ELSEVIER

Agricultural Economics 10 (1994) 1–11

AGRICULTURAL ECONOMICS

Evaluating alternative price expectation models for multiproduct supply analysis

Christopher S. McIntosh

Department of Agricultural Economics, University of Georgia, Athens, GA, USA

C. Richard Shumway

Department of Agricultural Economics, Texas A&M University, College Station, TX 77843-2124, USA

(Accepted 14 January 1993)

Abstract

Neoclassical economic theory provides an important conceptual framework for the analysis of agricultural production. Theory provides little guidance, however, in the actual specification of empirical models. This paper applies an integrated approach for choosing between price expectation mechanisms in a multiple-equation model when the alternatives are non-nested. Nine alternative specifications of market price and policy information are developed. Price forecasting accuracy, non-nested tests of hypotheses, and out-of-sample predictive accuracy are examined for agricultural production in Iowa. The results call into question the reliability of using forecasting accuracy as the sole guide to selecting a price expectation proxy.

Since producer price expectations typically are unobserved or unmeasured, empirical analyses of supply response must rely on proxies of these variables. Production decisions are based on forecasts of prices. An individual who consistently makes decisions based on poor forecasts will generally be unable to compete. It seems intuitively appealing then to use optimal forecasts as proxies for producer price expectations when estimating supply equations.

However, price forecasts generated by economic analysts are not necessarily highly correlated with the unobserved price expectations generated by producers. There is little agreement on a single best specification for price expectations proxies. Expectation proxies used in empirical studies of agricultural supply response tend to depend upon the individual analyst's preferences. Commonly used proxies include forecasts from historical cash prices (e.g. Askari and Cummings, 1977), futures prices (e.g. Gardner, 1976; Morzuch et al., 1980), and to a lesser extent combinations of futures and cash prices (Chavas et al., 1983).

This research was supported, in part, by the U.S. Department of Agriculture's Economic Research Service under cooperative agreement 58-3AEM-8-00104.
Texas Agricultural Experiment Station Technical Article No. 23218.

SSDI 0169-5150(93)E0017-H

Four recent papers have rigorously examined the choice of a price expectation proxy. Orazem and Miranowski (1986) examined the problem in the context of acreage response models for corn, soybeans, oats, and hay in Iowa. Their results were inconclusive in choosing a 'best' expectation proxy. Shideed and White (1989) examined the choice of price expectations for acreage response models using U.S. data for corn and soybeans. Their study examined a wider array of proxy choices but again stopped short of recommending a particular choice as 'best'. The Shideed and White study also examined within-sample mean squared error. Antonovitz and Green (1990) examined the choice among different proxies of price expectation for modeling supply response of fed beef and rejected all tested alternatives. Each of these three studies employed non-nested hypothesis tests as a tool in determining whether any expectation proxy dominated all others. A paper by Chavaz et al. (1983) used non-linear least squares to choose weights for each of lagged cash price, futures price, and effective support price, in a single equation analysis of corn and soybean acreage response. They found that the effective support price (as defined by Houck et al., 1976) played a major role in corn production decisions, and affected soybean production indirectly through the expected price for corn. None of these studies, however, examined the choice of proxies for a theoretically consistent multiple product model of output supplies and input demands. Because American agriculture is dominated by the competitive multiple-product firm, testing alternative measures of price expectation in a more theoretically rigorous model should be a useful addition to past research.

The objective of this study is to identify the 'best' price expectation proxy for use in a multiple-output–multiple-input analysis of agricultural supply and demand. Three alternative proxies are considered. They are examined from several important perspectives: (a) price forecasting accuracy, (b) non-nested tests of specification hypotheses, and (c) out-of-sample predictive accuracy of supplies and demands. Recognizing that there may be differences between a good forecast and a good expectation proxy, the latter two perspectives examine the performance of the variables as specifications of price expectations within the intended user model, a multiproduct output supply-input demand model.

1. Model description

With a large number of price-taking firms producing many non-differentiated products, profit-maximizing behavior in a competitive market is used as the underlying theoretical basis for this study. Assuming exogeneity of expected output and variable input prices, and a state-level production function that is concave and twice-continuously differentiable, the indirect restricted profit function is modeled using a normalized quadratic functional form (Lau, 1978; Huffman and Evenson, 1989). The normalized quadratic imposes linear homogeneity of the profit function in expected prices. It is a locally flexible functional form and as such does not impose arbitrary restrictions on substitution elasticities or returns to scale. The normalized quadratic does not restrict the underlying production technology to be homogeneous, homothetic, separable, or nonjoint [1]. However, the results of this study are conditional on each of the above assumptions, including risk neutrality, in state-level production behavior.

Following the netput convention (the output quantities are measured as positive while variable input quantities are measured negatively), the

[1] The choice of the normalized quadratic functional form among all possible second-order Taylor expansions is partially arbitrary. Like other second-order expansions the normalized quadratic does not impose cross-effect restrictions on comparative statics at a point. It does, however, impose some restrictions as do other second-order expansions. The normalized quadratic profit function implies a quasi-homothetic technology and, except for the numeraire netput, strongly separable netput supplies (Pope and Hallam, 1988). Unlike most other second-order expansions, it is self-dual so the production function has the same functional form as the profit function. It is also capable of satisfying curvature properties globally, so out-of-sample forecasts possess the same characteristics of the theory maintained within the sample.

normalized quadratic can be written as:

$$\pi = b_0 + CP + 0.5P'\mathrm{D}P \qquad (1)$$

where π is profit divided by price of netput 1; $P = [p_2, \ldots, p_m, x_{m+1}, \ldots, x_n]$ is the vector of prices of the variable netputs divided by the price of netput 1 ($p_2, \ldots, p_m$), and quantities of fixed inputs and related exogenous variables ($x_{m+1}, \ldots, x_n$); b_0, the vector C and the symmetric matrix D are parameters. The first derivatives of (1) with respect to normalized prices give output supply and variable input demand equations that are linear in the vector of normalized prices and other exogenous variables (Silberberg, 1974):

$$x_{it} = c_i + \sum_{j=2}^{m} d_{ij} p_{jt} + \sum_{j=m+1}^{n} d_{ij} x_{jt} \qquad i = 2, \ldots, m \qquad (2)$$

where t is time.

The numeraire (netput 1) demand equation can also be derived via the envelope theorem. It is quadratic in normalized prices and other exogenous variables:

$$x_{1t} = b_0 + \sum_{i=m+1}^{n} c_i x_{it} - 0.5 \sum_{i=2}^{m} \sum_{j=2}^{m} d_{ij} p_{it} p_{jt} + 0.5 \sum_{i=m+1}^{n} \sum_{j=m+1}^{n} d_{ij} x_{it} x_{jt} \qquad (3)$$

2. Empirical implementation

Data

Annual data for all commercial agricultural outputs produced and inputs used in Iowa, for the period 1956–1982, were used to estimate systems of supply and demand equations (2) and (3). All data required to estimate the supply and demand equations were compiled for the period 1950–1982. The first five observations were not used to estimate those equations because they were needed to construct the price expectations variables. As noted in the next section, price data beginning with 1939 were used to estimate price expectations in order to minimize the influence of the subjective priors. However, no prices before 1953 were actually used in any of the chosen expectation proxies. The exogenous variables in the profit function included output price expectations, observed prices of the variable inputs, quantities of fixed inputs, government policy variables, and time.

Government policies designed to control supplies of specific agricultural commodities were modeled in a highly simplified fashion. The variety of government programs, coupled with the production restrictions (e.g. set aside), make the specification of government policy variables difficult. We used the effective support price and effective diversion payment variables developed by Houck et al. (1976) and extended them following their procedures for each program crop for the rest of our data period [2]. National values were used (i.e., the effective support prices were based on national allotments and announced prices) due to the unavailability of detailed state-level data. The effective support prices were incorporated in the specifications of expected output prices in a variety of ways explained in the next section. Effective diversion payments appeared as separate variables, but only in the individual commodity supply equations because of limited degrees of freedom; cross-commodity effects of diversion payments were not examined. The data used to construct the effective diversion payment and support price variables were obtained from *Feed Situation* reports (USDA, 1949–1984c,d), *Commodity Fact Sheets* (USDA, 1972–1982) and from Cochrane and Ryan (1976).

Temperature and precipitation in critical planting and growing months were included in each of the crop supply equations. The weather data were from Weiss, Whittington and Teigen (1985) and were monthly state averages based on individual weather station observations of precipitation and temperature, weighted by acreage of harvested cropland. Temperature was measured as the average of the month immediately preceding normal planting dates plus the following month. Precipitation was included as the total for

[2] The actual data and details of the methods used are available from the senior author.

the first three months of the growing season. Precipitation was used in the model as an ex post output-influencing measure rather than as an ex ante decision variable. Time was included as a proxy for disembodied technological change.

The other fixed variables were family labor, service flows from capital stocks, and land. The service flows from capital stocks were an aggregate measure of depreciation of various capital items including service structures, trucks, tractors, automobiles and other equipment. Land was included as the number of acres in farms. These data, along with quantity and market price data for the outputs and variable inputs were obtained from the USDA's *Agricultural Prices* (1949–1984a), *Agricultural Statistics* (1949–1984b), *Field Crops Production, Disposition, and Value* (1949–1984e) and unpublished USDA sources, and from the Chicago Board of Trade's *Statistical Annual* (1939–1982). These data were compiled for the period 1950–1982 by Evenson (1986) and his associates. All data were gross measures, so feed fed to livestock was measured both as an output and an input. See McIntosh (1987) for further details.

Supply–Demand equations

Seven output supply equations were estimated. Individual supply equations were specified for program commodities – corn, grain sorghum, oats, wheat, and soybeans. All other crops were aggregated into a single category (other crops) and all livestock products were aggregated. The livestock category included cattle and calves, hogs and pigs, sheep and lambs, chickens, turkeys, milk, and eggs. Consistent aggregation of both quantity and price series is justified when the production function is homothetically separable. No tests of homothetic separability have been conducted in the Iowa livestock and 'other crops' partitions. Weak separability in the livestock partition was not rejected by Lim and Shumway's (1992) nonparametric stochastic test.

Four variable input equations were estimated. These included capital for the operation and repair of machinery and buildings (referred to in this study as capital operating inputs), fertilizer, hired labor, and other inputs. The other inputs category included items such as seed, feed, pesticides, outputs used on farms where produced, electricity and telephone, Federal crop insurance premiums, net insurance premiums (fire, wind and hail), machine hire and custom work, irrigation, veterinary services and medicines and miscellaneous tools and supplies. The price index of hired labor was used as the numeraire. All aggregates in this study were constructed using the Tornqvist index.

Parameters were estimated for a system of eleven supply and demand equations (2) and (3). Across-equation symmetry (shared parameter) restrictions were imposed. Homogeneity was maintained through normalization. Error terms were assumed to be additive, independently and identically distributed with mean zero and a constant contemporaneous covariance matrix. The econometric estimation was carried out using seemingly unrelated regressions. Because of computational burden, neither convexity nor monotonicity of the profit function was maintained. These restrictions take the form of inequalities; therefore, they do not affect the Cramer–Rao lower bound for the variance of the estimator nor the asymptotic properties of our tests (Rothenberg, 1973; Jorgenson and Lau, 1975).

The restricted profit function (1) was not included in the system of estimation equations [3]. The numeraire equation (3) was included in the estimations, but the interactions between fixed factors were not estimated due to the high degree of collinearity that resulted from their inclusion.

Price expectation variables

Three specifications of producer output price expectations based on market information were constructed for each of the individual crop supply equations. The specifications constructed for the

[3] Since profit for each observation is a linear combination of output and input quantities, the full covariance matrix of a system of Eqs. (1), (2), and (3) would be singular. Since prices are time-dependent, the variance of profit would also be time-dependent. All parameters of the profit function are estimated by the system of Eqs. (2) and (3); therefore this additional complexity is avoided by excluding (1) from the estimation system.

Table 1
Summary of cash-based and futures-based expectation models, parameter estimates [a]

Cash-based [b]	
Corn	$\hat{P}_t^c = P_{t-1}^c$
Sorghum	$\hat{P}_t^c = P_{t-1}^c$
Oats	$\hat{P}_t^c = P_{t-1}^c$
Wheat	$\hat{P}_t^c = P_{t-1}^c + \underset{(0.0706)}{0.0429} + \underset{(0.1532)}{0.4024}(P_{t-1}^c - P_{t-2}^c) - \underset{(0.1542)}{0.4821}(P_{t-2}^c - P_{t-3}^c)$
Soybeans	$\hat{P}_t^c = P_{t-1}^c + \underset{(0.1556)}{0.1488} - \underset{(0.1033)}{0.3396}(P_{t-1}^c - P_{t-2}^c)$
Futures-based [c]	
Corn	$\hat{P}_t^c = P_{t-1}^c + \underset{(0.0619)}{0.0160} + \underset{(0.1924)}{0.0819}(P_t^f - P_{t-1}^f)$
Sorghum	$\hat{P}_t^c = P_{t-1}^c + \underset{(0.0468)}{0.0037} + \underset{(0.1472)}{0.3114}(P_t^f - P_{t-1}^f)$
Oats	$\hat{P}_t^c = \underset{(0.0557)}{0.1026} + \underset{(0.0530)}{0.8217}P_t^f$
Wheat	$\hat{P}_t^c = P_{t-1}^c + \underset{(0.0592)}{0.0472} + \underset{(0.1154)}{0.5352}(P_t^f - P_{t-1}^f) - \underset{(0.1173)}{0.5515}(P_{t-1}^f - P_{t-2}^f)$
Soybeans	$\hat{P}_t^c = P_t^f$

[a] Standard errors are in parentheses. $\hat{P}_t^c$ is the price expectation in period t, P_t^c is the state average cash price received in period t, and P_t^f is the pre-planting-season average price of a futures contract for delivery at time t (post harvest). Cash price indices lagged one period were used as both the cash-based and futures-based expectations for the aggregate categories.

[b] Cash-based expectation models for corn, sorghum, and oats were identified as ARIMA (0, 1, 0) or random walk models.

[c] Chicago futures prices were used as the futures-based expectations for soybeans. The futures-based expectation for sorghum was modeled using the futures prices for corn.

individual crops included cash-based expectations from univariate forecasting models (Nerlove, 1979; Nerlove et al., 1979), a 'rational' expectation based on futures market prices (Gardner, 1976; Morzuch et al., 1980), and a composite of the cash-based and futures-based expectations. One-period lagged cash price indexes were used as price expectation proxies for the two aggregate categories, livestock and other crops.

The cash-based expectations are modeled following Nerlove's quasi-rational expectation model. Nerlove proposes that a producer's price expectation can be successfully modeled using a univariate ARIMA to generate minimum mean squared error predictions of subsequent prices [4]. The historic price series for each individual crop in the supply response models were analyzed to determine the appropriate specification of a univariate ARIMA model. In several cases the appropriate ARIMA model, as indicated by the autocorrelation, partial autocorrelation and final prediction error statistics, was a (0, 1, 0) or random walk model (Table 1). These models were fit over the period 1939–1955 and were used to generate one-step-ahead forecasts of annual prices for the period studied (1956–1982). The models were updated at each step using the Kalman procedure in the RATS software package (Doan and Litterman, 1984).

The futures-based expectations models were constructed as rational expectations of market price (Muth, 1961; Gardner, 1976; Morzuch et al., 1980). Under rational expectations, Gardner (p. 81) noted that "there is no reason for farmers to have different price expectations from futures speculators, nor for farmers who make no futures transactions to have expectations different from those who do." Since there is great incentive for anyone whose price expectations differ from the futures prices to enter the market, it is likely that those who do not engage in futures transactions

[4] Recent laboratory experiments fail to reject this approach as an appropriate model of aggregate expectations (Nelson, 1987).

have expectations similar to those who do. To construct futures-based price expectations, the accuracy of Chicago futures prices as predictions of state-level average cash prices was examined. The raw futures price data consisted of averages of three observations from early, mid and end of month prices on pre-plant contracts for post-harvest delivery [5]. Because basis data were not available for all crops and years covered by this study, raw futures prices were used to generate state-level expectations. Futures prices for corn were used to generate futures-based expectations for sorghum. The series were checked for bias following the procedures of Martin and Garcia (1981). Those series that provided unbiased forecasts were used directly, while transfer function models were constructed for the others to obtain unbiased predictions of cash prices (Table 1). These models were fit over the period 1939–1955 and were used to generate one-step-ahead forecasts for the period studied (1956–1982) [6].

The composite expectation series were constructed by combining the cash-based and futures-based expectations using an outperformance method of composite forecasting (Bunn, 1978; Bessler and Chamberlain, 1987). The outperformance method can be thought of as approximating the way a decision maker may use forecasts by increasing or decreasing the weight given to an individual forecast depending on its performance over time. Further details on construction of the price series and data used are available from the senior author.

Government programs also affect agricultural producers' expectations of output prices. Because inclusion of effective support price variables in addition to market price variables in supply models of this size greatly exacerbates collinearity problems, three approaches were used for combining effective support price (ESP) with market price expectations into a single price expectation variable. The first, market price only, was to simply assign a weight of one to the market price expectation and a weight of zero to the ESP in all periods. The second approach, binary weighted, was the same as that used by Shumway and Alexander (1988) and similar to that used by Gallagher (1978). The binary weighted approach assumes that the only time a producer is influenced by the effective support price is when it is greater than the expected market price; a weight of one is assigned to the higher of market price or ESP and a weight of zero to the other. However, it is quite possible that the announced government programs affect production decisions even when the effective support price is less than the expected market price. The third approach, weighted average, gave some weight to the effective support price and the expected market price in each period (Romain, 1983), with the amount of the weight depending on the relative magnitude of market price expectations, effective support prices and loan rates (Duffy et al., 1987) [7].

3. Choosing among alternative models of price expectations

Forecasting accuracy

One approach for choosing among a set of price expectation proxies is to identify the one that provides the lowest mean squared forecast error (MSFE) for out-of-sample forecasts. The

[5] September contracts for July delivery were used for winter wheat, April contracts for September delivery were used for spring wheat, and April contracts for December delivery were used for corn, sorghum, and soybeans.

[6] It should be noted that cash and futures market prices possess much of the same information. Government program effects and other features get incorporated to some extent in both series. A major difference, however, is that (except for the incorporation of effective support prices) the cash-based expectations rely totally on price information from past production while the futures-based expectations functionally anticipate forthcoming production.

[7] The methods of combining government price supports and market prices examined in this study does not represent an exhaustive list of those that have appeared in the literature. A notable method which was not examined here was developed in Shonkwiler and Maddala (1985). Their study investigates what the expected price would be, in light of the announced government program, using the rational expectations formula.

Table 2
Mean squared forecast errors of three specifications of price expectations variables for Iowa, 1956–1982

Crop	Futures-based	Cash-based	Composite
Corn	0.154	0.128	0.136
Sorghum	0.074	0.071	0.066
Barley	0.108	0.108	0.088
Oats	0.026	0.029	0.022 [a]
Wheat	0.179	0.278	0.196 [b]
Soybeans	0.799	0.612	0.642

[a] The composite had a significantly lower (0.01 level) mean squared forecast error than the cash-based model.
[b] The composite had a significantly lower (0.01 level) mean squared error than the cash-based model.
No other significant differences (0.01 level) were indicated by the tests.

MSFEs were calculated for each market price expectation series for the period 1956–1982 and are reported in Table 2. The composite series appears to provide the best overall predictions of subsequent annual average cash prices. The forecast errors were tested for significant differences using the test developed by Ashley, Granger and Schmalansee (1980). The MSFE's from the composite series were significantly better than those from the futures-based series for oats and from the cash-based series for wheat at the 0.01 level of significance. No other significant differences were detected. Although these results would tend to support the use of the composite series, this information by itself is not strong enough to suggest the existence of a single 'preferred' specification among these three alternatives.

Tests of non-nested hypotheses in multivariate models

The performance of each alternative was then examined in its intended use, i.e., the estimation of output supply and input demand relationships. The set of three market price expectations were combined with expected support prices using the three methods previously described. The systems of output supply and input demand equations were then estimated for each of the nine price mechanisms. These models were estimated using SUR to correct for contemporaneous correlation. Tests of the hypothesis of no significant first-order autocorrelation were inconclusive in all cases. The models differed only by the expected output price proxies. Davidson and MacKinnon's (1983) P_1 test procedures (a multivariate generalization of the P test) were used to evaluate the different specifications against the non-nested alternatives, and forecast error in predicting supplies and demands were compared.

Non-nested test procedures

Davidson and MacKinnon (1983) developed the P_1 test procedure for testing the specification of multivariate models with non-nested alternative hypotheses. Consider two alternative models:

$$H_0:\ y_{it} = f_{it}(\boldsymbol{X}_t, \beta) + \varepsilon_{0it} \tag{4}$$

$$H_1:\ y_{it} = g_{it}(\boldsymbol{Z}_t, \gamma) + \varepsilon_{1it} \tag{5}$$

where i indexes the equations. The y_{it} are the tth observation of the ith dependent variable and f_{it} and g_{it} are non-nested (possibly non-linear) functions which depend on vectors of exogenous variables $\boldsymbol{X}_t$ and $\boldsymbol{Z}_t$ and unknown parameter vectors β and γ. For a given t the ε_{jit} ($j = 0$ or 1) are assumed to be serially independent and multivariate normal with unknown covariance matrix Ω_j. In order to test the validity of H_0 in the presence of the non-nested alternative H_1, an artificial compound model is constructed using the maximum likelihood estimates of $\hat{f}_{it}$, $\hat{g}_{it}$, $\hat{\Omega}_0$ and $\hat{\Omega}_1$. For this example the artificial regression for testing the validity of H_0 would be:

$$\left(y_{it} - \hat{f}_{it}\right) = \alpha\hat{\Omega}_0\hat{\Omega}_1^{-1}\left(\hat{g}_{it} - \hat{f}_{it}\right) + \boldsymbol{X}_{it}\beta + u \tag{6}$$

This artificially nested model is estimated using generalized least squares. The ratio of the estimate of α to its estimated standard error provides the P_1 test statistic which converges in distribution to $N(0, 1)$. It should be noted, however, that the test is conditional on the truth of H_0, not of H_1. Thus, rejecting H_0 does not make any implication regarding H_1. If we desire to test H_1, we must reverse the roles of the hypotheses and carry out the test again. In addition, it should be noted that the tests are capable of rejecting or failing to reject both hypotheses at a given level of significance [8]. Failure to reject a particular null hypothesis indicates that the data supports that null hypothesis in the presence of the specified alternative.

Because of the computational burden of conducting the non-nested tests against eight alternatives in a system of equations, the tests were performed in two series of pairwise tests with each specification tested against a single alternative. First, each of the three methods of combining market and policy information were tested against each other for a given market price expectation model. The method of combining market and policy information was then held constant, and the tests were performed between the alternative market price expectation mechanisms.

Results of the P_1 test procedures

Table 3 contains the P_1 test results comparing alternative methods of combining market and policy information for a given set of market price expectations. Rejection of the null specification in these cases indicates that the alternative hypothesis provides significant information beyond what is contained in the null specification, i.e., the null does not represent 'truth' in the presence of the alternative at a given level of significance. All models for combining market and policy information were rejected against some alternative at the 0.01 level of significance. However, the binary-weighted models consistently achieved a lower test statistic for each pairwise comparison and were not rejected for four cases [9]. They were rejected less frequently; and when they were rejected, the rejections were less emphatic than for any of the other models.

The results of the second series of P_1 tests are reported in Table 4. Here the method of combining market and policy information was held constant and the tests were performed among the market price specifications. In each grouping, all price expectation models were rejected at the 0.01 level of significance. However, the futures-based expectations models achieved a lower test statistic for four of their six pairwise comparisons.

Table 3
Results of the pairwise P_1 tests among alternative methods of combining market and policy information

Null hypothesis	Alternative hypothesis	Asymptotic t-statistic [a]
Cash-based		
Market price only	Binary weighted	1.6667
Binary weighed	Market price only	1.3344
Market price only	Weighted average	3.6881 *
Weighed average	Market price only	3.6392 *
Binary weighed	Weighed average	6.0701 *
Weighed average	Binary weighed	8.1267 *
Futures-based		
Market price only	Binary weighed	1.8475
Binary weighed	Market price only	1.6251
Market price only	Weighed average	3.9250 *
Weighed average	Market price only	2.4447
Binary weighed	Weighed average	6.8245 *
Weighed average	Binary weighed	7.2138 *
Composite		
Market price only	Binary weighed	2.6599 *
Binary weighed	Market price pnly	2.5230
Market price only	Weighed average	3.8621 *
Weighed average	Market price only	3.4761 *
Binary weighed	Weighed average	6.5949 *
Weighed average	Binary weighed	8.0849 *

[a] The test statistic is asymptotically distributed $N(0, 1)$.
* Significant at the 0.01 level.

[8] Chalfant and Finkelshtain (1987) have examined the small sample properties of the P_1 test. They conclude that in small samples "there is a much higher probability of rejecting a correct specification than the nominal probability of Type-I error." Their analysis also concludes that the power of the P_1 test is "quite good; a false model is rejected with a high frequency even for 20 observations." The P_1 tests conducted in this study are based on 171 degrees of freedom.

[9] Within the group of 'cash-based' expectation models, the market-price-only model failed to provide significant information beyond what was contained in the binary-weighted model, and vice-versa. Both the market-price-only and binary-weighted models were deemed 'false' in the presence of the weighted-average model and vice-versa. Within the group of 'futures-based' models, the market-price-only model could not be rejected in the presence of the binary-weighted model, and vice-versa. The weighted-average model could not be rejected in the presence of the market-price-only model. The other tests in this grouping resulted in the rejection of the null hypothesis model. Within the group of 'composite' models, the binary-weighted model was judged to represent 'truth' in the presence of the market-price-only model. All other tests in this grouping resulted in rejection of the null-hypothesis model.

Table 4
Results of the pairwise P_1 tests among alternative market price expectations

Null hypothesis	Alternative hypothesis	Asymptotic t-statistic [a]
Market price only		
Cash-based	Futures-based	5.4457 *
Futures-based	Cash-based	5.0804 *
Cash-based	Composite	4.5781 *
Composite	Cash-based	6.0468 *
Futures-based	Composite	4.0178 *
Composite	Futures-based	4.9410 *
Binary weighed		
Cash-based	Futures-based	5.4412 *
Futures-based	Cash-based	4.6600 *
Cash-based	Composite	5.5222 *
Composite	Cash-based	5.6468 *
Futures-based	Composite	3.8259 *
Composite	Futures-based	4.3141 *
Weighed average		
Cash-based	Futures-based	7.0511 *
Futures-based	Cash-based	7.1660 *
Cash-based	Composite	6.3736 *
Composite	Cash-based	5.9732 *
Futures-based	Composite	5.8739 *
Composite	Futures-based	5.7576 *

[a] The test statistic is asymptotically distributed $N(0, 1)$.
* Significant at the 0.01 level.

In contrast, the composite expectations models achieved a lower test statistic for only two of their six pairwise comparisons.

The P_1 test results indicate a consistent pattern. Although no individual specification emerged unrejected from all tests, the binary-weighted models were rejected less frequently (not rejected in four tests) than the other market-policy weighting approaches and when rejected the rejections were less emphatic. Even though the binary-weighted models performed marginally better, we cannot conclude that they represent the 'true' expectations hypothesis in the presence of the alternatives tested. The fact that the composite expectation scenario provided 'better' forecasts of subsequent cash prices was not reflected in the P_1 tests.

Predictive accuracy in supplies and demands

P_1 procedures failed to identify a single 'true' expectations regime. However, since the binary-weighted models performed marginally better in the P_1 tests, these models were chosen as candidates for further examination. To provide additional insight into the performance of the price expectation mechanisms, the econometric supply–demand models were evaluated for out-of-sample predictive accuracy. This was done by refitting the models over the period 1956–1980 and forecasting for the two remaining periods.

Table 5
Root mean squared percent forecast errors for the binary weighed models, 1981 and 1982

Equation	Root mean squared percent error		
	Futures-based	Cash-based	Composite
Hired labor	21.130	32.095	30.199
Capital operating inputs	7.477	27.421	20.090
Fertilizer	12.299	21.943	18.753
Other inputs	2.253	5.051	2.574
Corn	18.081	19.028	19.274
Sorghum	4489.340	4195.410	5545.910
Oats	108.574	242.487	217.866
Wheat	634.286	290.847	442.868
Soybeans	7.119	8.464	8.828
Other crops	46.909	17.013	39.514
Livestock	5.911	8.114	6.684
Value-share weighted averages [a]			
Inputs	7.424	17.334	13.335
Outputs	7.860	9.541	9.498

[a] The value-share weighted averages were calculated by multiplying the root mean squared percent forecast error for each equation by its average share of expenditure or revenue over the two-year period, and summing for each category.

The root mean squared percent forecast errors and value-share weighted summaries of these statistics for input and output categories are reported in Table 5. All models gave very poor forecasts of sorghum, oats, and wheat. These three crops represented a small part of the value of agricultural production in the state over the data period. When combined they provided less than 1% of the value of 1982 agricultural production, and sorghum provided only 1/100 of 1%. The other crops category was also small, providing only 1.3% of 1982 production value. The futures-based model was the most accurate predictor of the three models for every input and every major output. It was followed by the composite model for every input, for livestock, for several minor crops, and for the value-share weighted average of all outputs.

4. Summary and Conclusions

The composite price expectations provided the most accurate forecast of subsequent cash prices of the three specifications examined. The mean squared forecast errors of prices from the composite specifications indicated that this model was never the 'worst' forecast, and was better than both alternatives for half of the crops. In two cases the MSFE of the composite model was significantly lower than those of the alternatives.

The results of the non-nested (P_1) tests were largely ambiguous. They yielded no clear test conclusions as to the single 'best' specification at the.01 level of significance. The binary-weighted models, however, were rejected less frequently; and when they were rejected, the rejections were less emphatic than any of the other models.

Among the binary-weighted models the futures-based expectation provided the most accurate out-of-sample forecasts of supplies and demands. Weighted average root mean squared percent forecast errors for both output supplies and input demands were lowest for the binary weighted models. These results stand in sharp contrast to those comparing the price forecasting accuracy of the three price expectation mechanisms (Table 2). Unfortunately these results leave one central question unanswered, whether there exists a single 'true' specification of a price expectations proxy for modeling state-level agricultural supplies and input demands. None of the nine scenarios examined was found to represent 'truth' in the face of information contained in the alternatives. Orazem and Miranowski (1986) earlier concluded that "a weighted average of several regimes may ultimately prove to be a dominant empirical regime." Our results show that although a weighted average (i.e., the composite expectation) may dominate other mechanisms in terms of price forecasting accuracy, it may not perform as well as its individual parts when used as a model of producer price expectations.

The empirical work presented here serves to illustrate that a good price forecast is not necessarily a good model of producer price expectations. Although using an accurate forecasting model to obtain proxies for producer price expectations is intuitively appealing, an accurate forecast may not contain more (or even as much) information when used in a model of output supplies and input demands. This is likely due to the information added by the supply–demand restrictions and by inclusion of government policy information. No general conclusions regarding the relative performance of various price expectations mechanisms can be made on the basis of this one sample. Expectations formation is likely conditioned by the particular geographic location, commodity, and institutional setting. This paper addresses the question of price expectations only for Iowa for the period 1956–1982. However, the application documents the relative performance of three expectations in this applied setting, judged from three perspectives.

5. Acknowledgements

Appreciation is extended to Robert Evenson for access to the extensive state-level data series compiled by him and his associates, and to David Bessler, Oral Capps, Jr. and the anonymous reviewers for helpful suggestions and comments on earlier drafts of this paper.

6. References

Antonovitz, F. and R. Green (1990) Alternative estimates of fed beef supply response to risk. Am. J. Agric. Econ., 72: 475–487.

Ashley, R., C.W.J. Granger and R. Schmalensee (1980) Advertising and aggregate consumption: an analysis of causality. Econometrica, 48: 1149–1167.

Askari, H. and J.T. Cummings (1977) Estimating agricultural supply response with the Nerlove model: a survey. Int. Econ. Rev., 18: 257–292.

Bessler, D.A. and P.J. Chamberlain (1987) On Bayesian composite forecasting. OMEGA, 15: 43–48.

Bunn, D.W. (1978) The Synthesis of Forecasting Models in Decision Analysis. Burkhauser, Basel/Stuttgart.

Chalfant, J.A. and I. Finkelshtain (1987) Small sample properties of multivariate nonnested hypothesis tests. Giannini Found. Pap. 848, University of California, Berkeley.

Chavas, J.P., R.D. Pope and R.S. Kao (1983) An analysis of the role of futures prices, cash prices, and government programs in acreage response. West. J. Agric. Econ., 8: 27–33.

Chicago Board of Trade (1939–1982) Statistical Annual: Chicago Board of Trade, annual series, 1939–1982.

Cochrane, W.W. and M.E. Ryan (1976) American farm policy, 1948–1973. University of Minnesota Press, Minneapolis, MN.

Davidson, R. and J.G. MacKinnon (1983) Testing the specification of multivariate models in the presence of alternative hypotheses. J. Econometrics, 23: 301–313.

Doan, T.A. and R.B. Litterman (1984) RATS: Regression and Time Series. VAR Econometrics, Minneapolis, MN.

Duffy, P.A., J.W. Richardson and M.K. Wohlgenant (1987) Regional cotton acreage response. South. J. Agric. Econ., 19: 99–109.

Evenson, R. (1986) State-level data set for U.S. agriculture, 1949–1982. Yale University, New Haven, CT.

Gallagher, P. (1978) The effectiveness of price support policy – some evidence for U.S. corn acreage response. Agric. Econ. Res., 30(4): 8–14.

Gardner, B.L. (1976) Futures prices in supply analysis. Am. J. Agric. Econ., 58: 81–85.

Houck, J.P., M.E. Abel, M.E. Ryan, P.W. Gallagher, R.G. Hoffman and J.B. Penn (1976) Analyzing the impact of government programs on crop acreage. USDA Agric. Res. Serv. Tech. Bull. 1548, U.S. Department of Agriculture, Washington, DC.

Huffman, W.E. and R.E. Evenson (1989) Supply and demand functions for multiproduct U.S. cash grain farms: biases caused by research and other policies. Am. J. Agric. Econ., 71: 761–773.

Jorgenson, D.W. and L.J. Lau (1975) The structure of consumer preferences. Ann. Econ. Social Meas., 4: 49–101.

Lau, L.J. (1978) Applications of profit functions. Chapter I.3 in: Production Economics: A Dual Approach to Theory and Applications 1, edited by M. Fuss and D. McFadden. North-Holland, Amsterdam.

Lim, H. and C.R. Shumway (1992) Separability in state-level agricultural technology. Am. J. Agric. Econ., 74: 120–131.

Martin, L. and P. Garcia (1981) The price-forecasting performance of futures markets for live cattle and hogs: a disaggregated analysis. Am. J. Agric. Econ., 63: 209–215.

McIntosh, C.S. (1987) Specification issues in agricultural supply. Ph.D. Thesis, Texas A&M University, College Station.

Morzuch, B.J., R.D. Weaver and P.G. Helmberger (1980) Wheat acreage supply response under changing farm programs. Am. J. Agric. Econ., 62: 29–37.

Muth, J.F. (1961) Rational expectations and the theory of price movements. Econometrica, 29: 315–335.

Nelson, R.G. (1987) Subjective probability elicitation and the formation of expectations: an experimental approach. Ph.D. Thesis, Texas A&M University, College Station.

Nerlove, M. (1979) The dynamics of agricultural supply: Retrospect and prospect. Am. J. Agric. Econ., 61: 874–888.

Nerlove, M., D. Grether and J.L. Carvalho (1979) Analysis of Economic Time Series: A Synthesis. Academic Press, New York.

Orazem, P. and J. Miranowski (1986) An indirect test for the specification of expectation regimes. Rev. Econ. Stat., 68: 603–609.

Pope, R.D. and A. Hallam (1988) Testing the separability of production using flexible functional form profit functions. Econ. Lett., 26: 265–270.

Romain, R.F.J. (1983) A commodity specific policy simulation model for U.S. agriculture. Ph.D. Thesis, Texas A&M University, College Station.

Rothenberg, T.J. (1973) Efficient estimation with a priori information. Cowles Found. Monogr. 23, Yale University Press, New Haven, CT.

Shideed, K.H. and F.C. White (1989) Alternative forms of price expectations in supply analysis for U.S. corn and soybean acreages. West. J. Agric. Econ., 14: 281–293.

Shonkwiler, J.S. and G.S. Maddala (1985) Modeling expectations of bounded prices: an application to the market for corn. Rev. Econ. Stat., 67: 697–702.

Shumway, C.R. and W.P. Alexander (1988) Agricultural product supplies and input demands: regional comparisons. Am. J. Agric. Econ., 70: 154–161.

Silberberg, E. (1974) A revision of comparative statics methodology in economics, or how to do comparative statics on the back of an envelope. J. Econ. Theory, 7: 159–172.

USDA (1949–1984a) Agricultural Prices, annual series, 1949–1984. U.S. Department of Agriculture, Washington, DC.

USDA (1949–1984b) Agricultural Statistics, annual series, 1949–1984. U.S. Department of Agriculture, Washington, DC.

USDA (1949–1984c) Feed Situation. Agric. Res. Serv., annual series, 1949–1984. U.S. Department of Agriculture, Washington, DC.

USDA (1949–1984d) Wheat Situation. Agric. Res. Serv., annual series, 1949–1984. U.S. Department of Agriculture, Washington, DC.

USDA (1949–1984e) Field Crops Production, Disposition, and Value. Econ. Stat. Coop. Serv., annual series, 1949–1984. U.S. Department of Agriculture, Washington, DC.

USDA (1972–1982) Commodity Fact Sheets. Agric. Stab. Conserv. Serv., annual bulletins, 1972–1982. U.S. Department of Agriculture, Washington, DC.

Weiss, M.D., M.W. Whittington and L.D. Teigen (1985) Weather in U.S. agriculture: Monthly temperature and precipitation by state and farm production region, 1950–1984. USDA Econ. Res. Serv. Stat. Bull. 737, U.S. Department of Agriculture, Washington, DC.