Granger Causality from the Exchange Rate to Agricultural Prices and Export Sales

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In-sample and out-of-sample Granger causality tests are applied to determine whether the real trade-weighted agricultural exchange rate helps predict monthly real prices and export sales of wheat, corn, and soybeans. An ARIMA model, alternative univariate and bivariate autoregressive models, and a restricted bivariate autoregressive model based on Hsiao's procedure are specified for each variable. Results of the causality tests are shown to be sensitive to specification choice. Forecasting performance of the models is compared and out-of-sample Granger causality is determined using univariate and bivariate models with the best (lowest mean-square forecast error) forecasting accuracy. These tests provide evidence supportive of Granger causality from the exchange rate to export sales, while the evidence on causality from the exchange rate to prices is mixed.

Key words: exchange rates, Granger causality, lag length selection criteria, out-of-sample causality tests.

The importance of macroeconomic-agricultural linkages has been evaluated empirically in recent work by, among others, Batten and Belongia (1984, 1986); Chambers and Just; and Orden (1986). While these studies employ diverse econometric models, each supports the view that some macroeconomic variables (in particular, exchange rates) are significant determinants of agricultural prices and export volumes. However, a disturbing aspect of these models is their poor forecasting performance. In a recent study, Bessler and Babula explored the relationships among the Federal Reserve Board's real trade-weighted exchange rate and cash prices, export sales, and shipments of wheat from a forecasting perspective explicitly. Bessler and Babula report mixed results when comparing forecasts from four-variable vector autoregressions (VARs) to those of univariate autoregressions. They conclude that forecasts of wheat sales are not improved by including the exchange rate as an explanatory variable but that "exchange rates seem to have an impact on real wheat prices" (p. 406).

In this article we evaluate further the importance of macroeconomic variables for agriculture from a forecasting perspective. We examine the impact of the real agricultural trade-weighted exchange rate on forecasts of real cash prices and export sales volumes of wheat, corn, and soybeans in bivariate models. Our emphasis is on carefully specifying the forecasting models in order to determine whether the exchange rate helps predict future values of agricultural prices and export sales.

To assess the exchange rate effects, we first examine the stationarity and seasonal properties of the series and transform the data appropriately. Then, for each price and sales variable, we specify eight models: an ARIMA model, three univariate autoregressive models, three bivariate autoregressive models with the exchange rate and equal numbers of own lags

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and exchange rate lags in each equation, and a restricted bivariate autoregressive model with (potentially) unequal numbers of lags of each variable in each equation. The ARIMA models are specified using Box and Jenkins techniques. The three univariate models and the three bivariate autoregressions are specified using, respectively, univariate and multivariate versions of the Schwartz Bayesian information criterion (BIC), the Hannan and Quinn criterion (HQ) and Akaike's final prediction error criterion (FPE). These criteria represent contrasting approaches to the bias/variance tradeoff inherent in lag length selection. The final restricted bivariate models are specified according to Hsiao's suggested procedure which provides an alternative approach to model specification. Each of these specifications is widely used for forecasting models. Comparing the results of Granger causality tests from the exchange rate to prices and export sales among these various models allows us to explore whether the causality tests are robust. In our results, the Granger causality tests are sensitive to the choice of a lag length selection criterion.

A second aspect of our study is that we use both in-sample and out-of-sample tests for Granger causality. By Granger's definition, whether or not there is causality from y to x is defined by whether or not an optimal forecasting model for x_t using past values of x and y performs better than one using only past values of x. In-sample tests which assess Granger causality by evaluating the statistical significance of blocks of cross-lags in an autoregressive equation are a relatively standard procedure. Ashley, Granger, and Schmalensee (AGS) have suggested, however, that tests based on out-of-sample forecasting competitions provide a more direct implementation of the definition of Granger causality than in-sample tests. They propose a test of the statistical significance of an increase in forecasting accuracy (measured by a decrease in mean-square forecast error (MSE)) in going from a univariate model to a bivariate model which contains the hypothesized causal variable.

In this article, we use the AGS test to base our final conclusions about Granger causality from the exchange rate to prices and export sales on out-of-sample forecasting comparisons between the univariate and bivariate models with the best (in a MSE sense) forecasting performance. To a large degree, this procedure avoids having to make an ad hoc choice among the available lag length selection criteria in specifying a model from which to test for Granger causality. The out-of-sample tests based on the best univariate and bivariate forecasting models provide evidence supportive of Granger causality from the exchange rate to export sales of all three commodities, while the evidence on causality from the exchange rate to prices is mixed.

Data Analysis and Model Specifications

Data Description

We analyze Granger causality from the real exchange rate to real agricultural prices and volumes of export sales using monthly data. The exchange rate used in our analysis is the real total agricultural trade-weighted exchange rate calculated by the Demand and Trade Section, Agriculture and Trade Analysis Division (ATAD), Economic Research Service (ERS), U.S. Department of Agriculture (USDA).[1] The price data, obtained from the Crops Section, ATAD, ERS, USDA, are the average monthly cash prices of No. 1 Hard Red Winter Wheat at Kansas City, No. 2 Yellow Corn at Chicago, and No. 1 Yellow Soybeans at the Illinois Processor. These prices are deflated by the U.S. CPI, published in the *Survey of Current Business*. The series for wheat, corn, and soybean export sales were computed from weekly data from the Export Sales Reporting Division, Foreign Agricultural Service, USDA. We use export sales rather than export shipments because export sales are an economic variable likely to be responsive to changes in the exchange rate. Export shipments are better characterized as a logistic variable, depending on such factors as transportation costs, the availability of freighter space, planned and unplanned delays in shipping, and other similar considerations (Ruppel).

The sample period for our analysis is from 1975:7 to 1986:12. Our models are estimated through 1985:2, with the 22-month period

[1] The weights for the index are average value shares of U.S. commercial agricultural exports from 1976–78. The current real exchange rate for each country is computed by taking a ratio of the U.S. consumer price index (CPI) to that of the country in question (*CPI**) and multiplying by the period average spot nominal exchange rate ($\$^*/\$$). The weighted changes are then summed to form the real index.

from 1985:3 to 1986:12 withheld to evaluate the forecasting accuracy of each model. The sample period was chosen for two reasons. First, we evaluate Granger causality from the exchange rate to the prices and export sales variables over a period of flexible, and largely market-determined, exchange rates. Second, from 1973 to mid-1975 there were large, unusual movements in grain export sales. This was due, among other things, to the direct and lingering effects of agricultural production shocks and the Russian grain purchases in the early 1970s, the oil price shocks of 1972–73, and the shift from a fixed to a flexible exchange rate regime (Orden 1987). By mid-1975, relative stability had returned to the export sales markets, providing a more reasonable basis for estimating the forecasting models.[2]

Stationarity Tests

Estimates of the autocorrelations and partial autocorrelations of the levels and first differences of the logged data series were examined as a starting point for evaluating the possibility of nonstationarity in the series. For the exchange rate and each of the prices, the autocorrelations of the levels are large at low lags and decay slowly, as shown in table 1. Autocorrelations through lag 24 are significant for the exchange rate and wheat and soybean prices. For corn prices, the autocorrelations through lag 17 are significant. By comparison, the autocorrelations of the first differences of the exchange rate and prices series are insignificant after one lag (see table 2). These patterns indicate the presence of at most one unit root in the data generating processes of these series. For the three export sales variables, in contrast, the autocorrelations of the levels die out by at most the third lag, indicating that the export sales series are probably stationary in their log levels.[3]

To confirm the implications of the autocorrelation functions, formal tests for the presence of a unit root were conducted following Dickey and Fuller (1979, 1981). The results of these tests are summarized in table 3. At the 5% level of significance, the presence of a unit root in an autoregressive model is not rejected for the exchange rate, wheat prices, or corn prices. Test results for the soybean price series are mixed. The two tests with models that exclude the possibility of a time trend under the alternative hypothesis do not reject the presence of a unit root. In the two tests that allow for a time trend, a unit root is rejected. Given these inconclusive results, we directly compared forecasts from soybean price models in levels with trend and first differences. First-differencing provided more accurate models.[4] Hence, we first-differenced the series for soybean prices in our forecasting models, as well as the series for the exchange rate, wheat prices, and corn prices.

In contrast to the results for the exchange rate and prices, the unit-root tests for the export sales series conclusively reject the unit-root hypothesis, confirming the observations on the autocorrelation functions for these series. Hence, the export sales series were modeled in levels. (Because time plots of the export sales series revealed no trends in mean, we did not examine the Dickey-Fuller test statistics which have linear trends as alternative hypotheses.)

Two other aspects of potential model misspecification also were examined. First, we tested for cointegration in the exchange rate–price bivariate systems to see if there are stationary linear combinations of these variables. No evidence of cointegration was found. Second, we examined the estimated autocorrelations of the stationary series to evaluate seasonality in the series. First differences of the exchange rate, wheat prices, and soybean prices show no seasonal spikes in their autocorrelation functions (see table 2). First differences of corn prices show a seasonal spike at lag 12 that

[2] As a result of the unusual movements in world agricultural markets during the mid-1970s, the export sales data prior to 1975:7 include many negative entries. In the period after 1975:7, two negative values appear (one each in the series for wheat sales and corn sales). These negative values are the result of the cancellation of sales to Afghanistan following the invasion by the Soviet Union. In order to log the data prior to estimation of the forecasting models, a relatively small positive value was assigned to the series in place of each negative observation. The logarithms of these entries resulted in the lowest logged value of the series over the sample period without substantially altering the existing smoothness of the series.

[3] Time plots of the data are available from the authors.

[4] We also explored the value of imposing the unit-root assumption on the exchange rate and the other prices series by comparing the forecasting accuracy of models in levels to models in first differences. For the various univariate and bivariate models examined, the differences models produced out-of-sample forecasts with lower MSE than the corresponding levels model in 22 of 24 cases. Although we did not calculate the statistical significance of these differences in MSE, the fact that the MSEs were lower in so many of the cases strongly suggests that the differences specifications provide superior forecasting models (see Bradshaw and Orden for further discussion).

Table 1. Estimated Autocorrelations (ACF) and Partial Autocorrelations (PACF) on Logged Data, Lags 1-24, 1975:8-1986:12

	Wheat Price		Corn Price		Soybean Price		Wheat Sales		Corn Sales		Soybean Sales		Exchange Rate	
Lag	ACF	PACF	ACF	PACF	ACF	PACF	ACF	PACF	ACF	PACF	ACF	PACF	ACF	PACF
1	.96	.96	.94	.94	.96	.96	.51	.51	.43	.43	.36	.36	.99	.99
2	.90	−.22	.86	−.21	.90	−.26	.27	.02	.28	.11	.23	.12	.98	−.17
3	.84	−.02	.76	−.12	.84	−.02	.16	.02	.18	.03	.06	−.07	.96	−.07
4	.78	.00	.68	.05	.79	.13	.10	.01	.14	.04	.02	−.01	.95	−.08
5	.72	.02	.61	.10	.75	.03	−.05	−.14	.04	−.07	−.08	−.09	.93	−.03
6	.72	.02	.56	.02	.72	.06	−.02	.07	.04	.03	.09	.17	.91	−.06
7	.63	.05	.53	.10	.69	−.00	.08	.11	.05	.03	−.05	−.12	.89	−.09
8	.59	.10	.50	−.04	.66	.03	.04	−.05	.00	−.04	−.05	−.05	.87	.00
9	.56	−.04	.47	.01	.64	.03	.11	.13	−.03	−.03	.06	.15	.85	−.05
10	.53	−.01	.45	.02	.62	−.05	.14	.03	.03	.06	.13	.09	.83	.01
11	.50	−.04	.42	−.04	.59	−.04	.23	.14	.10	.10	.19	.15	.81	−.03
12	.46	−.07	.39	−.08	.55	−.03	.25	.13	.24	.22	.24	.08	.78	−.01
13	.43	.01	.34	−.04	.52	−.01	.19	−.04	.08	−.14	.06	−.12	.76	−.03
14	.34	.03	.29	−.01	.49	.07	.05	−.11	.17	.12	.06	.08	.74	−.09
15	.36	−.04	.24	−.05	.47	−.03	.08	.12	.25	.17	.07	.05	.71	−.07
16	.33	.01	.21	.05	.45	.04	−.01	−.12	.14	−.09	.02	−.03	.68	−.14
17	.30	−.03	.18	.01	.43	−.02	−.06	.01	.06	−.04	−.12	−.16	.65	−.03
18	.27	.00	.16	−.01	.42	.08	−.05	−.01	.11	.06	.07	.17	.62	.06
19	.25	.01	.14	−.01	.41	.03	−.07	−.14	.06	−.03	−.14	−.15	.59	−.03
20	.23	−.03	.13	.01	.40	−.02	−.09	−.01	−.02	−.03	−.01	.04	.56	.15
21	.21	.08	.12	−.00	.39	−.07	−.03	.05	−.05	−.05	.11	.13	.53	.07
22	.20	.02	.10	−.01	.36	−.11	.08	.04	.00	.02	.12	−.04	.51	−.11
23	.20	.06	.09	−.01	.33	−.00	.12	.09	−.09	−.11	.03	−.00	.48	−.02
24	.20	.02	.07	.03	.31	.10	.16	.02	−.06	−.02	.01	−.15	.45	−.06

Note: Standard errors are approximately 1.96/SQRT (136) = ±0.17, where 136 is sample size.

Table 2. Estimated Autocorrelations (ACF) and Partial Autocorrelations (PACF) on First Differences of Logged Data, Lags 1–24, 1975:8–1986:12

	Wheat Price		Corn Price		Soybean Price		Wheat Sales		Corn Sales		Soybean Sales		Exchange Rate	
Lag	ACF	PACF	ACF	PACF	ACF	PACF	ACF	PACF	ACF	PACF	ACF	PACF	ACF	PACF
1	.34	.34	.43	.43	.37	.37	−.27	−.27	−.37	−.37	−.39	−.39	.24	.24
2	−.06	−.20	.12	−.08	.06	−.09	−.12	−.21	−.04	−.21	.36	−.14	.12	.07
3	−.13	−.04	−.14	−.20	−.18	−.21	−.05	−.16	−.06	−.18	−.11	−.18	.13	.09
4	−.09	−.05	−.18	−.04	−.16	−.02	.09	−.00	.06	−.06	.05	−.08	.07	.02
5	.02	.06	−.08	.06	−.13	−.06	−.18	−.21	−.10	−.16	−.22	−.30	.08	.04
6	−.03	−.10	−.12	−.16	−.06	−.03	−.06	−.22	.01	−.14	.25	.01	.07	.03
7	−.10	−.07	−.01	−.04	−.07	−.08	.14	−.02	.04	−.06	−.11	−.07	.04	.00
8	−.06	.00	−.17	−.13	−.05	−.05	−.11	−.20	−.01	−.07	−.09	−.25	.06	.03
9	−.02	−.02	−.06	.06	.06	.09	.03	−.09	−.09	−.16	.04	−.14	−.01	−.05
10	.04	.03	.07	.07	.01	−.08	−.05	−.18	.00	−.18	−.00	−.19	.01	.00
11	.10	.07	.18	.09	−.01	−.04	.06	−.15	−.06	−.27	.01	−.10	−.03	−.04
12	.07	.02	.18	.02	−.05	−.03	.07	.01	.27	.09	.18	.09	.00	.01
13	.00	−.02	.04	−.07	−.14	−.15	.09	.08	−.21	−.16	−.14	−.12	.08	.08
14	−.03	−.00	−.08	−.07	−.12	−.04	−.17	−.15	.00	−.22	−.01	−.07	.09	.07
15	−.03	−.01	−.11	.01	−.07	−.04	.13	.10	.17	.05	.05	.00	.08	.04
16	.04	.05	−.03	.03	−.02	−.05	−.05	−.04	−.04	−.01	.07	.12	.10	.06
17	−.01	−.06	−.08	−.13	−.09	−.15	−.04	−.01	−.11	−.10	−.26	−.21	−.10	−.18
18	−.04	.01	−.11	−.06	−.05	−.05	.02	.10	.08	−.01	.31	.11	−.04	−.02
19	.03	.06	−.05	.09	−.01	−.02	−.01	−.02	.03	−.01	−.26	−.08	−.17	−.20
20	−.04	−.10	.00	.02	.10	.04	−.09	−.08	−.04	.02	−.01	−.17	−.11	−.04
21	−.06	−.03	.04	−.07	.15	.13	−.05	−.06	−.07	−.03	.09	.02	−.00	−.05
22	−.06	−.04	.06	−.01	.08	−.03	.06	−.13	.13	.09	.09	−.01	−.01	.04
23	−.09	−.08	.02	−.04	−.09	−.16	.01	−.05	−.12	−.00	−.06	.13	.06	.12
24	−.04	−.02	−.06	−.08	−.10	−.01	.07	−.01	−.00	−.09	.04	−.04	.01	.00

Note: Standard errors of the estimates are 1.96/SQRT (135) = ±0.17, where 135 is sample size.

Table 3. Dickey-Fuller Tests for Unit Roots

Test[a]	Exchange Rate (1)	Prices			Export Sales		
		Wheat (2)	Corn (1)	Soybeans (1)	Wheat (1)	Corn (1)	Soybeans (1)
τ_μ	1.31	−2.28	−2.30	−2.38	−4.95*	−5.95*	−5.71*
τ_τ	−0.89	−2.81	−3.25	4.33*			
Φ_1	2.07	3.39	3.21	3.15	12.37*	17.65*	16.34*
Φ_2	3.63	3.77	4.08	6.14*			

Note: The sample period for these tests was 1974:1–1985:4 for the exchange rate and prices and 1975:8–1985:2 for the export sales. The number of lags included in the Dickey-Fuller regression to ensure that the residuals were uncorrelated is indicated in parentheses beside each variable. Critical values of the test statistics at the 5% confidence level are from Fuller (1976, p. 373) and Dickey and Fuller (1981, p. 1063). τ_μ:−2.89, τ_τ:−3.45, Φ_1:4.71, Φ_2:4.88.

[a] Dickey and Fuller suggest a number of different tests for the existence of a unit root based on the general regression $x_t = \alpha + \beta t + \rho x_{t-1} + \sum_{i=1}^{p} \phi_i \Delta x_{t-i} + \epsilon_t$. The null hypothesis for the first test, τ_μ, is that $\rho = 1$ or that x_t contains a unit root and is nonstationary, with an alternative model that the series is generated by a stationary autoregression ($\rho < 1$) with drift but no time trend (β set to zero). The null hypothesis for the second test, τ_τ, is again that $\rho = 1$, with an alternative that the series is generated by a stationary autoregression around a linear time trend. Fuller (1976, p. 373) provides critical values for τ_μ and τ_t which are both "t-ratios," on ρ, that follow nonstandard distributions. The third and fourth tests are likelihood ratio tests for the joint null hypothesis of a simple random walk. For the third test, Φ_1, the null hypothesis is $(\alpha,\rho) = (0,1)$ in a model that is assumed not to include a time trend. For the fourth test, Φ_2, the null hypothesis is $(\alpha,\beta,\rho) = (0,0,1)$ in a model that may have a linear time trend. Critical values for the latter tests are reported in Dickey and Fuller (1981, p. 1069).

* Reject at 5% significance level.

is barely significant. In addition, there is no seasonal spike at lag 24 (the autocorrelation there is negative) indicating that seasonal adjustment is not warranted. All of the export sales series in levels have seasonal spikes at lag 12, but, again, at lag 24 the autocorrelations are not significant. In sum, there is slight but not compelling evidence of seasonal variation. Therefore, no steps were taken to seasonally filter the data prior to the estimation of our forecasting models.

Specification of the Forecasting Models

The final specifications for the ARIMA models and the three univariate autoregressive models (AR) for each of the price and export sales variables are shown in table 4. The ARIMA model for each of the prices was found to be a low-order autoregression. In contrast, moving average terms were found to be significant in each of the export sales models. There are no autoregressive terms in the corn export sales model, one in the wheat export sales model, and two in the soybean export sales model.

Among the univariate autoregressive models, the BIC and HQ criteria agreed on the lag order in every case, therefore these models are reported together. The BIC/HQ criteria, which attempt to balance the bias/variance tradeoff by imposing penalties against increasing lag lengths, thus reducing the standard errors of the estimated parameters which remain, chose a one-lag model in all cases except soybean export sales which has two lags. The FPE criterion, which places relatively more importance on selecting unbiased parameter estimates, selected higher-order autoregressions (three to 12 lags) than the BIC/HQ criteria.[5]

[5] Such differences in lag length specification between the BIC/HQ and FPE criteria are observed frequently. The FPE criterion has been shown to overestimate with positive probability the true lag order of models in large samples (Judge et al.), and Lütkepohl has demonstrated that the BIC and HQ criteria perform well in a Monte Carlo simulation, correctly selecting the lag orders more often than ten other criteria (including the FPE) in moderate and large samples.

Table 4. Final Selected Lag Orders of the Univariate Forecasting Models

Variable Forecasted	Model		
	ARIMA (AR,I,MA)	BIC/HQ AR (AR,I)	FPE AR (AR,I)
Prices			
Wheat	(2,1,0)	(1,1)	(7,1)
Corn	(3,1,0)	(1,1)	(6,1)
Soybeans	(3,1,0)	(1,1)	(3,1)
Export Sales			
Wheat	(1,0,1)	(1,0)	(10,0)[a]
Corn	(0,0,1)	(1,0)[a]	(12,0)[a]
Soybeans	(2,0,1)	(2,0)	(10,0)

Note: BIC is the Bayesian Information Criterion of Schwartz, HQ is the Hannan-Quinn lag selection criterion of Hannan and Quinn, and FPE is the Final Prediction Error criterion. AR denotes univariate autoregressive models.

[a] Constant term excluded from the specification.

Table 5. Final Selected Lag Orders of the Bivariate Forecasting Models

Variable Forecasted	Model BIC/HQ VAR	FPE VAR	Hsiao RVAR[b]
Prices			
Wheat	1	10	7-10/10-1
Corn	1	10	6-10/1-1
Soybeans	1	10	3-10/10-1
Export Sales			
Wheat	1	9[a]	10-10/9-1
Corn	1[a]	10[a]	12-10/10-1[a]
Soybeans	1	9	10-9/0-1[a]

Note: BIC, HQ, and FPE are the multivariate analogs of the autoregressive lag selection criteria referred to in the note to table 4 and in the text. The notation for the lag structure on the RVARs is (own lags of forecasted variable)-(lags of exchange rate in forecasted variable equation)/(lags of forecasted variable in exchange rate equation)-(own lags of exchange rate).

[a] Constant term excluded from the specification.

[b] Hsiao's procedure for specifying the price and export sales equations for the restricted VARs can be summarized as: 1. Using the FPE criterion, select the order of a univariate autoregression for a price on an export sales variable varying the lag length j, from 0 to j^{max}. Call the optimal lag length $j^{\star}$. 2. Add the exchange rate to the univariate model chosen in step 1, again using the FPE criterion to determine a lag order $h^{\star}$. 3. Check whether upon the inclusion of the exchange rate some of the own lags of the price or export sales variable are unnecessary by setting the lag length $h^{\star}$ and varying the own-lag length from 0 to $j^{\star}$. The lag length selected may or may not equal $j^{\star}$. 4. Compare the models resulting from steps 1 and 3 and choose the model with the lowest FPE. The exchange rate equation of the VAR can be specified in a similar way. Finally, the resulting models are subjected to under- and overfitting to check for biases that may have been introduced by the sequential nature of the procedure (Hsiao). The models reported here are those that have survived such diagnostic checks, except for the test of exclusion restrictions on lags of the exchange rate. These results are reported in table 6.

Inclusion or exclusion of constant terms in the autoregressive specifications was determined by whether a given model provided better out-of-sample forecasts with or without a constant.

The final specifications for the bivariate price–exchange rate and export sales–exchange rate models are shown in table 5. The VARs were specified with lag lengths chosen, respectively, by the multivariate versions of the BIC, HQ, and FPE criteria. Again, the BIC and HQ criteria agreed on the lag order selected in every case. The FPE criterion again chose much more heavily parameterized models. The restricted VAR models (RVAR), specified using Hsiao's procedure, generally chose different lag lengths for each variable in each equation. Parameters of these models, which displayed a large number of lag restrictions compared to the FPE VARs, were estimated using a seemingly unrelated regressions procedure.

Table 6. In-Sample Tests for Granger Causality[a]

Variable Forecasted	Model BIC/HQ	FPE	Hsiao RVAR
	(Significance Level of the Test Statistic)		
Prices			
Wheat	.231	.849	.966
Corn	.111	.409	.067
Soybeans	.428	.799	.812
Export Sales			
Wheat	.106	.367	.172
Corn	.521	.127	.063
Soybeans	.920	.230	.535

[a] Standard F-tests (t-tests in the one-lag BIC/HQ specifications) of the null hypotheses that lags of the exchange rate are jointly zero in the forecasting equations for each of the price and export sales variables. See text or note to table 4 for definitions of BIC/HQ and FPE. See notes to table 5 for an explanation of Hsiao's procedure.

Granger Causality Tests

The marginal significance levels for in-sample Granger causality tests are reported for the alternative bivariate models in table 6. In each case, the null hypothesis is that the coefficients of the lag(s) of the exchange rate are jointly zero in the forecasting equation for the price or export sales variable. There is little a priori basis on which to choose among the alternative models. The BIC, HQ, FPE, and RVAR models all represent plausible specifications on which to conduct the in-sample tests.

Based on the in-sample results shown in table 6, Granger causality from the exchange rate to wheat prices and export sales and soybean prices and export sales is rejected in all three models, although only marginally in the BIC/HQ model for wheat sales. For corn prices and export sales, the RVAR models provide evidence of Granger causality from the exchange rate at the 10% significance level, while causality is rejected only marginally in the BIC/HQ model for prices and FPE model for sales.

To conduct the alternative out-of-sample Granger causality tests, Ashley, Granger, and Schmalensee (AGS) suggest the following procedure to compare univariate and bivariate models on the basis of the mean-square errors of their one-step-ahead forecasts. Let ϵ_t^u be the one-step-ahead postsample forecast error of a univariate model and let ϵ_t^b be the one-step-ahead postsample forecast error from a bivariate model. Define the following linear combinations of these variables:

(1) $\Delta_t = \epsilon_t^u - \epsilon_t^b, \quad \text{for } t = 1, \ldots, k,$

(2) $E_t = \epsilon_t^u + \epsilon_t^b, \quad \text{for } t = 1, \ldots, k,$

where k is the number of forecasts made to the end of the postsample period. Then estimate the following regression:

(3) $\Delta_t = \alpha_1 + \alpha_2(E_t - \bar{E}) + \nu_t,$

where $\bar{E}$ is the sample mean of E_t, $t = 1, \ldots,$ k, and ν_t is a white noise disturbance. AGS show that α_1 is the difference in mean-square forecast errors from the univariate and bivariate models, and α_2 is proportional to the difference in forecast error variance from the two models. A test for the significance of the decrease in the mean-square forecasting error in going from the univariate to the bivariate model can be based on the null hypothesis, H_0: $\alpha_1 = \alpha_2 = 0$, versus the alternative, H_A: $\alpha_1 > 0$ and/or $\alpha_2 > 0$, in equation (3).

Rejection of the joint null hypothesis, H_0, suggests that the bivariate model outperforms the univariate model in the MSE sense. A usual F-test can be employed if the two coefficients are positive. If, on the other hand, either of the two estimated coefficients is significantly negative, then one cannot conclude that the bivariate model provides better forecasts than the univariate model. If one coefficient is negative but not significant, a one-tailed t-test can be performed on the other coefficient to evaluate relative forecasting performance.[6]

To implement the AGS procedure, the univariate and bivariate models shown in tables 4 and 5 were used to produce a series of one-step-ahead out-of-sample forecasts of the log levels of the prices and export sales variables over the period 1985:3 to 1986:12. The post-sample mean-square error for each model is shown in table 7. As a benchmark for comparison, the MSEs of one-step-ahead forecasts from random walk models also are shown.

Examining the MSEs of the forecasts, the best univariate models provide better forecasts than the random walks in all cases except soybean export sales. No specification among the univariate models dominates across all of the variables in terms of out-of-sample forecasting performance. The BIC/HQ models produce the lowest MSE for wheat and soybean export sales; the FPE models produce the lowest MSE for corn price and corn export sales; and the ARIMA models produce the lowest MSE for wheat and soybean prices (for soybean prices the ARIMA and FPE specifications are the same, as shown in table 4).

In contrast to the diversity in forecasting performance among the univariate models, the RVARs uniformly produce the lowest MSEs among the bivariate models. The RVAR models provide lower MSEs than the random walk forecasts in all cases.

The results of the AGS out-of-sample tests for Granger causality from the exchange rate to the prices and export sales variables are shown in tables 8 and 9. The first column of table 8 shows the level of significance of the decreases in MSE in going from the univariate BIC/HQ to the bivariate BIC/HQ models. In only one case (wheat export sales) is the decrease in MSE statistically significant, indicating Granger causality from the exchange rate. The results of comparisons based on the univariate and bivariate FPE models are shown in column 2. A bivariate model produces lower MSE forecasts than the corresponding univariate model only for corn prices. The decrease in MSE, however, is not significant, indicating an absence of Granger causality.

The last column of table 8 shows the statistical significance of the decreases in the MSE of forecasts from RVAR models versus the ARIMA models. We paired these procedures because each is inherently more flexible than the uniform autoregressive lag length selection procedures and each involves more diagnostic checking. The results from this comparison are quite different from the results of the preceding two comparisons. The RVAR models provide lower MSE forecasts than the ARIMA models for all variables except soybean prices. The decrease in MSE from the ARIMA to the RVAR model is significant at the 10% level for corn prices and for all of the export sales and is marginally significant for wheat prices. Thus, a comparison between the RVAR and ARIMA models reverses most of the conclusions about the absence of Granger causality reached using the BIC/HQ or FPE models.

A final comparison between the forecasts

[6] Note that the F-test is four tailed because it does not take into account the signs of the estimated coefficients. In an extension of AGS, Brandt and Bessler (pp. 246–47) show that α_1 and α_2 are independent. Thus, one should report a significance level equal to one-fourth of that provided by the standard tables for the F distribution. In addition, if the sample mean of the forecast errors from either model is negative, the forecast error series must be multiplied by -1 before running regression (3).

Table 7. Postsample Mean-Square Error of One-Step-Ahead Forecasts

Variable Forecasted	Random Walk	Model					
		Univariate			Bivariate		
		ARIMA	BIC/HQ AR	FPE AR	BIC/HQ AR	FPE AR	Hsiao RVAR
Prices							
Wheat	3.3081	2.2964*	2.5138	2.3669	2.6175	2.8388	2.0897*
Corn	6.3953	4.3501	4.5578	4.2216*	4.8197	4.0348	2.6679*
Soybeans	0.8555	0.6821*	0.7243	0.6821*	0.8347	1.6108	0.7899*
Export Sales							
Wheat	141.34	84.49	83.54*	94.23	71.13	102.96	69.40*
Corn	198.35	298.69	197.75	193.08*	201.24	237.14	167.22*
Soybeans	173.60	201.69	178.54*	190.23	172.73	279.25	123.24*

Note: All reported values are $\times 10^{-3}$. See note to table 4 or text for definitions of BIC/HQ and FPE. See notes to table 5 for an explanation of Hsiao's procedure.
* Indicates the lowest mean-square error among the univariate or bivariate models for each price or export sales variable.

from the univariate and bivariate models is shown in table 9. Forecast MSEs are compared from the best univariate model and the best bivariate model for each of the price and export sales variables. As already noted, the best univariate specification varies among models, while the RVAR models produce all of the best bivariate model forecasts. The improvement in forecasting performance from the best univariate to best bivariate model is statistically significant at the 10% level for corn prices, wheat export sales, and (marginally) soybean export sales. Forecasts from the bivariate models also are superior to those from the univariate models, at slightly lower levels of confidence (higher probability values), for wheat prices and corn sales. The most noticeable change in the causality test results between the ARIMA/RVAR comparisons and the comparisons among best forecasting models is the lower significance level of the improvement in MSE for corn export sales. For this variable, the FPE univariate model provides much better forecasts than the ARIMA model.

Table 8. AGS Tests for the Significance of Decreased MSE from Bivariate Model Forecasts

Variable Forecasted	Model		
	BIC/HQ AR vs. VAR	FPE AR vs. VAR	ARIMA vs. Hsiao RVAR
	(Significance Level of the Test Statistic)		
Prices			
Wheat	—[a]	—	0.137
Corn	—	0.434	0.003
Soybeans	—	—	—
Export Sales			
Wheat	0.004	—	0.059
Corn	—	—	9.333×10^{-5}
Soybeans	0.509	—	0.098

Note: See note to table 4 or text for definitions of BIC/HQ and FPE. See notes to table 5 for an explanation of Hsiao's procedure.
[a] Mean-square error of forecasts from bivariate model exceeds that of the univariate model (no test).

Some additional evidence of the sensitivity of conclusions drawn from Granger causality tests to choice of lag-length selection criteria and test procedure arises from a comparison of the in-sample and out-of-sample test results in tables 6, 8, and 9. For the BIC/HQ models, whereas an out-of-sample test provides strong evidence of Granger causality from the exchange rate to wheat export sales, the in-sample test provides only marginal evidence of such a relationship. An in-sample test also provides marginal evidence of Granger causality to corn prices, whereas the out-of-sample test provides no such evidence. For the FPE models, the in-sample and out-of-sample tests largely are consistent in rejecting Granger causality from the exchange rate to prices and export sales.

The contrast between the in-sample and out-of-sample tests is more pronounced for the RVAR models. As shown in table 9, when the MSEs of the RVAR models are compared to those of the best univariate forecasting models, the out-of-sample tests provide at least marginal evidence of Granger causality from exchange rates to all of the export sales variables and to wheat and corn prices. In-sample tests based on the RVAR models also provide evi-

Table 9. AGS Tests for the Significance of Decreased MSE from Best Bivariate Model Forecasts

Variable Forecasted	Mean-Square Error		Significance Level of AGS Statistic
	Best Univariate	Best Bivariate	
Prices			
Wheat	2.296 (ARIMA)	2.090 (RVAR)	0.137
Corn	4.222 (FPE)	2.668 (RVAR)	0.006
Soybeans	0.682 (ARIMA/FPE)	0.790 (RVAR)	—[a]
Export Sales			
Wheat	83.54 (BIC/HQ)	69.40 (RVAR)	0.065
Corn	193.08 (FPE)	167.22 (RVAR)	0.134
Soybeans	178.54 (BIC/HQ)	123.24 (RVAR)	0.102

Note: See note to table 4 or text for definitions of BIC/HQ and FPE. See notes to table 5 for an explanation of Hsiao's procedure.
[a] Mean-square error of forecasts from bivariate model exceeds that of the univariate model (no test).

dence of Granger causality from the exchange rate to corn export sales and prices, but for wheat and soybean export sales and wheat prices the in-sample tests provide no evidence of Granger causality.

Conclusions

In this article we have evaluated Granger causality from the real agricultural trade-weighted exchange rate to real prices and export sales of wheat, corn, and soybeans. Previous studies have suggested that the exchange rate is particularly important in the transmission of macroeconomic effects to agriculture, but often the specified models have not forecasted well. Our analysis extends recent work by Bessler and Babula (who evaluate exchange rate effects on wheat prices, sales, and shipments from a forecasting perspective) by modeling prices and sales of two important additional commodities, by considering several model specifications based on alternative lag length selection criteria, and by formally testing the statistical significance of differences in forecast MSE between univariate and bivariate models to draw conclusions about Granger causality.[7]

Although our results are limited to bivariate models, making comparisons among our alternative model specifications allows us to determine whether the Granger causality tests are robust to choice among commonly used lag length selection criteria. In addition, by using out-of-sample tests for Granger causality, we are able to draw conclusions based on a comparison between the univariate and bivariate models with the best (lowest MSE) forecasting performance.

Our results demonstrate that model specification (how lag length is chosen) and the choice between an in-sample and an out-of-sample test are important in determining whether or not Granger causality is detected from the exchange rate to prices and export sales of wheat, corn, and soybeans. In terms of the choice between tests, in-sample tests suffer from the absence of a criterion on which to choose one model specification over another. By employing forecasting accuracy as the criterion for choosing the best univariate and bivariate models and basing tests for Granger causality on these best models, an out-of-sample test can avoid this ad hoc aspect of an in-sample approach.

In our analysis, using the AGS procedure to compare the best univariate and bivariate forecasting models supports Granger causality, at reasonable levels of significance, from the exchange rate to export sales of wheat, corn, and soybeans. The evidence from the comparison of best forecasting models is less conclusive for Granger causality from the exchange rate to wheat, corn, and soybean prices than it is for export sales. These conclusions derive from comparing restricted models specified by Hsiao's procedure, which perform well relative to uniform lag length VARs in terms of out-of-sample forecast accuracy, to a wide array of univariate specifications. Such conclusions would not have been reached had we evaluated

[7] The Federal Reserve Board real exchange rate used by Bessler and Babula is weighted by total trade shares not agricultural trade shares. Also, our models were estimated with 27 months of additional data and forecast accuracy was evaluated for a different postsample period.

only in-sample tests or had we restricted our attention to only BIC/HQ or FPE specified models.

Our out-of-sample Granger causality results (from comparing the best univariate and bivariate forecasting models) are consistent with an absence of short-run purchasing power parity in which movements in the real exchange rate have real effects. These effects should be observed over time on quantities of traded goods given past export quantities. In this context, the diversity of results on Granger causality from the exchange rate to agricultural prices merits further evaluation. However, it is not surprising that Granger causality from the exchange rate to flexible agricultural prices is harder to detect than Granger causality to export sales volumes. One would expect that market-determined prices reflect, to some degree, the same information about the macroeconomy as is reflected in the agricultural exchange rate. Nevertheless, our results indicate some role for the exchange rate in predicting agricultural prices.

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