A Generalized Supply Response/Factor Demand Model and Its Application to the Feeder Cattle Market

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The appropriate specification of expectations in empirical models of supply response or factor demand is discussed. A general model that admits both extrapolative and rational expectations is formulated and analyzed. The model is used to investigate the decision making process of cattle feeders by incorporating information on futures prices (as representations of rational forecasts) and lagged prices. The findings provide some evidence that cattle feeders form their expectations of future prices using both types of information.

Agricultural supply response or factor demand models represent attempts to characterize how producers allocate productive resources. The very nature of agricultural production imposes a temporal structure on the production process. This temporal structure or lag between the time resources are allocated and output harvested is generally well understood by producers and known with a degree of certainty. The economic factors which come into play due to the temporal dimension of production, however, may be difficult to describe or measure. At the beginning of the production process harvest prices are unknown to the producer. In order to allocate resources efficiently producers must form an implicit or expected price for their product. How such expectations can be quantitatively represented has been the major motivation for the development of supply response models.[1]

Typically producers' expectations are unobserved, yet the decisions based on these expectations are manifested by measurable changes; e.g., acres planted, crop yields, livestock placed on feed, livestock inventories, etc. In the past, empirical studies requiring expectations have assumed that the expectations are formed by a simple extrapolation of past prices. But by simply utilizing past prices, it is implied that a producer fails to include other more current economic conditions in formulating an expectation. Clearly, models of producer behavior should be endowed with some degree of rationality.

On the other hand past prices may represent important economic trends and thus should not be discarded completely. This suggests that expectations may be based on several different types of information—both current and past. In addition there is reason to believe that producers only partially respond to changing economic conditions during a given period due to the costs incurred. The approach adopted here formulates a very general model that has extrapolative and rational components as well as a partial adjust-

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[1] In the following discussion, the concept of "supply response" models is expanded to include factor demand models since the economic specification of supply $Q = s(w, P^*)$ and factor demand $x = d(w, P^*)$ can be expressed in terms of factor prices and expected product price [Gardner].

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ment mechanism. The rational component is based on Feige and Pearce's notion of economically rational expectations. This so-called "generalized" model is analyzed in terms of its identifiability, dynamic properties, and implications for estimation and testing. It will then be used to analyze an empirical supply response model for U.S. cattle feeders.

The discussion proceeds in three sections. First the generalized supply response model is formulated and analyzed. Then a factor demand model which represents the cattle feeder's decision to place cattle on feed is estimated and discussed. Finally, some summary comments are offered concerning the value of the model for empirical work.

Model Formulation

Adaptive expectations and the partial adjustment-adaptive expectations model have had a long and generally successful history of modeling agricultural commodity supply [Askari and Cummings]. The adaptive expectations model as formulated by Nerlove [1958] was based on the notion that producers do not give full weight to a recent or current price but take a weighted combination of past prices to represent a normal expected price. Nerlove's model has the form

$$P_t^* = P_{t-1}^* + (1 - \lambda)(P_t - P_{t-1}^*) \qquad (1)$$

where $(1 - \lambda)$ is termed the adjustment parameter.[2] This yields the familiar infinite geometrically distributed lag

$$P_t^* = (1 - \lambda) \sum_{i=0}^{\infty} \lambda^i P_{t-i}.$$

Problems associated with estimating models with infinite geometrically distributed lags have been discussed by Dhrymes and Just, among others.

Commonly supply response models combine both adaptive expectations and the partial adjustment rule since there exists a close relationship between expectations and adjustment lags [Kennan]. The partial adjustment mechanism relates planned and observed output according to the rule

$$Y_t = Y_{t-1} + \gamma (Y_t^* - Y_{t-1}) \qquad (2)$$

where γ is termed the coefficient of adjustment. It can be shown that the partial adjustment rule arises from minimizing a quadratic loss function that contains a disequilibrium cost and an adjustment cost [Kennan]. The econometric implications of the partial adjustment-adaptive expectations model have been discussed by Waud, Doran and Griffiths.

While the adaptive expectations and other distributed lag models are still widely used in agricultural response studies there has been increasing concern that these types of models are not necessarily accurate representations of the economic behavior implied by the underlying structure [Nerlove 1972, 1979].[3] Muth's concept of rational expectations has provided the impetus for specifying models of market participants which reflect the economic structure and operation of the market. Recent studies of agricultural commodities by Goodwin and Sheffrin, and Shonkwiler and Emerson have documented the superiority of the rational expectations hypothesis when compared to simpler models of expectations.[4]

Because the rational expectations hypothesis maintains that market participants act as if they were solving the market supply and demand system when forming their expectations, the implications of the hypothesis are not trivial in

[2] Alternatively (1) may be written $P_t^* = P_{t-1}^* + (1 - \lambda)(P_{t-1} - P_{t-1}^*)$ if P_t is not observable at the time expectations are formed.

[3] Alternatively, Bessler has analyzed adaptive expectations behavior in terms of providing an optimal univariate statistical representation of the observed series.

[4] Rational expectations models for agricultural products have not been found to be uniformly superior, however, as in the case of Shonkwiler.

terms of model specifications, identification, and estimation [Wallis]. It requires the specification of both sides of the market and specification of models for generating the expectations of exogenous variables. Furthermore, if the market model requires future (as opposed to current) expectations, insurmountable problems relating to model identification and uniqueness may be encountered [Pesaran, 1981].

Aside from such empirical difficulties, rational expectations have been criticized on the grounds that there is no consideration of the costs involved with acquiring the information necessary for making the theoretical model operational. Feige and Pearce have developed the concept of economically rational expectations as a means for balancing the costs and benefits of information acquisition. They state that

> "while the potential benefits of utilizing all available information are apparent, the absence of an explicit consideration of the information costs which would be incurred in forming rational expectations is a serious drawback" (p. 502).

Feige and Pearce have proposed that efficient autoregressive models may be one way to generate economically rational expectations. Yet this notion of economically rational expectations may be easily broadened to allow unrestricted reduced forms, combinations of key supply or demand shifters, or futures prices to represent expectations. The futures price may be one of the most cost effective means of obtaining market information and its use in response models has been promulgated by Gardner despite the controversy surrounding informational content [vid e.g., Grossman, Leuthold and Hartmann].

Model Specification

We have established that the partial adjustment-adaptive expectations (pa-ae) and economically rational expectations models are competing frameworks for positing supply response models.[5] In order to link the models we begin with an expression which relates the desired output (or input demand) to a vector of known variables, Z_t, and an expectational price P_t^e

$$Y_t^* = Z_t\alpha + P_t^e\beta \text{ or} \tag{3}$$

$$Y_t = Z_t\gamma\alpha + P_t^e\beta\gamma + (1 - \gamma)Y_{t-1} + u_t \tag{3a}$$

The unobserved expectation P_t^e can be expressed as a function of the adaptive expectation and economically rational expectation mechanisms such that

$$P_t^e = \Theta[P_{t-1}^e + (1 - \lambda)(P_t - P_{t-1}^e)] + (1 - \Theta)P_{t/\Omega_t}^e \tag{4}$$

where Ω_t represents the information available to the economic agent when forming his expectations and $0 \leq \theta \leq 1$. It is seen that P_t^e is determined by an economically rational expectations mechanism if $\theta = 0$, an adaptive expectations mechanism if $\theta = 1$, and a composite mechanism if $0 < \theta < 1$. It is also true that $0 \leq \lambda \leq 1$, and $(1 - \lambda)$ is interpreted as an adjustment parameter that tells the amount of the expectational error that is taken as permanent as opposed to transitory [Cagan].

By substituting equation (4) into equation (3) we obtain the structural representation

$$\begin{aligned} Y_t = {} & (1 - \gamma)Y_{t-1} + Z_t\alpha\gamma \\ & + [P_{t-1}^e\lambda + (1 - \lambda)P_t]\beta\gamma\theta \\ & + P_{t/\Omega_t}^e\beta\gamma(1 - \theta) + u_t \end{aligned} \tag{5}$$

In order to remove the unobservable variable P_{t-1}^e, equation (3a) is now lagged one period and multiplied throughout by $\theta\lambda$, and subtracted from (5) yielding

$$\begin{aligned} Y_t = {} & (1 - \gamma + \theta\lambda)\, Y_{t-1} - \theta\lambda(1 - \gamma)Y_{t-2} \\ & + \gamma(Z_t - \theta\lambda Z_{t-1})\alpha + \gamma\theta(1 - \lambda)P_t\beta \\ & + \gamma(1 - \theta)P_{t/\Omega_t}^e\beta + u_t - \theta\lambda u_{t-1} \end{aligned} \tag{6}$$

which is the empirical representation of the partial adjustment-general expecta-

[5] Under certain restrictive conditions the pa-ae may in fact represent a rational expectation [Muth]. The economically rational expectation, however, does not affect the structure of the model and thus its presence must not be interpreted as being similar to a strictly rational expectation.

TABLE 1. Classification of Response Models.

γ, λ	$\theta = 1$	$\theta = 0$
$0 < \gamma < 1$ and $0 < \lambda < 1$	Partial adjustment–adaptive expectations	Partial adjustment–economically rational expectations
$\gamma = 1$ and $0 < \lambda < 1$	Adaptive expectations	Economically rational expectations
$\gamma = 1$ and $\lambda = 0$	Cobweb	Economically rational expectations
$0 < \gamma < 1$ and $\lambda = 0$	Dynamic cobweb	Partial adjustment–economically rational expectations

tions model, where $0 \leq \gamma \leq 1$, $0 \leq \theta \leq 1$, $0 \leq \lambda \leq 1$, and $u_t - \theta\lambda u_{t-1}$ is generated by a first-order moving average process.

Model Interpretation

Before discussing the estimation of the generalized supply response model, it may be helpful to summarize its properties vis-a-vis other supply response models. It is possible to recover certain nested models given the various parameter ranges detailed in the previous discussion. Table 1 classifies the outcomes for the boundary points of the parameter θ. Note that these are just a few of the possible outcomes, as it would be expected that most estimated parameters will not lie on boundary points. It does provide a systematic set of restrictions which can be imposed to conveniently categorize the type of response mechanism estimated.

Identification and Estimation

Before being able to estimate the model in equation (6) it is necessary to determine if the model is identifiable. There are five unknowns within the model (γ, α, λ, θ, and β) that need to be estimated. Both α and β can be vectors of unknowns, but are viewed as scalars without loss of generality. By allowing $a_1 = 1 - \gamma + \theta\lambda$, $a_2 = \theta\lambda(1 - \lambda)$, and $a_3 = \gamma\alpha$, $a_4 = \gamma\theta\lambda\alpha$, $a_5 = \gamma\theta(1 - \lambda)\beta$, $a_6 = \gamma(1 - \theta)\beta$, and $a_7 = \theta\lambda$, it can be shown that the equation is indeed identified and that all five unknowns can be determined. The Jacobian of the transformation from (γ, α, θ, λ, β) to the a_i parameters does not vanish, therefore the unknowns are all uniquely identified. Specifically we have $\gamma = 1 - a_1 + a_7$, $\alpha = a_3/(1 - a_1 + a_7)$, $\theta = (a_5 + a_6a_7)/(a_5 + a_6)$, $\lambda = a_7(a_5 + a_6)/(a_5 + a_6a_7)$, $\beta = (a_5 + a_6)/(1 - a_1 + a_7)(1 - a_7)$. Two restrictions also arise: $a_2 = (a_1 + a_7)a_7$ and $a_4 = a_3a_7$.

Now that it is clear that the equation is identified, a nonlinear estimation technique is required because the model is both nonlinear in its parameters and has a first order moving average error process (MA-1). Typically nonlinear least squares (NLS) is used, often in conjunction with a grid search technique, to minimize a quadratic loss function that depends on the unknown parameters. There are two drawbacks with estimating this model with NLS. First, the likelihood function for the MA-1 model contains an additional term involving the coefficient on u_{t-1}. As Balestra points out, this term is wrongly neglected when NLS is used. Secondly, when grid search techniques are employed some care must be exercised when calculating the variance–covariance matrix of the estimated parameters [Estes *et al.*]. For these reasons the method of maximum likelihood is proposed.

Unlike the simple differencing transformation that may be introduced to estimate the parameters of a model specified with disturbances following a first order autoregressive process, models with MA-1 disturbances are more difficult to recast so that the transformation of the data does not depend on unknown parameters. This is a rather important concern because most maximum likelihood algorithms require that the likelihood function be specified for each observation. Fortunately, Pesaran [1973] has detailed a technique which employs an orthogonal transformation, T, that does not depend on unknown parameters. By denoting $\bar{y} = Ty$ and $\bar{X} = TX$ and $c = \theta\lambda$, the MA-1 parameter, Pesaran's approach permits writing the logarithmic likelihood function for the i^{th} of n observations as

$$L_i = -\log \sigma - \frac{1}{2n} \log \frac{(1 - c^{2n+2})}{1 - c^2} - \frac{1}{2\sigma^2} \frac{(\bar{Y}_i - f(\bar{X}_i, b))^2}{c^2 + 2cv_i + 1} \qquad (7)$$

where b is the vector of unknown parameters and $v_i = \cos(i\pi/n + i)$.

Estimation now becomes a matter of selecting a maximum likelihood algorithm, transforming the data, and specifying equation (7). If the algorithm requires analytical derivatives then the first, and perhaps second, derivatives of L with respect to b are required. Finally, parameter covariances may be calculated from the matrix of second derivatives or approximated by using only first derivatives as proposed by Berndt *et al.*

Application to the Feeder Cattle Market

U.S. cattle feeders typically purchase steers and heifers at about 600 pounds per head, and feed them for five or six months; at which time they weigh about 1,000 pounds and are sold for slaughter [Gilliam]. The two major inputs into the production of fed cattle are the feeder animals themselves and the feed they consume. These two inputs alone account for over 80 percent of the direct costs of producing fat cattle [Gee *et al.*].

It is assumed that the cattle feeder's decision to place cattle on feed is motivated by some optimizing behavior such as profit maximization. The derived demand for the input (feeder cattle) is therefore hypothesized to depend upon the price of feeder cattle, the price of feed (corn), and the expected price of fed cattle approximately six months hence. It is recognized that the selection of the appropriate expectational measure is very important since the price of fed cattle is by far the most important factor affecting net returns received by cattle feeders.

Assuming that the price of feeder cattle and the price of feed are known, cattle feeders have information necessary to make their placement decisions apart from the knowledge of the price of fat cattle five to six months hence. The cattle feeders, as economic agents, must weigh the costs and benefits associated with acquiring information about future product prices. Of course the process by which cattle feeders form an expected price for their product is unobserved. It is hypothesized that cattle feeders form expectations by taking both past trends and current information into account. Past trends are assumed to be reflected by an adaptive expectations mechanism and current information is assumed to be summarized by current futures prices. Thus the futures price of fat cattle six months hence will be assumed to represent the economically rational component of their expectation.

The Model

Fifty-eight bimonthly observations from February 1972 through August 1981 were collected for the beginning months of February, April, June, August, October, and December. These are the contract delivery dates for live cattle futures. The price of choice 900 to 1,100 pound steers at Omaha was used for the corresponding cash price. Bimonthly placements data were also collected. The data represent the seven major cattle feeding states which are surveyed monthly by the USDA.[6] Feeder steer prices and corn prices were also collected for the same period. A proxy or instrumental variable was created for the feeder steer prices since it could be argued that feeder steer prices are simultaneously determined with placements.[7]

In the model, feeder steer prices are expressed in terms of the Kansas City price of choice 600 to 700 pound feeder steers in cents per hundred-weight. Corn price is the average price received by farmers in cents per bushel and steer placements are the seven state bimonthly placements of cattle on feed measured in thousands of head.

The cattle placements model is specified in terms of the derived demand for feeder cattle. Referring to equation (6), Z consists of the exogenous variables: feeder steer price, corn price, binary dummy variables and lagged steer placements; the current steer price is represented by P_t and the futures price is used as an observable measure of fat cattle prices six months hence and represents the economically rational expectation.[8]

TABLE 2. Cattle Placements on Feed.

Parameter[a]	Dependent Variable: Cattle Placements		
	Estimate	Standard Error	H_0: $b_i = 1$ t test
γ	.6301	.120	3.07
λ	.3989	.157	3.84
θ	.5094	.115	4.27
β	123.46	46.3	
α_0	792.17	1,093	
α_1	−86.939	34.7	
α_2	−9.326	2.51	
α_3	.7127	.280	
α_4	188.16	338	
α_5	53.051	481	
α_6	1,577.4	484	
α_7	2,357.0	450	
α_8	262.70	331	
$R^2 = .883$			
Q(12) = 9.35[b]			

[a] Where Z_1 = feeder steer price (\$/cwt), Z_2 = corn price (ct/bu.), Z_3 = cattle placements lagged three bimonthly periods, Z_4 = binary variable (1 for April–May), Z_5 = binary variable (1 for June–July), Z_6 = binary variable (1 for August–September), Z_7 = binary variable (1 for October–November), Z_8 = binary variable (1 for December–January).

[b] Q statistic for testing whether the residuals from the fitted model are white noise. Null hypothesis that residuals up to a twelfth order lag are white noise may be rejected at the .05 level if $Q \geq 21.03$.

Following the estimation procedure outlined above, the data were transformed using the method of Pesaran [1973]. The Edlefsen and Jones maximum likelihood algorithm written in their GAUSS microcomputer matrix programming language was used to estimate the model. This algorithm employs the method of scoring to compute maximum likelihood estimates [Berndt *et al.*].[9] The program only requires that the likelihood function be specificed for each observation because numerical gradients are used.

[6] Full seven state reporting series began October 1971.

[7] This proxy variable was obtained from the fitted values of a regression of feeder steer prices on lagged feeder steer price, corn price, lagged placement variables, time, and dummy (binary) variables. The binary dummy variables were created to account for the substantial degree of seasonality in cattle feeding.

[8] Note that in the present example the time indexes on P and P^e in expression (6) would be incremented to reflect the fact that future, rather than current, expectations were being analyzed. In terms of the adaptive expectations component, we are actually interested in P^*_{t+3}. However, the property that adaptive expectations may be expressed as exponentially weighted forecasts establishes the equivalence between P^*_{t+1} and P^*_{t+3} [Bessler].

[9] Due to the fact that the model specifies first, second, and third order lags of the dependent variable as regressors, these estimates are maximum likelihood estimates when it is assumed that the first three observations of the dependent variable are nonstochastic.

TABLE 3. Elasticities of Feeder Cattle Placements.

Elasticity with Respect to	Calculated Value
Expected Cattle Price	1.221
Feeder Steer Price	−.909
Corn Price	−.435

Several different sets of starting values were found to generate the results reported in Table 2, suggesting that the likelihood function is well-behaved.

The results in Table 2 show that the signs on the coefficients conform to a priori notions. The variable inputs (feeder steer price and corn) possess negative coefficients and the coefficient β on the expected cattle price is positive. The estimated coefficients on the economic variables are substantially larger than their associated standard errors. An additional test was performed on the coefficients γ, θ, and λ to check the upper boundary points for each coefficient. Looking at Table 1, it is apparent that diffferent expectation mechanisms may be categorized when the coefficient values are not significantly different than the boundary points. Therefore a t-test was performed under the hypothesis that some of the key parameters are equal to one. In this application γ, θ, and λ were all found to be significantly different than one, implying that the more naive models in Table 1 would be rejected when testing their validity in terms of the generalized model.

The parameter estimates given in Table 2 suggest that cattle feeders base their expectations on a partial adjustment-adaptive expectations-economically rational expectations mechanism, which is fairly complex. The partial adjustment parameter, γ, is statistically different than one showing that past placements are indeed important to the model. However, the finding that γ is statistically different than zero at conventional levels of significance indicates that producers are continually moving toward some desired or planned level of output. The significance of the economically rational expectations component, based on the rejection of the hypothesis that $\theta = 1$ shows that some rationality in the decision to place cattle on feed does exist. Yet the significance of the adaptive expectations component, based on the rejection of the hypothesis that $\theta = 0$, clearly shows that the futures price is not used exclusively in determining expectations, but that recent choice steer prices are important as well. Moreover the fact that the hypothesis $\lambda = 0$ is rejected implies that both the recent cash price as well as past price trends are used in forming the expectation.

The dynamic properties of the placement series are in part captured by the inclusion of placements lagged three bimonthly periods. Note that equation (5) also explicitly introduces a first order lag of the dependent variable into the estimation procedure. Thus the estimated parameters in Table 2 may be used to obtain an explicit dynamic representation as

$$(1 - .3699L - .4491L^3)SP_t = W_t$$

where SP is bimonthly seven-state placements, W accounts for the remaining terms in the equation, and L is the lag operator. The third order polynomial in the lag operator was found to possess one real and a pair of complex conjugate roots. These latter roots implied a period of 6.39 months which closely corresponds to the average time cattle are kept on feed.

Table 3 lists the implied elasticities for the expected product price and input costs. These were derived using the structural equation (5) with all variables evaluated at their means. The elastic value of the expected cattle price and the magnitudes of the cost elasticities indicate that cattle feeders exhibit a substantial degree of sensitivity to economic variables. In addition, the sum of the price and cost elasticities is not statistically different than zero at conventional levels of significance.

Summary

The use of simple models of expectations may belie the sophistication of agricultural producers. Yet there is no theoretical or empirical model of expectations that has been universally embraced as the true or optimal representation. Trends in past prices, rational price expectations, and futures prices have all been successfully used to represent future price expectations. In view of this, empirical research must, at least to some extent, rely on the data to discriminate between such competing formulations. The generalized model presented provides one systematic way to aggregate information and weigh its relative value.

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