003)	−.00288 (.003)

Estimated with weekly data from nine marketing years, from June 1980 through May 1989. Standard errors are in parentheses. *Indicates significance at 5 percent level; ** indicates significance at 1 percent level.

Variable Notation:

C	natural log of corn price;
B	natural log of barley price;
ΔC(−1)	first difference, lagged once;
Z(−1)	lagged residual from cointegrating regression, with indicated normalization;
SEAS1−4	seasonal indexes (see text)

Table 3
Forecast Models for DNS and HAD Wheat

	Unconstrained Model		E-C Model with DNS Normalization		E-C Model with HAD Normalization	
Dep. Var:	ΔS	ΔD	ΔS	ΔD	ΔS	ΔD
Const.	.09694*	.12718	.00053	-.00221	.00052	-.00231
	(.048)	(.071)	(.001)	(.002)	(.001)	(.002)
S(-1)	-.03867**	.02515				
	(.013)	(.020)				
D(-1)	.02225*	-.04630**				
	(.011)	(.015)				
Z(-1)			-.03874**	.02007	.02192*	-.04651**
			(.013)	(.020)	(.011)	(.016)
ΔS(-1)	-.09639*	.20034**	-.09666*	.18888**	-.10861*	.18410*
	(.049)	(.072)	(.049)	(.073)	(.049)	(.072)
ΔD(-1)	.00977	-.09004	.00958	-.10622*	.01318	-.08505
	(.034)	(.050)	(.034)	(.050)	(.034)	(.050)
ΔS(-2)	.04265	.24347**	.04219	.22225**	.03071	.22722**
	(.050)	(.073)	(.050)	(.074)	(.050)	(.073)
ΔD(-2)	.01500	-.06784	.01478	-.08545	.01713	-.06461
	(.033)	(.049)	(.033)	(.050)	(.034)	(.050)
ΔS(-3)	.13749**	.20054**	.13700**	.17929*	.12670**	.18593*
	(.049)	(.073)	(.049)	(.073)	(.049)	(.073)
ΔD(-3)	.03249	.03502	.03227	.01907	.03424	.03769
	(.033)	(.049)	(.033)	(.049)	(.033)	(.049)
SEAS1	-.00246		-.00247		-.00219	
	(.002)		(.002)		(.002)	
SEAS2	-.00094		-.00100		-.00103	
	(.002)		(.002)		(.002)	
SEAS3	-.00297		-.00294		-.00307	
	(.002)		(.002)		(.002)	
SEAS4	-.00075		-.00158		-.00092	
	(.002)		(.002)		(.002)	

Estimated with weekly data from nine marketing years, from June 1980 through May 1989. Standard errors are in parentheses. *Indicates significance at 5 percent level; ** indicates significance at 1 percent level.

Variable Notation:

S	natural log of spring wheat price;
D	natural log of durum price;
ΔS(-1)	first difference, lagged once;
Z(-1)	lagged residual from cointegrating regression.

Table 4

Mean Absolute Forecast Errors For Various Horizons

	Corn/Barley Unconstrained Model		DNS/HAD Error-Correction Model Normalized on HAD	
Forecast Horizon (weeks)	Corn	Barley	DNS	HAD
	(cents per bushel*)			
1	4.9	4.1	5.9	6.4
5	7.6	9.5	12.5	15.7
10	9.6	11.8	20.1	22.8
15	11.1	12.3	28.9	25.8
20	13.6	12.8	38.4	31.7
25	15.3	13.5	49.9	37.0

*Based on average prices during the simulation period. The 90-week average prices for corn and barley were $2.38 and $2.17, respectively; for DNS and HAD the average prices were $3.60 and $3.75.

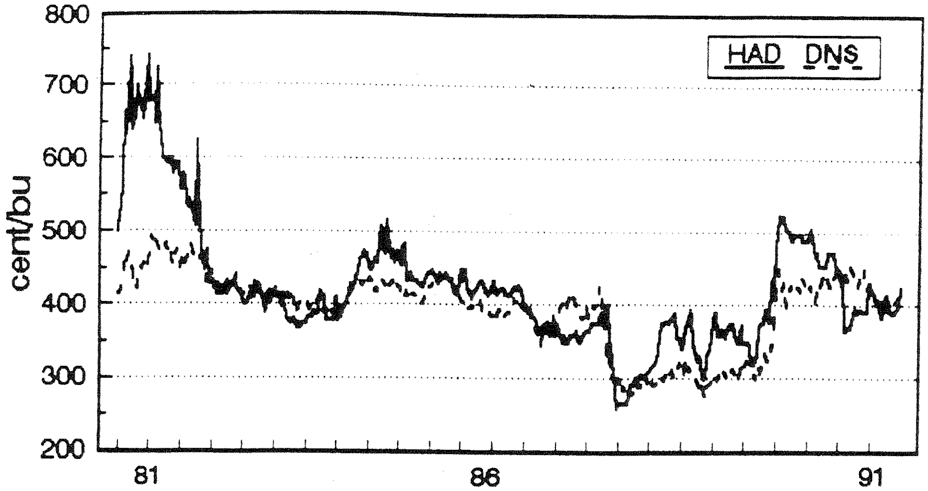

Figure 1. Weekly price movements of HAD and DNS

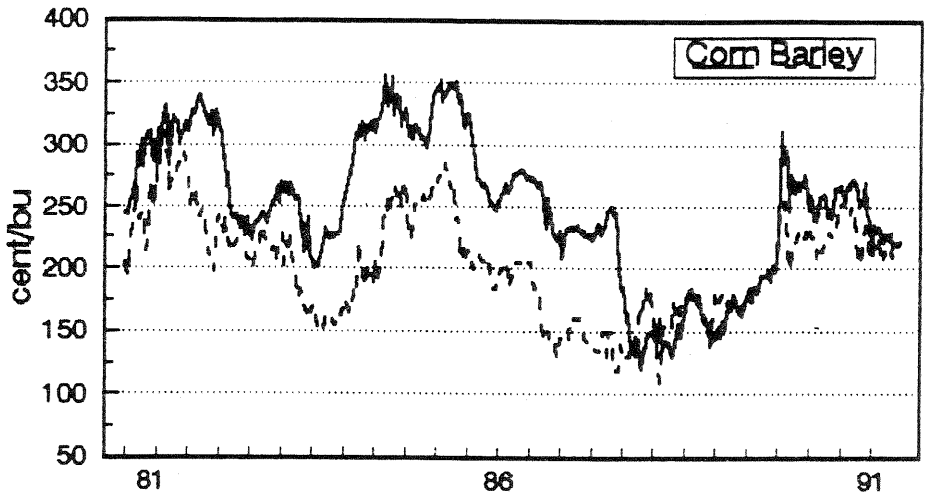

Figure 2. Weekly price movments of corn and barley

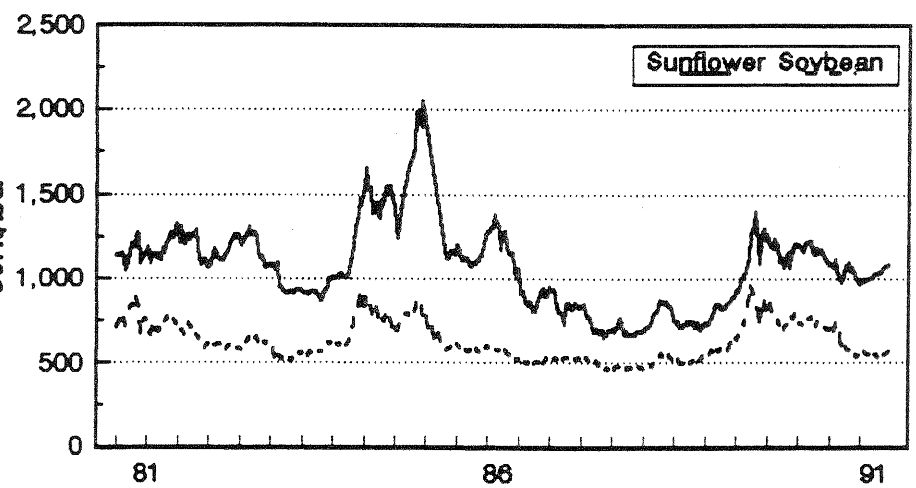

Figure 3. Weekly price movements of soybean and sunflower

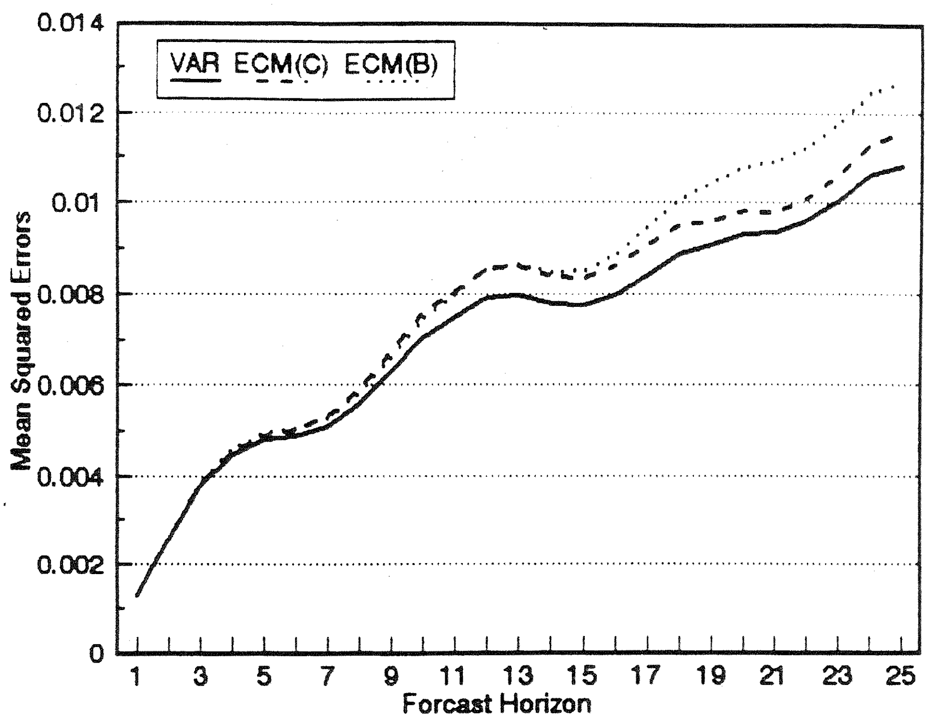

Figure 4. Mean Squared Forcast Errors: System (Corn + Barley)

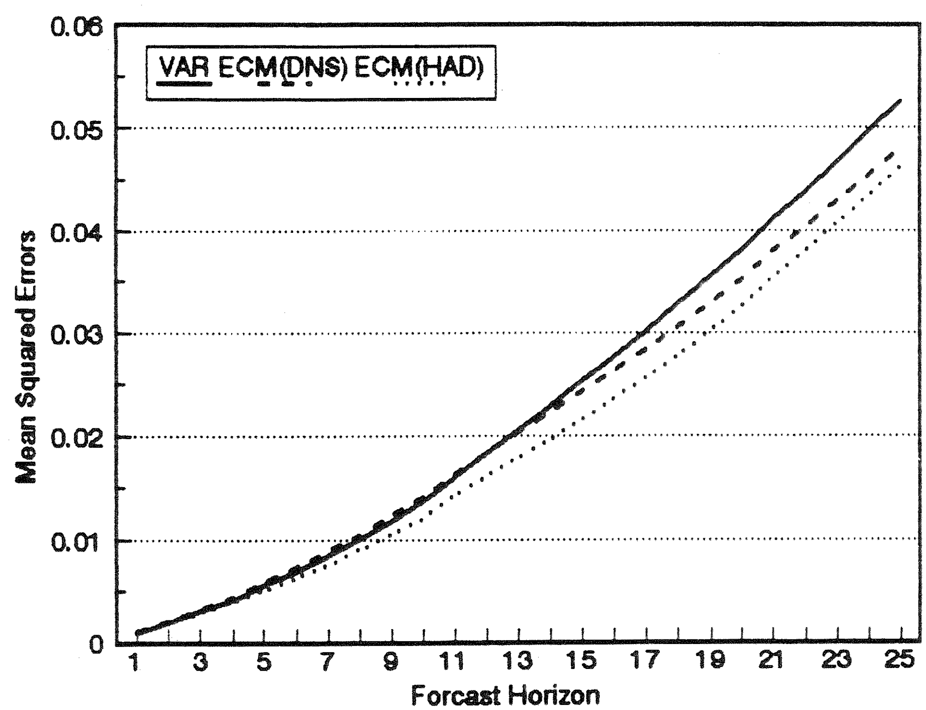

Figure 5. Mean Squared Forcast Errors: System (DNS + HAD)