Time-Varying Weighting Schemes for the Combination of Forecasts: An Application to Supply Response of U.S. Soybean Acreage

by

Kamil H. Shideed and Fred C. White

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Introduction

Procedures for combining individual forecasts have become increasingly evident in agricultural economic research for, at least, two reasons. First, combining forecasts from individual methods into a composite forecast reduces the forecast error below that of any individual approach (e.g., Brandt; Brandt and Bessler; Leuthold and Hartmann). Second, price forecasts as proxies for "true" unobservable prices are subject to the bias and inconsistency problems associated with errors-in-variables and specification bias. The impact of specification bias can be minimized by using more than one variable as the proxy for the true price (Garrod and Roberts).

Simple averaging methods and more flexible weighting schemes are often used in the literature. Composite forecasts generally are superior to constituent forecasts. These procedures assume that combining weights sum to unity and are fixed over time. For many reasons, however, the true but unknown variance-covariance matrix of primary forecasts, and hence the optimal combining weights, may not be fixed over time. In such situations, the use of the estimated combining weights may be severely "suboptimal" (Diebold and Pauly). To circumvent problems of fixed weighting procedures, "time-varying" coefficient combining methods within the context of the "variance-covariance" approach are used in the literature.

Regression is another approach that can be used to combine forecasts. Under the assumption that the weights sum to unity, a "regression-based" method provides optimal combining weights similar to those estimated by the variance-covariance method. Failure to impose this constraint leads to a combined forecast that is likely biased. However, the bias that may be present in the composite forecast may be eliminated by including an intercept in the combining regression; the resulting combined forecasts will be unbiased and have smaller forecast errors that the forecast obtained by any other combining method. In addition, the relaxation of the restriction that the weights sum to unity results in lower forecast errors than if the constraint had been imposed (Diebold and Pauly).

Combining primary forecasts by regression with time-varying parameters is the procedure to be used in this study. The purpose of this research is twofold. First, different weighting schemes will be evaluated in terms of their effectiveness to minimize forecast errors of the combined forecast. Second, the combined as well as the primary forecasts will be used as decision guides to replace price expectations in supply response analysis.

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*The authors are Postdoctoral Research Associate and Professor, respectively, Division of Agricultural Economics, University of Georgia, Athens, Georgia 30602.

The effectiveness of these forecasts to improve forecasting accuracy of crop acreages beyond the period of study will then be analyzed.

The primary forecasts to be combined are futures and cash prices. The commodities to be studied are corn and soybeans. The application of time-varying weighting procedures to supply analysis are of particular importance for two main reasons. First, the presence of high multicollinearity between the primary forecasts results in coefficient estimates which are statistically insignificant and makes it difficult to isolate the net effect of any individual price on the supply response of a particular crop. On the other hand, exclusion of a price series from the variables used to capture expectations may lead to biased estimates. Therefore, price variables need to be combined into one price expectation measure. Second, the application of combining procedures to supply analysis is still limited. Further, available studies pay no attention to the concept of time-varying weights, a topic of particular relevance to agriculture given the myriad of government farm programs that have been used to support price and control production.

Theoretical Framework

Consider the following model:[1]

(1) $P_t = \beta_1 P_t^i + \beta_2 P_t^j + e_t$

where P_t^i and P_t^j are two price forecasts of P_t made at time t-1.

Under the assumption that weights sum to unity ($\beta_1 + \beta_2 = 1$), equation (1) can be rewritten as,

(2) $P_t = \phi P_t^i + (1 - \phi) P_t^j + e_t$

The variance-covariance procedure produces the following solution to the optimal weight which minimizes the variance of the forecast error, e_t.:

(3) $\phi^* = (\sigma_j^2 - \sigma_{ij})/(\sigma_i^2 + \sigma_j^2 + 2\sigma_{ij})$

The exact solution of ϕ under the same assumption of the fixed-weight combination can be obtained by using the ordinary least-squares (OLS) procedure (Diebold and Pauly). This can be done by rewriting (2) in the following form and applying the OLS method:

(4) $(P_t - P_t^j) = \phi(P_t^i - P_t^j) + e_t$

A number of authors, however, have argued that the assumption of constant parameters is frequently "untenable" and that it would be more reasonable to assume that relationships vary over time (Cooley and

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[1]For simplicity only two primary forecasts are considered. The extension to m forecasts is straightforward.

Prescott; Goldfeld and Quandt; Belsley; and Sarris). Parameter variations may arise because of the problems of structural changes, new technological advances, misspecification, and aggregation. In addition, theory suggests that relationships may change over time as the dynamic behavior of the decision makers implies that optimal decision rules vary systematically with changes in the structure of underlying series (Cooley and Prescott).

Since parameter changes are likely to come from a variety of sources, it is difficult to explicitly locate and compensate for the changing structure in the constituent forecasts (Diebold and Pauly). Alternatively, adaptive techniques are used to address the issue of nonconstant combining weights for the variance-covariance combining method. The adaptive techniques have the advantages of allowing for time-varying parameters and giving more weights to the most recent observations. However, the choice of the most recent observations is arbitrary and, thus, directly affect the combining weights. Combining by a regression method with time-varying parameters, on the other hand, uses all the observations. In addition, the relaxation of the restriction that the weights sum to unity and the ability to handle biased forecasts are strong advantages of the regression approach. Following the work of Diebold and Pauly, three general approaches can be identified to handle time-varying weights by the regression method. They are weighted least squares (WLS), deterministic time-varying parameters, and stochastic time-varying parameters.

The WLS estimator for combining weights is:

(5) $\hat{\beta}_{WLS} = (X'WX)^{-1}X'WP$

where $\hat{\beta}$ is a vector of combining weights; X is a (T x 3) matrix of the primary forecasts (including the constant term); W is the (T x T) matrix of the weighting matrix; and P is a (T x 1) vector of observations of the dependent price variable. The weights matrix, W, is specified to be diagonal:

$$W = \text{diag}\ (W_1, W_2, \ldots, W_t)$$

To ensure that recent observations are more heavily weighted than the past observations, $W_t \geq W_{t-1}$ $t = 2, \ldots, T$. For this study four specifications of W are used. In the linear specification $W_{tt} = t$ for all t. Two geometric specifications are used: $W_{tt} = \lambda^{T-t}$ for $0 < \lambda \leq 1$ and $W_{tt} = \lambda^t$ for $\lambda \geq 1$. The WLS scheme is the t-lambda specification: $W_{tt} = t^\lambda$ for $\lambda \geq 0$.

Two models of deterministic time-varying parameters are used. These are linear- and polynomial-deterministic time-varying models. The combining regression for the linear time-varying parameter model is:

(6) $P_t - P_t^j = \phi_0(P_t^i - P_t^j) + \phi_1 t(P_t^i - P_t^j)$

For the polynomial (quadratic) deterministic time-varying model, the combining regression is:

$$(7)\ P_t = A_0^0 + A_1^0 t + A_2^0 t^2 + A_0^i P_t^i + A_1^i t P_t^i + A_2^i t^2 P_t^i + A_0^j P_t^j + A_1^j t P_t^j + A_2^j t^2 P_t^j$$

For the stochastic and systematic time-varying model, the combining weights are obtained using the the following approach. Rewrite the combining regression (1) as:

$$(8)\ P_t = \sum_{i=0}^{2} \beta_t^i P_t^i \qquad , P_t^0 = 1 \text{ for all } t$$

where $\beta_t^i = g^i(t) + U_t^i$, $EU_t^i = 0$, $\mathrm{var}(U_t^i) = \gamma^i$ for all $i =$ 0, ...2 and all t.

Thus, equation (8) can be rewritten as:

$$P_t = \sum_{i=0}^{2} (g^i(t) + U_t^i) P_t$$

or

$$(9)\quad P_t = \sum_{i=0}^{2} g^i(t) P_t^i + W_t$$

where $W_t = \sum_{i=0}^{2} P_t^i U_t^i$, $EW_t = 0$, and

$$\mathrm{cov}(W) = \Omega = \mathrm{diag}\left[\sum_{i=0}^{2} (P_1^i)^2 \gamma^i \ . \ . \ . \sum_{i=0}^{2} (P_T^i)^2 \gamma^i\right]$$

An estimation of γ^i is essential for estimating Ω (see Diebold and Pauly for details).

Rewrite equation (9) in the form:

$$(10)\ P = Xg + W$$

where $X_t = (1, t, t^2, P_t^1, tP_t^1, t^2P_t^1, P_t^2, tP_t^2, t^2P_t^2)'$ and

$$g = (g_0^0, g_1^0, g_2^0, g_0^1, g_1^1, g_2^1, g_0^2, g_1^2, g_2^2)'.$$

Given an estimation for $\hat{\Omega}$, the systematically stochastic combining weights can be obtained as a generalized-least squares estimator:

$$\hat{\beta}_{GLS} = (X'\hat{\Omega}^{-1}X)^{-1}X'\ \hat{\Omega}^{-1}P$$

An Application to U.S. Soybean and Corn Prices

Futures price and naive expectations are widely used in empirical supply response models. With naive expectations the expected price is the same as the lagged cash price. In the futures price case, the price associated with a futures contract at harvest is used for price expectations. Since futures and cash prices reflect different information, forecasts can be improved by including market information from both sources. The argument that futures and cash markets are based on different information stems from the fact that futures prices are determined by the interaction of <u>expected</u> supply and demand relationships, while cash prices result from the equilibrium of current supply and demand relationships (Garcia, Leuthold, and Sarhan).

In this study futures and lagged cash prices were combined for corn and soybeans by using various time-varying combination methods. Following Chavas et al., futures prices of corn and soybeans were collected for December and November contracts, respectively. Futures prices observed on March 15 by the Chicago Board of Trade were chosen in the analysis for both corn and soybeans. The choice of a single observation of futures prices is based on the assumption that daily price movements are closely related due to the continuous inventories of corn and soybeans. For each commodity, the following time-varying combining methods were used:

(a) Restricted combination (variance-covariance combination)
(b) Deterministic - linear
(c) Unrestricted regression-based combination
(d) Deterministic - nonlinear (quadratic)
(e) Stochastic, systematically stochastic time-varying weights
(f) WLS - linear
(g) WLS - geometric ($0 \leq \lambda \leq 1$)
(h) WLS - geometric ($1 \leq \lambda$)
(i) WLS - t^{λ}

These methods were used to combine futures and cash prices for the 1951-82 period. The combining regressions were then used to produce one-step ahead post-sample forecasts for the 1983-86 period. The results of the post-sample forecasts are summarized in Table 1. For corn all combining methods, except the restricted (variance-covariance) and deterministic schemes (both linear and nonlinear) produce smaller MSE's than the primary forecasts. The unrestricted regression method followed by the WLS procedures are the best in the sense that they cause the greatest reduction in forecasting errors. For soybeans, deterministic-nonlinear, stochastic, and variance-covariance methods provide larger MSE's than the primary forecasts. All other combining methods have smaller MSE's than the worst of the primary forecasts, which is lagged price. But, only the geometric WLS methods provide smaller forecast errors than the futures price.

Forecasting Efficiency

The relative efficiency of alternative combining procedures in forecasting corn and soybean prices is represented by the MSE. To test for significant differences among the forecast errors of the combining methods, a procedure suggested by Ashley, Granger, and Schmalensee is used. This procedure can be conducted by estimating the following regression:

$$(11)\quad \Delta_t = \beta_0 + \beta_1(\Sigma_t - \bar{\Sigma}) + U_t$$

where $\Delta_t = e_{it} - e_{jt}$ and $\Sigma_t = e_{it} + e_{jt}$; e_{it} and e_{jt} are the forecast errors made by forecasting models i and j, respectively; and U_t is a zero mean error term independent of Σ_t.

The estimated regression equation is then used to test the null hypothesis that $\beta_0 = \beta_1 = 0$ against the alternative that both

Table 1. Post-Sample Forecasts for U.S. Corn and Soybean Prices, 1983-86

Combining Method	Soybeans (5.832)[a] Average Forecasted Price	Soybeans MSE[b]	Corn (2.287)[a] Average Forecasted Price	Corn MSE[b]
	--------------------$/bu.	--------------------	--------------------	--------------------
(1) Single-lagged price	6.100	2.290	2.345	.0595
(2) Single-futures price	6.135	1.494	2.650	.1683
(3) Restricted combination	6.611	3.484	2.382	.0545
(4) Deterministic-linear	6.116	1.595	2.576	.3972
(5) Unrestricted regression	5.448	1.555	2.238	.0091
(6) Deterministic-nonlinear	5.638	7.635	2.518	.5424
(7) Stochastic	6.304	2.833	2.344	.0502
(8) WLS-linear	6.016	1.799	2.311	.0337
(9) WLS-geometric (λ = .80)[c]	5.873	1.304	2.307	.0228
(10) WLS geometric (λ = 1.20)[c]	5.912	1.317	2.303	.0254
(11) WLS-t (λ = .40)[c]	6.031	1.942	2.309	.0331

[a]Numbers in parentheses refer to the average values of actual prices for the 1983-86 period.

[b]The MSE is defined as: $MSE = \frac{1}{n} \sum_{t=1}^{n} (P_t - \hat{P}_t)^2$, where P and $\hat{P}$ are actual and predicted prices, respectively, and n is the number of observations.

[c]Numbers in parentheses are the corresponding optimal λ obtained by a grid search.

Table 2. Testing the Statistical Differences Among Corn Price Forecasting Errors

	1	2	3	4	5	6	7	8	9	10	11
1				*	*	**		*	**	*	
2					**						
3				*		**					
4					**		*	**	**	**	**
5						**					
6							**	**	**	**	**
7								*	**	**	*
8									***	**	
9										**	***
10											
11											

Note: Asterisks refer to the significant levels as follows: * is 10 percent, ** is 5 percent, and *** is 1 percent.

[a]Numbers 1 through 11 represent the corresponding combining methods in Table 1.

coefficients are nonnegative and at least one is positive. This procedure is to jointly test whether $COV(\Delta,\Sigma) = 0$ and $U(\Delta) = 0$. If either of the estimated coefficients, $\hat{\beta}_0$ and $\hat{\beta}_1$, is significantly negative, the forecasting procedure, j, cannot be judged superior to procedure i. If either coefficient is negative but not significant, a one-tailed t-test on the other one is used. If both coefficients are positive, an F-test of the null hypothesis is performed.

The results from the above test indicate that no significant differences are found among the MSE's of various combining procedures for soybean price. This is not the case, however, for corn price forecasting errors. The performance of various combining weights in corn price forecasting is summarized in Table 2. These results reveal the following points. First, composite forecasts significantly reduced the forecasting error compared to the primary forecasts. For example, the unrestricted regression combination outperforms both lagged cash price and futures price at the 10 percent level and 5 percent level, respectively. Similarly, linear as well as geometric WLS schemes statistically reduced corn price forecasting errors. Second, both deterministic time-varying methods have the worst performance among all other combining schemes. In fact, the deterministic methods generate price forecasting errors far above those of the primary forecasts.

Decomposition of the Mean Squared-Errors (MSE)

To further analyze the alternative combining methods, the MSE's were decomposited into bias, variance, and covariance components following a procedure outlined by Just and Rausser. The results of this process are presented in Table 3. The main implication of the decomposition is that the various combining methods have different types of error which may not be consistent for soybeans and corn. Forecast variability (variance) is the main source of both corn and soybean forecast errors for restricted combination, deterministic linear, deterministic nonlinear, stochastic, and linear WLS combining methods. In both geometric WLS procedures the covariance component is the major source of the forecast error for both corn and soybeans. With the unrestricted regression, bias is the main component for soybean forecast errors, whereas, the covariance component is the largest for corn forecast errors. With the WLS-t^{λ} method, the variance component exceeds the bias and covariance components for soybeans, whereas, the covariance component is the main source for corn forecast errors.

The primary forecasts exhibited different types of errors. The main sources of forecast errors associated with lagged price are variance for soybeans and covariance for corn. With the futures price, on the other hand, covariance is the main component for soybean forecast errors, while bias is the major source for corn forecast errors.

Application to Supply Response Analysis

The basic supply response model of soybeans can be simplified as

$$(12)\quad SPA_t = \beta_0 + \beta_1 SP^*_t + \beta_2 CP^*_t + SSP_t + U_t$$

Table 3. Decomposition of the Mean-Squared Errors into Bias, Variance, and Covariance Components

	Soybeans (1.49832)[a]				Corn (.032968)[a]			
Combining Method	MSE	Bias Component	Variance Component	Covariance Component	MSE	Bias Component	Variance Component	Covariance Component
Single-lagged price	2.290	.07155	1.06430	-.34417	.0595	.00331	.00982	.01339
Single-futures price	1.494	.09151	.52227	-.61810	.1683	.13141	.10970	-.10578
Restricted combination	3.484	.60612	1.10028	.27927	.0545	.00886	.01184	.00082
Deterministic linear	1.594	.08044	.38346	-.36753	.3971	.08309	.26857	.01256
Unrestricted regression	1.554	.14727	.02669	-.11739	.0090	.00241	.04996	-.07626
Deterministic nonlinear	7.635	.03778	6.06896	.03003	.5423	.05351	.73706	-.28116
Stochastic	2.833	.22268	1.50269	-.39059	.0502	.00318	.01116	.00288
WLS-linear	1.799	.03379	.64261	-.37533	.0337	.00058	.01139	-.01122
WLS-geometric (λ = .80)	1.304	.00163	.04049	-.23570	.0228	.00039	.01118	-.02170
WLS-geometric (λ = 1.20)	1.317	.00639	.06939	-.25616	.0254	.00026	.01139	-.01914
WLS-t (λ =.40)	1.942	.03940	.79590	-.39148	.0330	.00049	.01217	-.01257

[a]Numbers in parentheses are variances of the actual prices.

where SPA is planted acreage of soybeans (1000 acres), SP^* represents expected price of soybeans ($/bu.), CP^* is expected price of corn as a competing crop ($/bu.), SSP is support price of soybeans ($/bu.), and U_t is a stochastic error term.

The optimal one-step forecasts of corn and soybean prices generated from various time-varying combining methods are substituted for SP_t^* and CP_t^* as data in equation (11). Therefore soybean acreage response models are estimated for the 1951-82 period under various scenarios of combination methods. The estimated acreage equations are then used to generate one-step forecasts of soybean planted acreage for 1983-86. The results of post-sample forecasts of U.S. soybean acreage are presented in Table 4. On the average all methods, except the deterministic linear, overestimated actual soybean plantings during the 1983-86 period.

To evaluate the performance of alternative time-varying combining methods in forecasting post-sample soybean acreage, both statistical and economic criteria are used. Two statistics are calculated for statistical evaluation. One is a linear loss criterion called the mean absolute percentage error (MAPE) following Brandt and Bessler. The calculated MAPE's for corresponding methods are shown in Table 4. Larger MAPE's are associated with restricted combination, both deterministic methods (linear and nonlinear), and geometric WLS methods. The other statistical criterion is called "sign-preserving correlations." This criterion specifies the smallest correlation between the proxy and the true variables that guarantees the correctness of the sign of the price coefficient in the proxy regression, regardless of any other correlations with unobserved variables or error terms (Krasker and Pratt). The criterion is of significant importance in supply analysis since the theory predicts not the magnitude but only the signs of the price coefficients. The expression for calculating the sign-preserving correlations is:

$$(13)\quad r = [1 - (R^2_{y,x} - R^2_{y,x_2})\,(1 - R^2_{x_1,x_2})/(1 - R^2_{y,x_2})]^{1/2}$$

where $R^2_{y,x}$ is the fraction of the variation of the dependent variable explained by all explanatory variables; R^2_{x,y_2} is the fraction of the variation of the dependent explained by the explanatory variables excluding the explanatory variable in which its sign is of concern; and $R^2_{x_1,x_2}$ is the fraction of the variance in the explanatory variable under consideration explained by other explantory variables in the model. Equation (12) is used to calculate the correlations between the proxy and actual soybean prices to guarantee the correctness of the signs of their regression coefficients. The calculated correlations, which are called "required" correlations are reported in Table 4. Comparing the required with the actual correlations may suggest that lower priority is given to restricted combination, deterministic-nonlinear, linear- and geometric-WLS methods. These five time-varying combining methods require correlations considerably exceeding the actual correlations.

Table 4. Post-Sample Forecasts of U.S. Soybean Acreage and Related Statistics

Combining Method	Forecasted Acreage (1983-86)		Correlation Coefficients		
	Average (1,000 Acres)	MAPE[a]	Required	Actual	Difference
Single-lagged price	64046.02	5.187	.9183	.8989	.0194
Single-futures price	64696.59	4.765	.9487	.9178	.0309
Restricted combination	64837.10	8.212	.9594	.8934	.066
Deterministic linear	62972.56	8.208	.9550	.9159	.0391
Unrestricted regression	65348.16	6.853	.9739	.9377	.0362
Deterministic nonlinear	65201.62	9.277	.9949	.8663	.1286
Stochastic	64625.82	5.501	.9115	.8918	.0196
WLS-linear	63760.19	5.615	.9726	.9085	.0641
WLS-geometric (λ = .80)	68201.07	8.378	.9994	.9053	.0941
WLS-geometric (λ = 1.20)	66621.54	7.613	.9985	.9158	.0827
WLS-t (λ = .40)	63923.51	5.177	.9576	.9059	.0517

[a] $MAPE = \frac{1}{n}\Sigma\,|\text{Actual acreage} - \text{predicted acreage}|/\text{actual acreage}$. The average of actual acreage for the 1983-86 period is 630142.25 (1,000 acres).

For the economic criterion, both own- and cross-price elasticities are estimated and compared with previous studies. The estimated elasticities are reported in Table 5. Elasticity estimates from selected studies (Gardner; Chavas et al.; and Shideed, White, and Brannen) suggest that the range of the own-price elasticity of soybeans is .274 to .61, whereas the range of the cross-price elasticity is -.130 to -.611. Comparing the estimates of Table 5 with those of previous studies shows that the elasticities of restricted combination, both deterministic methods, nonrestricted regression, and both geometric-WLS methods are considerably lower than the lower-bound of previous elasticity ranges.

Concluding Remarks

Composite forecasts of futures prices and no change (naive) models using various time-varying parameter schemes were generated for corn and soybeans. The composite forecasts were, then, used as proxies for expected prices in the soybean acreage response model. Empirical results support the following remarks. First, the regression-based combining models outperform the variance-covariance approach. For example, the unrestricted combined (i.e. unrestricted OLS) forecasts absolutely dominate the restricted variance-covariance combination, cutting the MSE by approximately 80 percent for corn and by 55 percent for soybeans. This, together with the arbitrary specification of the most recent observations and thus the sensitivity of the estimated weights to this specification, may suggest that the variance-covariance approach is of little use.

Second, allowing for quadratic specification in the deterministically time-varying models yields higher MSE than the linear form. The MSE of soybeans increases from 1.59 to 7.63, whereas the MSE of corn increases from .39 to .54. This increase in the MSE reflects the estimation inefficiency incurred by the quadratic term, which had a relatively large influence in the out-of-sample data.

Third, apart from the deterministic time-varying models, other schemes show substantial improvement in forecasting accuracy due to combining. For example, the geometric-WLS with $0 < \lambda \leq 1$ for soybeans has a MSE of 1.30, which is 13 percent lower than the best primary forecast for soybeans. Likewise, the same procedure has a MSE which is 62 percent lower than the best forecast for corn.

Fourth, the decomposition of the MSE into its bias, variance, and covariance components indicates that combining methods do not make the same types of errors. For example, in corn the stochastic time-varying method makes most of its forecast errors because of variability in the composite forecast. The unrestricted regression method, on the other hand, makes a large portion of its corn price forecasting errors because of positive covariance between actual and forecasted prices. A majority of the combining methods commit most of their errors because of variability in soybean and corn price forecasting.

Table 5. Estimates of Short-Run Acreage Supply Elasticities for Soybeans[a]

Combining Method	Own-Elasticity	Cross-Elasticity
Single-lagged price	.263	-.149
Single-futures price	.291	-.174
Restricted combination	.182	-.113
Deterministic linear	.201	-.115
Unrestricted regression	.083	-.066
Deterministic nonlinear	.026	-.042
Stochastic	.255	-.163
WLS-linear	.301	-.185
WLS-geometric (λ = .80)	.033	-.124
WLS-geometric (λ = 1.20)	.098	-.139
WLS-t (λ = .40)	.302	-.186

[a]The elasticities were calculated at the mean values of the corresponding variables for the 1983-86 period.

Fifth, the trade-off between bias and variance components among various combining methods has an implication for the use of forecasts with respect to risk preference. For example, the results of soybean price forecasting imply that a risk-neutral firm may prefer the forecasts of the WLS methods, while a similar risk-averse firm may prefer the lower variability of the unrestricted regression. This argument is based on the assumption that a risk-neutral firm may prefer lower bias and be willing to accept higher variance, while a risk-averse firm may be willing to use biased but precise forecasts, given that the firm's profit is inversely related to forecast errors (Just and Rausser).

Sixth, evaluation of soybean acreage forecasting shows that the MAPE for various methods does not exceed 10 percent. The highest MAPE of 9.3 percent is associated with the deterministic nonlinear (quadratic) combining method, whereas the lowest MAPE of 4.7 percent is associated with using futures prices alone. However, most of the time-varying parameter methods require considerably higher correlations between the actual and forecast prices to guarantee the correctness of the soybean price coefficient in the estimated supply equations. Further, some of the estimated elasticities lie out of the range of previous studies, which is explained at the mean values of 1983-86, a period of decreasing prices.

Finally, although model selection and the criteria used to evaluate the forecasting technique depend mainly on the intended use of the forecast, the results from this study have identified those combining procedures that hold considerable promise for future study. These methods include unrestricted regression combination, stochastic, and WLS methods.

References

Ashley, R., C. W. J. Granger, and R. Schmalensee." Advertising and Aggregate Consumption: An Analysis of Causality." Econometrica 48(1980): 1149-67.

Belsley, D. A. "On the Determination of Systematic Parameter Variation in the Linear Regression Model." Annals of Economic and Social Measurement 2(1973):487-94.

Brandt, J. A. "Forecasting and Hedging: An Illustration of Risk Reduction in the Hog Industry." Amer. J. Agr. Econ. 67(1985):24-31.

Brandt, J. A. and D. A. Bessler. "Price Forecasting and Evaluation: An Application in Agriculture." J. Forecasting 2(1983):237-248.

Chavas, Jean-Paul, et al. "An Analysis of the Role of Futures Prices, Cash Prices and Government Programs in Acreage Response." W. J. Agr. Econ. 8(1983):27-33.

Cooley, T. F. and E. C. Prescott. "Estimation in the Presence of Stochastic Parameter Variation." Econometrica 44(1976):167-84.

Diebold, F. X. and P. Pauly. "Structural Changes and the Combination of Forecasts." J. Forecasting 6(1987):21-40.

Garcia, P., R. M. Leuthold, and M. E. Sarhan. "Basis Risk: Measurement and Analysis of Basis Fluctuations for Selected Livestock Markets." Amer. J. Agr. Econ. 66(1984):499-504.

Gardner, B. L. "Futures Prices in Supply Analysis." Amer. J. Agr. Econ. 58(1976):81-84.

Garrod, P. V. and R. K. Roberts. "Prices as Proxies for Prices." Amer. J. Agr. Econ. 68(1986):626-33.

Goldfeld, S. M. and R. E. Quandt. "The Estimation of Structural Shifts by Switching Regressions." Annals of Economic and Social Measurement 2(1973):475-84.

Just, R. E. and G. C. Rausser. "Commodity Price Forecasting with Large-Scale Econometric Models and the Futures Market." Amer. J. Agr. Econ. 63(1981):197-208.

Krasker, W. S. and J. W. Pratt. "Bounding the Effects of Proxy Variables on Regression Coefficients." Econometrica 54(1986):641-55.

Leuthold, R. M. and P. A. Hartmann. "A Semi-Strong Form Evaluation of the Efficiency of the Hog Futures Market." Amer. J. Agr. Econ. 61(1979): 482-89.

Sarris, A. H. "Kalman Filter Models: A Bayesian Approach to Estimation of Time-Varying Regression Coefficients." Annals of Economic and Social Measurement 2(1973):501-23.

Shideed, K. H., F. C. White, and S. J. Brannen. "The Responsiveness of U.S. Corn and Soybean Acreages to Conditional Price Expectations: An Application to the 1985 Farm Bill." So. J. Agr. Econ. 19(1987): 153-61.