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The Use of Expectations In Agricultural Supply Response

by

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Watermelons - Prices

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ABSTRACT

A composite supply response model is formulated that has extrapolative and rational components as well as a partial adjustment mechanism. The model is applied to the Florida Watermelon Market to investigate how producers are forming their expectation of watermelon prices at harvest time. The results show that a dynamic cobweb mechanism is a valid representation of the data and suggests that producers are not using all the relevant information in the market.

INTRODUCTION

Agricultural supply response models represent attempts to characterize how producers respond to price changes and how these changes affect their production decisions. The nature of agricultural production imposes a temporal structure on the production process. The lag between the time when resources are allocated and output is harvested is generally well understood by producers. The corresponding economic factors which come into play however, may be highly variable and difficult to describe or measure. At the beginning of the production process, product prices are in effect unknown to the producer unless he has contracted or hedged his output. Therefore, in order to make the most educated and responsive production decisions, producers must form an implicit or expected price for their product. How such expectations can be quantitatively represented has been a major motivation in the development of supply response models.

Typically the producer's expectations are unobserved, yet the decisions based on these expectations are manifested by measureable changes; e.g., acres planted, crop yields, livestock placed on feed, livestock inventories, etc. If aggregate producer decision-making is based on some expectation of future product price, then an accurate measure of this expectation in an appropriately specified supply response model should yield an accurate representation of observed output or derived demand of inputs. In the past, empirical studies requiring expectations have assumed that the expectations are formed by a simple extrapolation of past prices. But, if prices are not sufficient statistics for the market, 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 economic 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 during the adjustment (Kennan). The approach adopted here formulates a very general model that has extrapolative and rational components as well as a partial adjustment mechanism. 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 Florida watermelon producers.

The discussion proceeds in three sections. First, the generalized supply response model is formulated and analyzed. Then a supply response model which represents Florida watermelon producers decisions to produce watermelons 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

$$(1) \quad P^*_t = P^*_{t-1} + (1-\lambda)\,(P_{t-1} - P^*_{t-1})$$

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

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

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

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

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 implicatations 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). 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.

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 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).

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 devoloped the concept of economically rational expectations as a means for balancing the costs and benefits of information acquisition. They state that

> while the potential benefit 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 response models.[1] In order to link the models we begin with an

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[1]Under certain restrictive conditions the pa-ae may in fact represent a rational expectation (Muth).

expression which relates the desired output (or input demand) to a vector of known variables, Z_t, and an expectational price P^e_t

$$(3) \quad Y^*_t = Z_t \alpha + P^e_t \beta \quad \text{or}$$

$$(3a) \quad Y_t = Z_t\gamma \alpha + P^e_t\beta\gamma + (1 - \gamma) Y_{t-1} + u_t$$

The unobserved expectation P^e_t can be expressed as a function of the adaptive expectations and economically rational expectations mechanisms such that

$$(4) \quad P^e_t = \theta [P^e_{t-1} + (1-\lambda)(P_{t-1} - P^e_{t-1})] + (1-\theta)P^e_{t/\Omega_{t-1}}$$

where Ω_{t-1} represents the information available to the economic agent when forming his expectations and $0 \leq \theta \leq 1$. It is seen that P^e_t is determined by an economically rational expectations mechanism if $\theta = 0$, an adaptive expectations mechanism if $\theta = 1$, and a composite mechanism if $0 < \theta < 1$. Note that $0 \leq \lambda \leq 1$, and $(1 - \lambda)$ is interpreted as an adjustment parameter 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

$$(5) \quad Y_t = (1-\gamma)Y_{t-1}+Z_t\alpha\gamma + [P^e_{t-1}\lambda+(1-\lambda)P_{t-1}]\beta\gamma\theta + P^e_{t/\Omega_{t-1}}\beta\gamma(1-\theta) + u_t$$

In order to remove the unobservable variable P^e_t, equation (3a) is now lagged one period and multiplied throughout by $\theta\lambda$, and subtracted from (5) yielding

$$(6) \quad Y_t = (1-\gamma+\theta\lambda)Y_{t-1} - \theta\lambda(1-\gamma)Y_{t-2} + \gamma(Z_t-\theta\lambda Z_{t-1})\alpha$$
$$+ \gamma\theta(1-\lambda)P_{t-1}\beta + \gamma(1-\theta)P^e_{t/\Omega_{t-1}}\beta + u_t - \theta\lambda u_{t-1}$$

which is the partial adjustment-general expectations 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. Note that if θ or λ equals zero, the moving average error process drops out of the model.

Indentification 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 ($\gamma, \alpha, \lambda, \theta$ 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. It can be shown that these unknowns are uniquely determined by the model.

Given that the structural parameters in the equation are identified, a non-linear estimation technique is required because the model is both non-linear in its parameters and has a first order moving average error process (MA-1). Balestra's exact transformation of a MA-1 process can be used to provide maximum likelihood estimates of the parameters if the model can be expressed in a linear form. This is accomplished by iterating over θ and λ. Defining $c = \theta\lambda$ equation (6) collapses to

$$(7)\quad Y_t = (1-\gamma+c)Y_{t-1} - c(1-\gamma)Y_{t-2} + (Z_t - cZ_{t-1})\alpha' + [(\overline{\theta}-c)P_{t-1} + (1-\overline{\theta})P^e_{t/\Omega_{t-1}}]\,\beta' + u_t - cu_{t-1}.$$

Although certain non-linear parameter restrictions exist, (i.e. $\alpha' = \alpha\gamma$, $\beta' = \beta\gamma$, $c = \theta\lambda$) the equation is now linear in the transformed parameters. Thus we interate over the intervals $0 \leq \theta \leq 1$, $0 \leq \lambda \leq 1$ and for each interation transform equation (7) using Balestra's method to calculate the value of the likelihood function.

To estimate the asymptotic covariance matrix for the untransformed parameter estimates we follow the suggestion of Estes et al. to estimate the inverse of the information matrix using

$$\text{as}\hat{y}\ \text{cov}B = \hat{\sigma}^2 [\sum_{t=1}^{T} (\partial Y_t/\partial\beta)(\partial Y_t/\partial\beta)']^{-1}.$$

This approach permits the estimation of standard errors for θ and λ, however it is complicated by the fact that there is a moving average error process. This necessitates deriving recursions for the derivatives of the disturbances with respect to the parameters θ and λ (Harvey). This approach is useful when subsequent tests on the parameters and are to be performed. In particular it facilitates the use of Wald-type tests which do not require the estimation of the restricted model.

Model Interpretation → Lagrange Multiplier test

Before we turn to the empirical estimation of the generalized supply response model it is possible to recover certain nested models given the various parameter ranges. Table 1 classifies the outcomes for the boundary points of the parameter θ.

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, Rational expectations
$\gamma = 1$ and $0 < \lambda < 1$	Adaptive expectations	Rational expectations
$\gamma = 1$ and $\lambda = 0$	Cobweb	Rational expectations
$0 < \gamma < 1$ and $\lambda = 0$	Dynamic cobweb	Partial adjustment, Rational expectations

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.

APPLICATION TO THE FLORIDA WATERMELON MARKET

Typically the Florida watermelon market produces over one-third of the total United States watermelon production and over 70 percent of the spring production (Federal-State Market News Service). The Florida harvesting season typically begins the first week of April and continues through the middle of August. However, many Florida producers view July 4th as the effective end of the season. This is a result of a noticable price decline after this date and thus very few shipments of Florida watermelons are made after this date (Wall, Tilley and VanSickle). It is necessary to note that yields are highly variable. Ease of entry and exit into the industry, lack of irrigation in some areas, differences in the characteristics of soil and weather may all account for some degree of yield variability.

It is assumed that the Florida watermelon producer's decision to plant watermelons is motivated by some optimizing behavior such as profit maximization. It is therefore hypothesized that the supply of Florida watermelons depends upon the number of acres planted which in turn depends upon past plantings, total growing costs and the expected price of watermelons in the upcoming season. An expected price is necessary since the crop is perishable and planting decisions must be made in the absence of knowledge about prices at harvest time (Suits). It is generally assumed that watermelon growers have few if any alternative crops (Wall, Tilley and VanSickle). Therefore the selection of the appropriate expected price becomes very important to modeling the planting decision since the price of watermelons is the most important factor affecting net returns received by Florida watermelon producers.

Given that growing costs and previous plantings are known, Florida producers have all the information necessary to make their planting decisions apart from the price of watermelons at harvest time. It is therefore incumbent upon the producer to acquire information about future watermleon prices, while at the same time weighing the cost and benefits associated with the acquisition. Of course the process by which watermelon producers form an expected price is unobserved. It is hypothesized that due to the highly competitive nature of the industry, long run equilibrium watermelon prices will depend upon equilibrium costs of production. It is assumed that watermelon growers would rationally expect current prices to be related to some normalized cost of production. Since costs tend to fluctuate greatly from one season to another, it is beneficial to use a series of past costs to represent the expected costs of production and hence harvest prices.

The expectation is represented by a price forecast which is based upon a regression of price on lagged total costs. Note that total costs are expressed in costs per acre and as such are representative of an average cost. In a highly competitive market like watermelons, price can be equated to an average cost, and thus a regression of observed price on this "average cost" is representative of the expected price.

The Model

Thirty annual observations were collected from 1951 to 1981. The data represent the amount of acres planted in Florida on a yearly basis. Also included is the price paid to the Florida producer and the costs (both growing and harvesting) incurred during production.

In the model total acres planted are expressed in hundreds of acres. Both growing and harvesting costs are expressed in dollars per acre, while the price received is in cents per hundredweight.

The watermelon model is specified in terms of acres planted by Florida watermelon producers. Referring to equation (6), Z consists of the exogeneous variable - growing costs; the current price of Florida watermelons is represented by P_t; and the price forecast based upon the regression of observed current price on lagged "average costs" represents the economically rational expectation, assuming price may be represented by an "average cost" in the long run due to the highly competitive nature of the watermelon market.

Following the estimation technique described above, we iterate over θ and λ and transform the equation in accordance with Balestra's representation of a moving average error process. The value of the likelihood function is maximized when $\theta = .927$ and $\lambda = .248$. The empirical results are presented in Table 2.

The results in Table 2 show that the signs on the coefficients conform to a priori notions. Growing costs exhibit a negative coefficient while the coefficient β on the expected price of watermelons is positive. Standard t tests show that the coefficients on the all economic variables but λ are significantly different than zero at conventional levels. An additional test was performed on the coefficients γ, θ and λ to check the upper boundary points for each coefficient. The t test was performed under the null hypothesis that $b_i=1$. All but θ were found to be significantly different than one. Given that $0 < \gamma < 1$, Table 1 suggests that a dynamic cobweb mechanism is possible if $\theta = 1$ and $\lambda = 0$. To jointly test these two restrictions a Wald test (Harvey) was performed. A value of $W = .003942$ resulted when the null hypothesis $\theta = 1$ and $\lambda = 0$ was tested. Under the null hypothesis $W \overset{A}{\sim} \chi^2(2)$ with a critical value of 5.99147 at the .05 confidence level. Thus the null hypothesis that a dynamic cobweb mechanism exists could not be rejected.

Table 3 lists the implied elasticities for the expected price of watermelons and the growing costs. The highly elastic value of both estimates suggests that producers are very sensitive to economic variables when expectations are represented by the measure used.

The above results suggest that the dynamic cobweb mechanism provides a valid representation of the Florida watermelon market's observation. The results provide no evidence, however, of an economically rational expectations mechanism in the model. These observations raise some questions as to the validity of the criticisms of extrapolative mechanisms. Pashigian shows that under some circumstances rational expectations may be reasonably approximated by adaptive expectations. However, use of an extrapolative mechanism does not allow for any learning process by the producers. The cyclical planting activity of watermelon producers appear to be inefficient since producers are not learning from past history (Suits, Wall, Tilley and VanSickle). Yet the results show that a dynamic cobweb mechanism is a valid representation of the data. It appears that the mechanism captures the dynamics of the market even though producers are apparently ignoring some of the relevant information available to them when making their production decisions.

Summary

There has been no theoretical or empirical model of expectations that has been universally embraced as the true or optimal optional representation. Trends in past prices, economically 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 here provides one systematic way to aggregate information and weigh its relative value.

Table 2. Florida Watermelon Acreage Response Model

Dependent Variable: Acreage Planted

Parameter	Estimate	Standard Error	Ho: $b_i = 0$ t test	Ho: $b_i = 1$ t test
γ	.215585	.114252	1.89	6.866
λ	.248	.321391	.272	2.340
θ	.927	.202138	4.586	.361
β	6.01907	2.75239	2.187	
α: INT	385.645	240.769	1.602	
α: GC	-2.6762	1.75676	1.520	

Table 3. Elasticities of Watermelon Acreage Response Model

$e_{\text{expected watermelon price}} = 2.4059$

$e_{\text{growing costs}} = -2.0677$

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