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An Econometric Model of Barley Acreage Response to Changes in Prices and Wheat Acreage in the Northwest



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SUMMARY

Parameters of an econometric acreage response function were estimated for barley in the Northwest using pooled time-series and cross sectional data. Barley acreage was found to be significantly affected by the price of barley, the price of wheat and wheat acreage (a proxy for the "cross-planting" substitution component of government programs). The acreage elasticity with respect to barley price is 0.55 in the Northwest, which is greater than national estimates of 0.30 to 0.36. Wheat was found to be a substitute for barley in Oregon, but was not statistically found to be a substitute in Washington and Idaho.

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1. INTRODUCTION

Considerable research has been done on estimating supply response models for agricultural crops. These models provide an understanding of the particular crop in question and provide estimates of future quantities supplied. This information is important to agricultural policymakers given the persisting conditions of relatively low farm income and instability of commodity prices.

The objective of this paper is to develop an acreage response model for barley in the Northwest (Idaho, Oregon, and Washington) using pooled time-series and cross-sectional (TS-CS) data, and to compare this model with a U.S. model developed by Houck *et al.* The utilization of pooled TS-CS data has become quite popular for estimating acreage response models because of its advantages over techniques which use only one type of data. The use of pooled data is especially helpful when the parameters of a model are to be estimated for a region which contains sub-regions that may be significantly different from each other, e.g., the differences between states in the Northwest. In addition, pooling data facilitates parameter estimation where either time-series or cross-sectional data are limiting. Pooling time-series and cross-sectional data also enables the researcher to use a relatively small number of time series observations, thereby minimizing the effect of technology which changes unevenly over time and is difficult to quantify.

An additional objective of this paper is to provide an example of an empirical pooled TS-CS model which can be useful for instructional purposes.

An overview of the general structure of pooled TS-CS econometric models is presented in the next section. This section also includes a brief summary of the more common data adjustments of estimation techniques employed in such models. Section 3 contains the conceptual specification of the Northwest barley acreage model. The empirical estimation results for the model are presented and discussed in Section 4. In addition to a summary of the paper, Section 5 includes conclusions with respect to the empirical results and possible re-specifications.

2. POOLED TIME-SERIES AND CROSS-SECTIONAL ECONOMETRIC MODELS: AN OVERVIEW

As was noted above, pooling time-series and cross-sectional data enables the researcher to overcome some common problems of parameter estimation. Pooling data also presents some new problems for the researcher because the model may contain serial correlation, heteroskedasticity, and contemporaneously correlated error terms. Pooled data may also be influenced by shifting intercepts in the cross-section units and/or the time series units.

The acreage response model to be estimated uses the data pooling technique to develop a covariance model. This model employs binary variables to account for shifting parameters between cross sectional units. This is an appropriate specification since barley acreage differs between states, even when all explanatory variables are equal, because of structural differences between states.

The model is assumed to be "time-wise autoregressive and cross-sectionally heteroskedastic" and to be cross-sectionally independent. In general, the pooled TS-CS model may be specified as

$$y_{it} = \beta_0 + \beta_1 x_{it,1} + \beta_2 x_{it,2} + \dots + \beta_k x_{it,k} + \varepsilon_{it} \quad (1)$$

where:

y_{it} \equiv endogenous variable for CS unit i during time period t ,

$x_{it,j}$ \equiv j th exogenous variable for CS unit i during time period t ,
 $j = 1, \dots, k$,

ε_{it} \equiv stochastic disturbance term for CS unit i during time period t , and

$\beta_0, \beta_1, \dots, \beta_k$ are unknown parameters.

The assumptions associated with the disturbance term ε_{it} are

$$\varepsilon_{it} = \rho_i \varepsilon_{i,t-1} + v_{it} \quad (\text{autoregression}) \quad (2)$$

$$E(\varepsilon_{it}^2) = \sigma_i^2 \quad (\text{heteroskedasticity}) \quad (3)$$

$$E(\varepsilon_{it}, \varepsilon_{jt}) = 0, i \neq j \quad (\text{cross-sectional independence}) \quad (4)$$

for

$i = 1, 2, \dots, N$ (the number of cross-sectional units)

$t = 1, 2, \dots, T$ (the number of time-series units) ,

and where the v_{it} are assumed to be unobserved disturbances with the usual desirable properties, i.e., constant variance, expected values of zero, and serially uncorrelated (Kmenta).

The assumption of serial correlation indicated that the errors in period t are correlated with the errors in period $t-1$. Heteroskedasticity occurs when the variances of the error terms are not constant across all observations.

With pooled data, the variance of the error term typically varies across cross-sectional units. Either of these problems results in ordinary least squares estimates of the regression coefficients which are unbiased and consistent but are not efficient (Kmenta, p. 51). Therefore, correcting for these problems should improve the efficiency of the estimated model, i.e., decrease the standard errors of the regression coefficients.

Ordinary least squares (OLS) is applied to data which are corrected for serial correlation resulting in estimates of the regression coefficients which are asymptotically efficient, if the model is not heteroskedastic and assumption (4) holds. To test the assumption of serial correlation, the errors in time period t are regressed on the errors in time period $t-1$, i.e.,

$$e_{it} = \hat{\rho}_i e_{i,t-1} + \mu_{it}, \quad t = 1, 2, \dots, T. \quad (5)$$

This is done independently for each cross-sectional unit. Serial correlation is assumed to exist in cross-sectional unit i if the estimated $\hat{\rho}_i$ is significant. This test is employed for the empirical model discussed below because there are insufficient time-series observations on the cross-sectional units to use the Durbin-Watson test which is commonly used to test for serial correlation.

If serial correlation is found to exist in a cross-sectional unit, the observations for the respective unit are adjusted using the estimated $\hat{\rho}_i$. The variables in the model are transformed as follows:

$$\begin{aligned} Y_{it}^* &= Y_{it} - \hat{\rho}_i Y_{i,t-1} \\ X_{ij,t}^* &= X_{ij,t} - \hat{\rho}_i X_{ij,t-1} \quad (i = 1, 2, \dots, k) \\ \mu_{it}^* &= e_{it} - \hat{\rho}_i e_{i,t-1} \end{aligned} \quad (6)$$

After the data are adjusted for serial correlation, ordinary least squares is used to estimate the regression coefficients using the transformed data, i.e.,

$$Y_{it}^* = \beta_0 (1 - \hat{\rho}_i) + \beta_1 X_{it,1}^* + \beta_2 X_{it,2}^* + \dots + \beta_k X_{it,k}^* + \mu_{it}^* \quad (7)$$

The estimated residuals (μ_{it}^*) are calculated from this equation, and a consistent estimate of the variance for each cross sectional unit is obtained, i.e.,

$$s_{ui}^2 = \frac{1}{T-K-1} \sum_{t=2}^T \mu_{it}^{*2} \quad (8)$$

The estimates of the variances are then used to test the assumption of heteroskedasticity between the cross-sectional units using Bartlett's test of homogeneity of the variances (Intriligator, p. 157).

If the model is found to be heteroskedastic with respect to the cross-sectional units, the transformed observations from (6) are again transformed so as to obtain homogeneity, i.e.,

$$Y_{it}^{**} = Y_{it}^* / s_{ui}$$

$$\beta_0^{**} = \beta_0^* (1 - \hat{\rho}_i) / s_{ui}$$

$$X_{it,k}^{**} = X_{it,k}^* / s_{ui} \quad (k = 1, 2, \dots, K) \quad (9)$$

$$\mu_{it}^{**} = \mu_{it}^* / s_{ui} ,$$

where

$$s_{ui} = \sqrt{s_{ui}^2} .$$

OLS is then applied to the transformed data from (9) to obtain asymptotically efficient estimates of the regression coefficients,

$$Y_{it}^{**} = \beta_0^{**} + \beta_1 X_{it,k}^{**} + \beta_2 X_{it,k}^{**} + \dots + \beta_k X_{it,k}^{**} + \mu_{it}^{**}. \quad (10)$$

It is also possible that the assumption of cross-sectional independence [equation (4)] may not hold. As is noted by Kmenta, this may occur "... when the cross-sectional units are geographical regions with arbitrarily drawn boundaries such as states." (Kmenta, p. 512). Thus, violation of this assumption could be caused by an omitted variable such as weather which could affect all of the states in the region. If mutual correlation exists between the cross-sectional units, the "time-wise autoregressive and cross-sectionally correlated model" is appropriate. This technique uses the same correction procedure, as the "time-wise autoregressive and cross-sectionally heteroskedastic model," for serial correlation. An Aitken estimation technique is used to correct for heteroskedasticity (Kmenta, p. 513).

The estimated barley acreage response model may, or may not, have error terms which are cross-sectionally independent. If cross-sectional independence does not exist, there are two reasons to believe that the gains in efficiency from using an Aitken estimator would be small. First, weather is usually the omitted variable which causes mutual correlation in models such as the one to be estimated. The dependent variable in the model is acres of barley planted. Weather may affect planting dates, and thereby, total production. It is assumed that the effect on acres planted is likely to be small. The second reason is that the gains in efficiency from using an Aitken estimation technique are inversely related to the degree of correlation between independent variables (Kmenta, p. 523-524). In the estimated model, a high degree of correlation exists among the independent variables across equations, which in turn, reduces

the gains in efficiency from correcting for mutual correlation if it exists.

The model will be tested for independence of the cross-sectional units.

3. MODEL SPECIFICATION

The barley acreage response model which will be estimated is a single linearequation in double log form with two binary intercept shifters to account for the different states. The model is specified in log-log form to take into account that an equal increase in acres planted in each state is not an equal percentage increase in each state's total acres of barley planted. The model to be estimated is specified in functional form as

$$\begin{aligned} \ln ABP_{it} = & \beta_0 + \beta_1 \ln PB_{i,t-1} + \beta_2 \ln AWP_{it} \\ & + \beta_3 \ln PW_{i,t-1} + \gamma_1 DO_i + \gamma_2 DW_i + \epsilon_{it} , \end{aligned} \quad (11)$$

$$i = 1,2,3, t = 1, \dots, 12 ,$$

where

- $\ln ABP_{it}$ = is the natural logarithm of the acres of barley planted in year t for state i,
- $\ln PB_{i,t-1}$ = is the natural logarithm of the price of barley in year t-1 for state i,
- $\ln AWP_{it}$ = is the natural logarithm of the acres of wheat planted in year t for state i,
- $\ln PW_{i,t-1}$ = is the natural logarithm of the price of wheat in year t-1 for state i,
- DO_i = the binary dummy variable for Oregon (=1 if the observation is for Oregon, and =0 if otherwise),
- DW_i = the binary dummy variable for Washington (=1 if the observation is for Washington and =0 if otherwise),
- ϵ_{it} = the disturbance term for state i in year t (with assumed properties as given in equations 2-4 above), and $\beta_0, \beta_1, \beta_2, \beta_3, \gamma_1$, and γ_2 are unknown parameters.

The prices of barley and wheat are lagged one year since it is assumed that the rancher does not know what the market price for his crop will be at the time when he is making planting decisions.

Acreage response models for cereal grains have traditionally included explanatory variables for the various government price support programs which affect acres planted. Acres of wheat planted is used as a proxy for these variables in this model. This specification is used because barley and wheat are principally grown on non-irrigated cropland in the Northwest, and there are not any crops which are substitutes on this type of land. In addition, wheat is the more profitable crop to raise. Thus, those factors which affect wheat acreage should effectively alter barley acreage. It is important to note that the price of wheat is expected to have an effect on the acres of barley planted. In this model, it is expected that each of these variables will have distinct effects on the dependent variable. This is explained further in the following paragraphs.

The above conclusions follow from a rancher facing nearly identical technology in raising barley and wheat. The only difference in cost is the cost of seed, and this difference is negligible. In turn, the gross returns per acre of wheat have been consistently higher than that of barley [Miles, 1981 (a) and (b)]. Thus, it is assumed that if a rancher is given a choice, he will plant wheat instead of barley, all other factors equal.

There are cases where barley may be the preferred crop. For example, in drought plagued areas, barley is often planted for its drought resistant qualities. Spring barley may also be planted when winter wheat fails to germinate.

The rancher does have the alternative of participating in government price support programs. Participation in these programs usually has resulted

in certain acreage restrictions, e.g., price support and acreage diversion programs. Thus, if the incentive is sufficient for the rancher to participate in wheat price support programs, he can only do so by meeting the acreage restriction requirements. Therefore, if wheat acreage is reduced on non-irrigated cropland, it is expected that the rancher will either plant barley on this excess land or leave it fallow. (This assumption only applies if the diversion program does not affect barley acreage.) One might expect that there would be a one to one tradeoff between acres of wheat planted and acres of barley planted.

Thus, it is assumed that acres of wheat planted is an appropriate proxy for the government price support programs affecting acres of barley planted in the Northwest. This specification implicitly assumes that the government variables effectively operating on barley in the Northwest are the wheat price support programs, and not the barley price support programs. It is also possible for wheat to be a substitute for barley. This factor is accounted for by the lagged price of wheat in the model.

The data which will be used to estimate the model consist of three cross-sectional observations (Idaho, Oregon and Washington), and the 12 time-series observations (1967-1978) on each cross-sectional unit. These states were chosen so the barley acreage response model would complement a wheat acreage response model estimated for the Northwest by Winter and Whittaker in 1978.

4. EMPIRICAL RESULTS

The model in equation (12) was estimated by ordinary least squares using the pooled data for the three states with the following results:

$$\ln ABP_{it} = 17.548 + .914 \ln PB_{i,t-1} - 1.536 \ln AWP_{it} - .517 \ln PW_{i,t-1} \quad (12)$$

$$\begin{array}{ccccccc} & (2.319) & (.481) & & (.330) & & (.470) \\ -1.265 & DO_i & + .609 & DW_i & , & R^2 = .86 & , \\ & (.103) & & (.289) & & & \end{array}$$

where the numbers in parentheses below the coefficient estimates are the estimated standard errors. The signs on all of the coefficients are as expected, and only the coefficients for the price variables are not twice their standard error.

The above specification of the model implicitly assumes that the cross-sectional units only affect the intercept coefficient. This assumption was tested by multiplying each binary dummy variable by each of the other three explanatory variables. This created six new interaction explanatory variables. The coefficient for each of these interaction variables may be interpreted as the addition to the respective slope coefficient when the observation is from a given state. Ordinary least squares was applied to this expanded model which included the original explanatory variables plus the six new interaction variables. This estimation resulted in "only" the price of barley and the acres of wheat planted being significant at an 80 percent level of confidence. In addition, the coefficient on the price of barley had the wrong sign when the observation was from Oregon. The poor results of this estimation were caused partly by the high degree of multicollinearity which existed among the explanatory variables.

The economic theory underlying the model and the empirical results were combined to re-specify the model as

$$\ln ABP_{it} = 14.532 + .493 \ln PB_{i,t-1} - 1.138 \ln AWP_{it} - .656 (DO_i * \ln PW_{i,t-1})$$

$$\begin{array}{ccccccc} & (1.863) & (.103) & & (.265) & & (.135) \\ -.734 & DO_i & + .246 & DW_i & , & R^2 = .92 & . \\ & (.134) & & (.231) & & & \end{array} \quad (13)$$

This specification appears to have reduced the degree of multicollinearity. All the coefficients have the appropriate signs, and only the coefficient for the binary intercept shifter for Washington is not twice its standard error.

The reader will note that the price of wheat has been dropped from the model, and the model includes the binary dummy variable for Oregon multiplied by the price of wheat. The interpretation of this specification is that wheat is a substitute for barley in Oregon but statistically is not found to be a substitute in Idaho and Washington.

The model was tested for serial correlation and the null hypothesis of the absence of serial correlation could not be rejected at an 80 percent level of confidence.^{1/} The model was also tested for independence of the cross-sectional units. The null hypothesis of independent cross-sectional units could not be rejected at a 90 percent level of confidence. The test for serial correlation was performed as is shown in equation (5). The results of this test are presented in Table I.

Table I. Results of testing equation (13) for serial correlation

State	$\hat{\rho}_i$	Standard Error	t-Statistic	R ²
Idaho	.153	.340	.449	.020
Oregon	.010	.317	.034	.001
Washington	-.287	.276	-1.042	.098

^{1/} It is possible that serial correlation might have been a problem in the observations for Washington. The data were transformed using the correction procedure in equation (6), and ordinary least squares was applied to the transformed data. The result of transforming the data for serial correlation in the Washington observations did not reduce the standard error of the coefficients. Thus, the transformed model was not used.

The model was next tested for heteroskedasticity. This test resulted in the conclusion that the null hypothesis of homogenous variances could be rejected at a 50 percent level of confidence. The presence of heteroskedasticity was tested with Barlett's test (Intriligator, p. 157).

The next step was to adjust the data for heteroskedasticity. This was done as shown in equations (10). The reader will note that it was not necessary to adjust the data for serial correlation since it was not identified as a problem in this model.) Ordinary least squares was applied to the transformed data and with the following results:

$$\begin{aligned} \ln AWP_{it} = & 14.779 + .552 \ln PB_{i,t-1} - 1.176 \ln AWP_{i,t} - .689 (DO_i * \ln PW_{i,t-1}) \\ & (1.664) \quad (.100) \quad (.237) \quad (.111) \\ & - .715 DO_i + .276 DW_i \quad R^2 = .99 \\ & (.110) \quad (.210) \end{aligned} \quad (14)$$

All the coefficients have the appropriate signs, and all the coefficients, except for the coefficient for the binary intercept shifter for Washington, are at least twice the size of their standard errors.

Correcting for heteroskedasticity decreased the estimated standard errors on all the regression coefficients. As previously noted, the regression coefficients are now asymptotically efficient if the model is not cross-sectionally correlated. The assumption of cross-sectional independence will not be dealt with for reasons already cited.

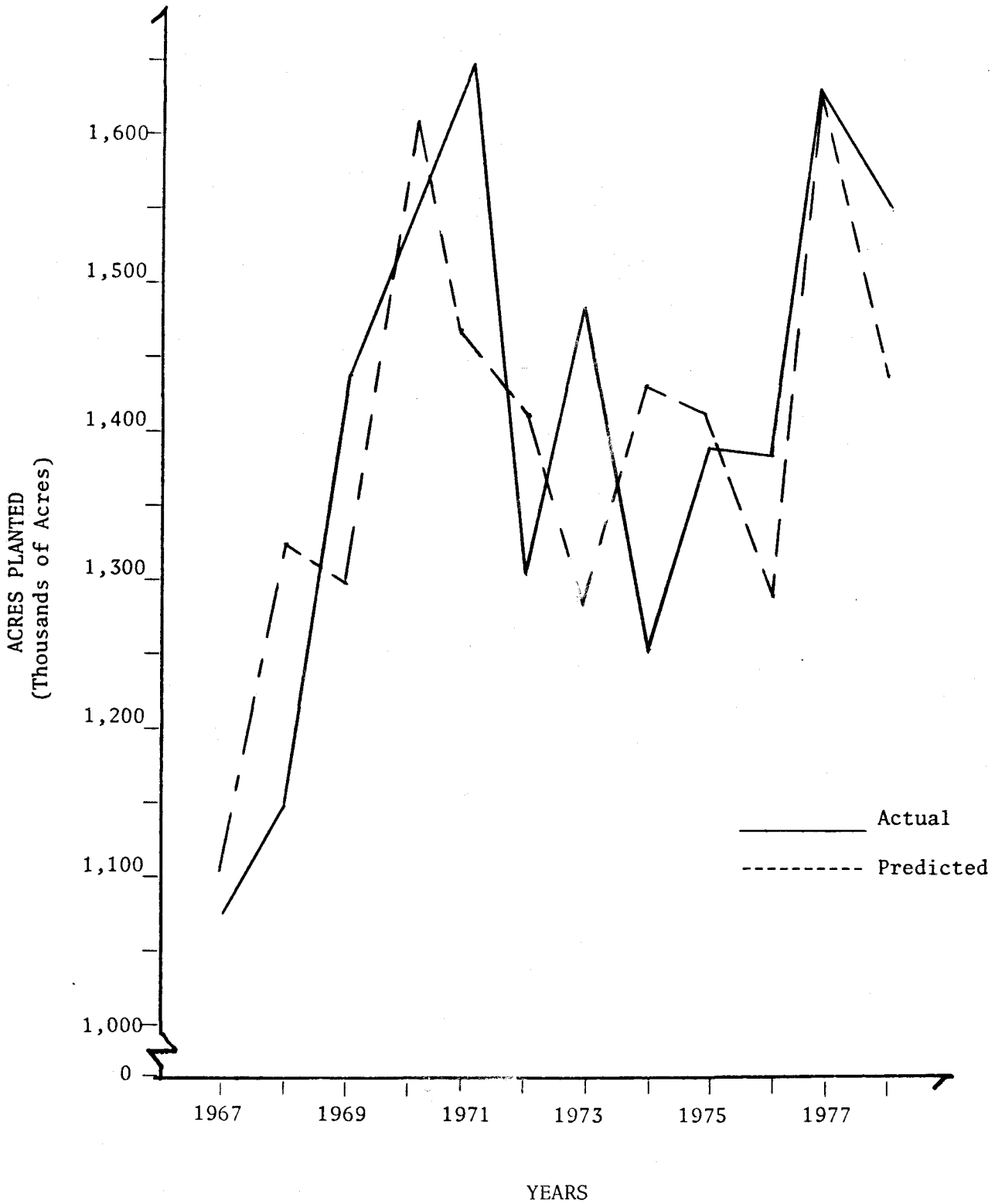
In the section on Model Specification it was noted that there was an expected one-to-one tradeoff between acres of barley planted and acres of wheat planted. This expectation was tested, and the null hypothesis, that the coefficient on the acres of wheat planted is not statistically different from one, could not be rejected at a 70 percent level of confidence.

Next the coefficient for the price of barley was tested to see if it was significantly different from national estimates made by Houck *et al.* Houck and associates estimated that the barley price elasticity of supply ranged from 0.30 to 0.36. The regional elasticity estimated in this paper (0.55) was found to be significantly different than Houck's estimates at a 95 percent level of confidence. These differences are assumed to arise because of differing production practices between the Northwest and the major barley-producing states in the Midwest. That is, as noted earlier, barley and wheat are grown on dryland ranches in the Northwest, and wheat has a higher yield per acre and commands a high price per bushel. Thus, a small change in the price of barley can have a significant effect on its relative profitability, thereby, having a significant effect on the acres planted. This result seems reasonable since barley is planted as a secondary crop in the Northwest and is used primarily as a feed grain.

Houck's national estimates are dominated by the barley grown in the Midwest. Of the states which grow more than 100,000 acres, the Midwest accounts for more than 63 percent of the production (Heid and Leath, p. 10). These states produce barley as a principal crop and primarily grow malting barley. In addition, malting barley is often grown on a contract basis (Heid and Leath, p. 40). Thus, given these conditions, it is not expected that a small change in the price of barley would have a relatively large effect on the acres of barley planted. In turn, this information supports the difference in price elasticities between Houck's national model and the regional model estimated here.

To test how well the transformed model fits the data, the predicted and actual acres of barley planted were plotted in Figure I. The model predicted

FIGURE I. Actual and Predicted Acres of Barley Planted in the Northwest, 1967-1968



the turning points well from 1975 through 1977. The model did not predict any of the turning points in the early years (1967-1974), and the model completely broke down over the period 1973 through 1974. Four of the years had prediction errors greater than 10 percent, and the average prediction error was 7.9 percent.

The reason for the model's poor tracking over the middle years, with respect to the actual data, could be from an inappropriate specification of the model. It is possible that using acres of wheat planted as a proxy for the government variables did not completely catch the entire effect of these programs.

The transformed model, equation (14), was also tested for its forecasting capabilities by forecasting for 1979. The forecast results are presented in Table II. The forecast errors for Idaho and Washington were quite high for 1979. This model is actually a regional acreage response model; therefore, the error of interest is that for the region as a whole. The prediction error for the entire region was 7.3 percent which is fairly close to the average prediction error for the previous 12 years (7.9 percent).

Table II. Using the transformed model to forecast for 1979

State	Actual Acreage (1,000's of acres)	Forecasted Acreage (1,000's of acres)	Percent Error
Idaho	880	714	18.9
Oregon	180	176	2.2
Washington	330	398	20.6
Total	1,390	1,288	7.3

5. SUMMARY AND CONCLUSIONS

The objective of this paper was to develop a barley acreage response model for the Northwest (Idaho, Oregon and Washington) using pooled time-series and cross-sectional data, and to compare it with a national model estimated by Houck *et al.* This type of model has purposes: description and prediction.

As noted in the previous section, the model did not track exceptionally well over the sample period. The model performed better for forecasting with an error of 7.3 percent for 1979. It was noted that the model's poor tracking could be caused partly by the current specification of the model. This problem could be caused partly by a relaxing of the government acreage restrictions on price support programs in (approximately) 1974 (Houck *et al.*, p. 3). In addition, the effective price support as a percent of parity has declined since 1970, thereby reducing the incentive for ranchers to participate in this program. This decline has been rather erratic with support price as a percent of parity first falling and then rising slightly, but the overall effect has been a decline.

Acreage restrictions were reintroduced in 1977 (Rasmussen and Baker, 1979). It is at this point that the model does well at predicting the turning points. It appears that the model is relatively more stable when acreage restrictions are in effect.

Another specification of the model may possibly catch the effects which the present model was unable to explain. It is possible that these changes have a lagged effect on wheat acreage. That is, the ranchers' planting decisions may not change simultaneously with changes in government price

support programs. It is also possible that a more appropriate specification would include the government support program as direct explanatory variables instead of using a proxy for them. This procedure has been used in other acreage response models with successful results (Moe and Whittaker, 1980; Winter and Whittaker, 1979; Wilson, *et al.*).

It was noted that there is (statistically) a one-to-one tradeoff between acres of wheat planted and acres of barley planted. This result suggests that a recursive model may be an appropriate specification. In such a model, the first equation would be a wheat acreage response model such as the one developed by Winter and Whittaker (1979). The second equation would be the acreage response model for barley.

The results of this model were also compared with national estimates by Houck *et al.* It was found that the barley price elasticity for the Northwest was statistically different than Houck's national estimate. It was concluded that this difference is because of differing production practices, that is, differing production practices between the Northwest and the major barley-producing states in the Midwest which grow the majority of the barley produced in the nation.

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APPENDIX - DATA^{1/}

	Year	Barley acres planted (1,000 acres)	Lagged barley price (\$/bu.)	Wheat acres planted (1,000 acres)	Lagged wheat price (\$/bu.)
Idaho	1967	542	1.04	1398	1.53
	1968	537	.92	1080	1.32
	1969	596	.89	1166	1.15
	1970	673	.92	983	1.25
	1971	759	.97	1046	1.38
	1972	745	1.05	1034	1.33
	1973	835	1.32	1200	1.92
	1974	720	2.80	1550	3.91
	1975	775	2.35	1480	3.43
	1976	810	2.10	1575	2.51
	1977	1000	2.10	1190	2.51
	1978	950	1.90	1295	2.55
Oregon	1967	298	1.16	1080	1.58
	1968	336	1.11	980	1.42
	1969	444	1.01	834	1.28
	1970	440	.94	735	1.31
	1971	392	1.03	809	1.46
	1972	281	1.08	918	1.42
	1973	270	1.45	1100	2.05
	1974	215	2.95	1278	4.20
	1975	200	2.55	1260	3.80
	1976	180	2.35	1370	2.85
	1977	210	2.35	1230	2.85
	1978	200	1.90	1225	2.65
Washington	1967	235	1.08	3002	1.57
	1968	273	1.05	2775	1.42
	1969	393	.97	2890	1.29
	1970	436	.88	2039	1.30
	1971	502	.99	2416	1.48
	1972	272	.97	2746	1.41
	1973	380	1.41	3345	2.04
	1974	325	2.60	3280	4.20
	1975	420	2.55	3180	3.85
	1976	400	2.30	3285	2.85
	1977	420	2.30	2985	2.85
	1978	400	1.85	2910	2.65

^{1/} All data were obtained from sources 11, 12, and 13.