Price Expectations and Supply Response

Carlos Arnade and Joseph Cooper*

This paper has not been previously presented in any other meetings.

*Arnade (Carnade@ers.usda.gov) and Cooper (jcooper@ers.usda.gov) are economists with the Economic Research Service, USDA. The views expressed are the authors' and do not necessarily represent those of the Economic Research Service or the US Department of Agriculture.

Price Expectations and Supply Response

Abstract

Price in agricultural supply equations is usually the expected price. In general, models of agricultural supply response assume that their representation of producer expectations is correct. If this assumption is wrong, the supply response parameter will have embodied within it an estimate of the expected price distortion, biasing the estimated parameter. Furthermore, no effort has been made in existing models to allow for heterogeneous price expectations. In almost every supply model, one price estimate is used to represent the price expectations of hundreds or thousands of producers, which could masks a wide range behavior among heterogenous producers. Rather than assuming the model's representation of producer expectations is correct, the goal of this paper is to use revealed producer behavior to assist in the estimation of producer's expected prices. To explicitly address producers' formation of the expected price, this study jointly estimates the supply equation and the price expectation equation. The empirical application is a pooled time-series cross-section data analysis of U.S. wheat and corn supply data at the county level.

Introduction

Agricultural economics have a long history of estimating agricultural supply functions. Beginning with Griliches (1958) and Nerlove, (1958), to Tweeten and Quance (1968), to the many Nerlovian based models of the 1970's (Askari and Cummings, 1977), to the rational expectation models of the 1980's (Seale and Shonkwiler, 1987), and finally to the large number duality based models of the past 30 years (Ball, 1988, Shumway and Alexander, 1988), a wide range of methods have been used to estimate producer reaction to price changes. Regardless of the choice of the model, output price elasticities are derived from the coefficient on the expected price. However, this coefficient is actually determined by two relationships: the relationship between producer's expected price and supply, and the relationship between the modeler's representation of the expected price and the producer's true price expectation.

This here-to-for unaddressed complexity of the price coefficient arises from the fact that agricultural supply equations must reflect the gap between planting decisions and the time when a crop is harvested.[1] That is, unless the modeler has exact data on producer's expected prices, the parameter on the model's output price (or expected price) will not be the true supply response parameter. Most supply response models assume away this issue and focus on estimating the producers' supply response. For example, expected prices are represented by naïve expectations (Shumway and Chang (1980), futures prices, (Gardner, 1976), effective support prices (Houck and Ryan, 1972), or by an autoregressive lags (Nerlove, 1958; Wallis, 1980). Often, a forecast price is generated from an equation estimated equation prior to estimating the supply model (Nerlove, Grether, and Carvalho,1979). Alternatively the parameters of the expected price

[1] For this initial paper we ignore the expectations of producers who hedge by selling output in the futures market.

equation are substituted into the model and estimated (see Shideed and White,1989). In rational expectation models, the price expectation parameters and supply equations also are jointly estimated (Seale and Shonkwiler, 1987).

In each of these models, it is implicitly or explicitly *assumed* that the model's representation of producer expectations is correct. If this assumption is wrong, the supply response parameter will have embodied within it an estimate of the expected price distortion. Furthermore, no effort has been made to allow for heterogeneous price expectations. In almost every supply model, one price estimate is used to represent the price expectations of hundreds or thousands of producers.

In summary, despite impressive efforts to date to measure producer's price response, there has been little empirical investigation of producer's formation of price expectations, which is the other behavioral component of supply response. At best, the parameters of assumed expectation model, such Nerlove's (1958) adaptive expectations or the Lucas (1975) and Muth's (1961) rational expectation model, are estimated. Rare exceptions are the studies which have tested the performance of different expectation schemes against each other (Fisher and Tanner. 1978; Shideed and White,1989; Orazem and Miranowski,1986; and Turnovsky,1970).

Other Studies

Several reasons may account for the small number of empirical papers which test producer price expectations. For one, there is a belief that surveys of producer expectations would be unreliable. Second, many of the different expectation models are not nested (Shideed and White, 1989*;* Orazem and Miranowski, 1989*)* and thus are difficult to test against each other. Third, the degree of aggregation of most data and the underlying belief that expectation rules vary among producers has deterred many economists from investigating the issue. And the few papers that have compared producer price expectations have not been able to resolve the issue of whether one expectation rule better represents producer behavior than any other.

For example, in experiments using hypothetical price data, Fisher and Tanner found that Australian farmers came closest to using Nerlove's adaptive expectations formula to predict prices. Shideed and White compared elasticity estimates of six supply models and found that acreage response equations that used market signals to represent the expected price (futures price, Koyck lags, naïve price) were significantly higher than elasticites based on prices that reflected government support rates. Using a nonested J-test to examine model specification, these authors found that no particular price expectation scheme was best suited for estimating acreage response for both commodities. Orazem and Miranowski also applied a J-test to determine whether acreage responses models for corn, soybeans, and hay should be specified using future price, naïve price expectations, or an exact forecast of the harvest price. They found that the model that used futures price performed slightly better than the other models. Turnovsky (1970) looked at price formulation by businessmen and found evidence that price expectations were formed through a method that he called extrapolative expectations.

Rather than assuming the model's representation of producer expectations is correct, as in the case in existing literature, the goal of this paper is to use revealed producer behavior to assist in the estimation of producer's expected prices.   To explicitly address producers' formation of the expected price, this study jointly estimates the supply equation and a lagged price expectation equation. Following this discussion, a supply relationship is postulated that allows producers to respond to *both* prices and past price expectation errors. This provides a second way to incorporate the parameters of the supply equation (reflecting producer behavior) into the price expectation equation.The ensuing sections discuss this method, time-series and cross-sectional data, and the estimation of wheat and corn supply models which serve as an empirical example of the techniques developed in this paper. Importantly, we allow for the possibility that price expectations can vary across cross-sections. The final section summarizes our results and offers suggestion for future research.

Joint Estimation of Supply and Producer's Expected Prices

We begin by writing a simple supply equation with two output prices and one input price as:[2]

1) $S_1 = bo + \pi * p_1^{me} + \beta_2 * p_2 + b_3 * w$,

where the modeler's depiction of the expected price, a known substitute price, and an input price, are p_1^{me} , $p_{2,}$ and w, respectively.

Consider the relation between the *modele*r's depiction of the expected price at planting and the realized harvest price to be $p_1^{me} = a_1 p_1$. Suppose the relationship between producer's *true* expectations, $p_{1.}^{pe}$ and the actual harvest price (p_1) can be written as: $p_{1.}^{pe} = a_2 p_1$. The producer's expectations, p_1^{pe}, and the coefficient a_2 are unknown. Given these relationships, it is not possible to recover the true supply response coefficient from an estimate of equation 1.

To further illustrate this limitation of standard supply models, we write the relationship between modeler and producer price expectations as:

2) $p_1^{me} = p_1^{pe} * (a_1/a_2)$

In terms of the model in equation (1), the producer's true price response is thus:

3) $\partial S_1/\partial p_1^{pe} = \partial S_1/\partial p_1^{me} * \partial p_1^{me}/\partial p_1^{pe} = \pi * (a_1/a_2)$

The natural question to ask is: If one estimates a supply equation using p^{me}_1 (which could be the actual price, the futures price, or some other representation of expected producer prices), is there

[2] For ease of exposition we write supply as a function of one input price, and one competing output price. This could easily be replaced by an output and input price vectors.

a way to recover the coefficient a_2? Supply response models that only focus on estimating a supply response parameter imply that $a_2 = a_1$.

Our alternative approach to identifying the producer's true price response is to jointly estimate the supply equation with an equation representing a lagged version of producer's expected price. By estimating a lagged expected price equation, simultaneity is avoided, thus precluding the need for including in the model, a price which is not available at the time of the producer's decision. Yet it is possible to use the estimated parameters from the lag price equation to obtain a better estimate of this season's expected price. In specifying an equation to represent the expected price, assume that modelers/economists do not know how producers form price expectations but do have access to *some* of the key variables which producers use to predict price. That is, allow for that fact that there may be latent variables which different producers use to derive their own particular price forecast.[3] Suppose producers use the following rule to form their expectations of the harvest price of product 1

$$.4a)\ P_{t,1}^{pe} = \ {}_{i}^{n}\gamma_i P_{t-1,1} + \mu Z_1,$$

where P_{t-1} represents the i^{th} lag of the price of product 1, and γ_i represents the weight producer's put on the past prices of the same product. Z_1 represents a variable (or group of variables) which producers use, but which the modeler does not know about or have access to, to forecast the harvest season's price. This unknown variable (group of variables) could include output price lags greater than *t-n* periods back and can vary among producers. For example suppose a

[3]In our empirical example we use county data; which aggregates expectations less than state or national data. Our model allows distinct price expectations to be estimated for each country. However, even counties contain hundreds or thousands of producers, each who may have a distinct method of forecasting price.

modeler estimates price expectations from the following equation whose exogenous variables are lagged prices and the variable(s) Z_2, then

$$4b) P_{t,1}^{me} = \ {}_{i}^{n} b_i P_{t-1,1} + \alpha Z_2,$$

where b_i represents the coefficients on past prices, which may or may not closely reflect how producers weigh past prices, and Z_2 represents a variable or group of variables modelers use to estimate the harvest price and which could be viewed as proxy variables for Z_1.

Both equations 4a) and 4b) are general enough to allow price expectations to be represented by a geometric decay in lagged prices or by a futures price (as a Z_1 and/or Z_2. variable). [4] The equations also allow producers (and/or modelers) to heavily weigh a price representing a specific growing season or to discount a price from a specific growing season in the past. As noted earlier, the unknown or unavailable variable Z_1 might include price lags beyond *t-n* which producers use in making their own forecast. Of course, producers may form expectations based on the very same information which the modeler uses, and if so, Z_1 and Z_2 would be one and the same. Or, the parameters on Z_2 and Z_1 could equal zero.

In any case, it is unlikely the analysts can ever know what variable(s) are contained in $Z_{1.}$ Producers are idiosyncratic, and what is contained in Z_1 is likely vary from producer to producer or even region to region (say due to region specific price basis difference). Nonetheless, there are several ways to improve estimates of producer's expected prices. Suppose a data-base contains both time series and cross-sectional data. A cross section dummy variable or some dummy interaction term can be used as a proxy for Z_1.

[4] Substituting Nerlove expectations into a supply equation produces a decaying lag in prices.

$4c)\ p^{pe}_{1,kt} = \sum_{i}^{n} b_i P_{kt-i,1} + \sum^{k} D_k * \alpha_k Z_{2,kt},$

where D_k is a farm or regional dummy variable. When Z_2 equals 1, dummy variables alone are used to represent the missing variables producers use to form price expectations. The dummy variable alone may not represent the information in Z_1 but at least it allows for heterogenous producers to have distinct expectations of the expected price.

Having set up a price expectation equation, it is possible to exploit the behavior of producers to improve the estimates of parameters contained in this equation. One simple way of doing so is to jointly estimate the producers supply and price expectation equation. That is, specify the following two equation system:

5a) $s_{1,kt} = \beta_o + c_1 s_{1,k,t-1} + \pi * p^{pe}_{1k,t} + \beta_2 * p_{2,k,t} + \beta_3 * w_{kt}$

5b) $p^{pe}_{1,kt-1} = \sum_{i}^{n} b_i p_{1,k,t-2,1} + \sum^{k} D_k * \alpha_k Z_{2,kt-1}$.

Equation 5a represents a supply function which includes as explanatory variables: the previous year's supply, the expected price, another product price, and an input price. Equation 5b represents a lagged price expectation equation. Lag expectations are specified to avoid simultaneity. Thus, 5a and 5b represent a recursive system. Substituting the *current* price expectation equation directly into the supply equation obtains:

6a) $s_{1,k,t} = \beta_o + c_1 s_{1,k,t-1} + \pi * \left(\sum_{i}^{n} b_i p_{1,k,t-1} + \sum^{k} D_k * \alpha_k Z_{2,k,t} \right) + \beta_2 * p_{2k,t} + \beta_3 * w_{k,t}$

6b) $p^{pe}_{1,k,t-1} = \sum_{i}^{n} b_i p_{1,k,t-2} + \sum^{k} D_k * \alpha_k Z_{2,k,t-1}$.

Equations 6a and 6b can be jointly estimated as a recursive system. Cross equation restrictions on the common parameters of the supply and price expectation equations can be imposed. This systems estimation allows modelers to exploit revealed producer behavior to obtain a more realistic depiction of producers expected price, and hence, allows one to obtain a more accurate estimate of the supply response parameter.

A General Supply Function and Exploitation of Forecasting Errors

In this section, we expand the producer's supply decisions to exploit additional information on behavior to assist estimating producers' price expectations. Suppose a producer's response to his or her expected harvest price is, in part, a function of how strongly he or she trusts his or her own prediction. That is, each farmer forms a subjective probability estimate of the reliability of his or her price prediction. We hypothesize that if in the previous period producers had over (under) predicted the previous planning season's price, they supply less (more), than they otherwise would in the current period. That is, if producers had over-predicted (under-predicted) the price in prior seasons, the supply function shifts back (forward) in the current period.

As before, for simplicity of exposition, allow for one other known output price and one input price. Write the supply equation as:

$$7)\ s_{t,1} = \beta_o + c_1 * s_{t-1,1} + \pi * p_{t,1}^{pe} + \eta_1 * \ \ p_{t-1,1}^{pe} - p_{t-1,1} \ \ + \beta_2 * p_2 + \beta_3 * w$$

where $n_1<0$ if our expected price hypothesis is correct.

Equation 7 depicts producer response to the output price as consisting of two components: the typical price response, and a second response that is a function of the size and direction of the previous period's forecasting error.[5] [6] The expected sign on the lagged forecasting error is negative. The more producers over-forecast the previous period's price, the less producer's will supply in the current period. Note we do not square the forecast error. There a negative η_1 in

[5] If variables are in logs forecast errors are portrayed as rotating the slope of the supply curve.
[6]It is a simple matter to generalize the equation, by including lags of past forecast errors.

equation 7 means that a past expectation error that is positive (i.e., over-predicts) will decrease current period supply via increased planted acres, while a past forecasting error which is negative (i.e., under- predicts) will increase current period supply. The other advantage, as will become apparent below, is that the specification in equation 7 provides another means for recovering information relating to producer price expectations.

First, consider the reasoning behind the specification in equation 7. This specification nests those producers who change their forecasting method after over-predicting a price as well as those producers who may stick with their old forecasting approach but become more wary about acting on it. In either case, the specification applies to producers who use past forecasting errors to help form their current predictions of the harvest price, as in Nerlove (1958). It would also apply to producers who continue to rely on the method they have always used to generate predictions of the harvest price. Whatever the case, equation 7 applies to any producer who acts more cautiously (or recklessly, if η_1>0) in a planting season following a season when their method of predicting prices had led to an overly high price forecast.

Furthermore, when estimating equation 7, modelers can test the idea that past prediction errors influence supply. That is, only if a test revealed that η_1=0 would that indicate past forecast errors have no effect on current producer decisions. If η_1 <0, producers act more cautiously after seeing that in the previous season they had over-forecasted the price, and [if η_1 >0], producers act more confidently after seeing that in the previous season they had under-forecast the price. Furthermore, modelers can use estimated elasticities to evaluate the relative importance of past forecasting errors and current price expectations in determining the amount supplied. In any case, that equation 7 provides an additional way to exploit producer behavior to estimate the parameters of a price expectation equation. That is, there will be additional parameter restriction on the expectation error term in the supply equation and the price expectation equation.

Three additional points should be made regarding equation 7. At first glance, the supply equation may look somewhat like a model which uses Nerlove's (1958) adaptive expectations. However, this paper assumes the method producer's use to determine expected prices is unknown. What equation 7 does is allow past expectation errors to play a direct role in determining output supply. That is, we depict farmers as actively responding to their past mistakes when they make output or acreage decisions. In playing an active role in supply response forecasting, errors become an integral part of producer's behavior. In contrast, a model which uses Nerlovian expectations assumes a specific price expectation rule, and allows forecasting errors work their way indirectly into the supply equation through the insertion of Nerlove's expected price into the supply function.

Second, in equation 7, price expectation errors influence the amount producer's supply, as they do in the Lucas model of an economy's **aggregate** supply (Lucas, 1975). However, unlike the Lucas model, we are not forced to assume expectations are "rational". In fact we make no claim of how expectations are formed. And unlike the Lucas aggregate supply function, we do portray supply as **only** responding to forecast errors (See Sheffrin, 1983). In equation 7, the relative importance of past forecast errors in determining producer supply response is revealed only by empirical estimates of the parameters η_1 and the supply response parameter π . In any case, equation 7 could be considered a general supply equation since it nests a both typical supply equation and a Lucas-like aggregate supply equation as special cases.[7]

[7] The Lucas supply equation is an aggregate supply equation for the entire economy.

Finally, agricultural economists should not view the supply equation (7) as being unusual. It is common to include an ex-ante generated price (or revenue) variance variable in agricultural supply equations to capture producer response to price risk (Brorsen et al., 1987; Just and Pope, 1991; Lin and Dismukes, 2005). A typical measure of price risk is a squared moving deviation from the expected price (Brorsen et al., 1987; Coyle, 1992). Aside from averaging over several lags, our model differs in the treatment of price risk by not squaring the price forecasting error.[8] Thus, we allow producer supply to be influenced by not just the size, but also the *direction* of the forecasting error from the previous period(s). When price expectations are substituted into equation 7 below, other advantages to not squaring the price error will become apparent.

Making the Model Operational

There are several ways to estimate supply equation 7). The obvious way is to jointly estimate the supply equation 7) with the price expectation equation and to twice substitute the entire price expectation equation into the supply equation. That is, in estimating equation 7) there are two substitutions, one for the price response term (whose coefficient is π) and one for the lag price contained in the error response term (whose coefficient is η_1). Making this double substitution, the time-series cross-section version of equation 7 becomes:

$$8)\ s_{1,k,t} = \beta_o + c_1 s_{1,k,t-1} + \pi * \left(\sum_{i=1}^{n} b_i p_{1,k,t-i} + \sum_{k=1}^{k} D_k * \alpha_k Z_{2,k,t} \right)$$

$$+\eta_1 * \sum_{i=2}^{n+1} b_i p_{1,k,t-1-i} \sum_{k=1}^{k} D_k * \alpha_k Z_{2,k,t-1}) - p_{t-1,1} + \beta_2 * p_2 + \beta_3 * w.$$

Rearranging one arrives at a two equation system that can be jointly estimated:

[8] This paper uses the previous season's price forecasting error. Yet one can easily incorporate lagged forecasting errors.

$$9a)\ s_{1,k,t} = \beta_o + c_{1*}s_{1,k,t} + \pi * (b_1 P_{k,t-1,1} + \sum_{k=1}^{k} D_k * \alpha_k Z_{2,k,t}) + \ \pi + n_1 \ * (\sum_{i=2}^{n} b_i p_{1,k,t-i,1})$$

$$+\eta_1 * (b_n p_{1,k,t-n+1} + \sum_{k=1}^{k} D_k * \alpha_k Z_{2,k,t-1}) - \eta_1 * p_{1,k,t-1} + \beta_2 * p_2 + \beta_3 * w$$

$$.9b)\ p_{1,k,t-1} = \sum_{i=i}^{n+1} b_i p_{\,1,k,t-1-i,1} + \sum_{k=1}^{k} D_k * \alpha_k Z_{2,k,t-1}) \quad .$$

When estimating the two equation system above, cross equation restrictions between the common parameters of price expectation equation and supply equation can be imposed. Again, this allows revealed producer behavior to assist in the estimation of parameters of the price equation. Also note that the existence of a lagged price term in equation 9a) poses an additional challenge for joint estimation of the two equation system. If the covariance of the error term between the two equations is sufficiently high, the coefficient on the lag price will be inconsistent. This is further discussed in the empirical section.

An Empirical Example

Using a cross section-time series database, output supply and price expectation equations, as specified in equation 6) and 9) were jointly estimated for three commodities: wheat, corn, and soybeans. The consisted of 341 cross-sections representing Midwestern 341 counties, and 23 time periods representing the years 1985 to 2007. Lag variables represent lags in time, so considerable effort was used to insure no time lag, crossed over into another cross section. That is, variables representing time lags before to the first year of the model (1984), were created *prior* to combining the times series with cross-sectional data. This ERS county data base is described in Arnade and Cooper (2012). The price data for this study was obtained from commodity analysts at USDA’s Economic Research Service.

For each of three commodities, (wheat, corn, and soybeans), supply and price equations were estimated separately, with each commodity serving as a two equation system.[9] Prices expectations were specified as a function of three exogenous factors: the past two years of harvest prices, the previous season's change in price between planting and harvest dates, and the change in price four months prior to planting. Dummy variables were multiplied by a combination of all three of these variables and were used to distinguish price expectations among different regions (crop reporting districts). The exogenous variables in the price expectation equation were chosen to best represent information available to most producers; not to produce the most accurate forecast.

Supply equations were specified to be a function of expected prices, and when estimating equation 9, lagged price forecasting errors were included. Input prices were represented by separate variables representing the price of fuel, the price of fertilizer and an index representing a weighted average of fuel, fertilizer, machinery, and pesticide costs, discounted by interest rates. Dummy variables representing different crop reporting districts were multiplied by the cost index variable to capture the variation in regional production costs (Arnade and Cooper, 2012). The previous year's supply (a lagged time dependent variable) also served as an explanatory variable.

For each commodity, the supply equation was first estimated alone. For this first estimation an expected price variable was generated from a price equation that was estimated *prior to* estimating the supply equation. The supply equation was then re-estimated jointly with lag price expectations were equation and prices in the supply equation replaced by the explanatory variables of the expected price equation (equations 6a and 6b). Cross equation restrictions

[9] Price expectations from the soybean equation were inaccurate and we do not report the failed soybean model.

between common parameters of the lag price equation and the variables representing expected price in the supply equations were imposed. Finally, the supply equation was estimated a third time; this time as specified in equation (9). In doing so, the price equation was substituted for the expected price, and a lag version of the equation substituted in for the lag expected price.

Results

To determine whether equation 6) or 9) better represented producers, we tested whether the coefficient η_1 was zero. If η_1=0, lagged price surprises do not influence supply and the more typical supply equation (6) best represents producer behavior. A likelihood ratio testsrevealed that with 95% confidence, η_1 does not equal zero for the wheat and corn models (table 4). In both models, the estimated coefficient η_1 was less than zero. Therefore, in years following an overly high forecast, producers supply less than they otherwise would have for a given level of the expected price.

The existence of a lag price term in equation 9b) posed an additional challenge for joint estimation of this most general form of the two equation system (where $\eta_1 \neq 0$). If the covariance of the error terms between the two equations is sufficiently high, the coefficient on the lag price variable in the supply could be inconsistent. For the wheat and corn models the correlation coefficients between the two equations error terms were low enough to avoid worrying about an inconsistent estimator of the η_1 parameter, -0.237, -0.152, respectively.

Table 1 reports estimates of the wheat supply equations.[10] The first reported estimate represents a typical wheat supply equation estimated (alone) using expected prices derived from a price equation that was estimated *prior* to estimating the supply equation. The second reported

[10] Estimated corn model can be provided upon requests.

estimate represents the more general supply equation and lag price equation represented by equations 9a and 9b. In estimating this system, both the equation for expected price and lag of the expected price are substituted into the supply equation. Cross equation restrictions between the common parameters of the supply and price expectation equation were imposed.

The estimated corn supply models were similarly specified. However, a crop rotation variable and a soybean price variable were added. As with the wheat equation, corn prices were specified as a function of two lags of the harvest price, the previous year's change in price, between planting and harvest dates, and the change in price four months prior to harvest. In addition tests showed that lagging the variable that represents the change in corn prices four months prior to planning for two years, and adding both annual lags of this variable to the model, significantly improved the forecast of the harvest price of corn.

Table 2 reports impact and long run elasticity estimates of various wheat and corn models. The first reported set of elasticties represents those of typical wheat and corn supply equations, each which were estimated by OLS. The second reported elasticity estimates represents estimates from the two equation system in (6a) and (6b). In this estimation the expected price equation was once substituted into the supply equation to represent the expected price. The third, reported elasticity estimates represents the general supply and lag price equations represented by (9a) and (9b). In this system the both the equation for expected price and lag of the expected price are substituted into the supply equation; once to represent expected price, and once to represent a component of the lagged price expectation error. Cross equation restrictions between the common parameters of the supply and price expectation equation were imposed.

Supply response elasticities reported in table 2 illustrate that there is a significant difference in the estimated supply response when both equations are jointly estimated and cross equation restrictions are imposed. The wheat supply elasticity rises from 0.116 in the single supply equation to 0.461 and 0.464 in the two versions of the jointly estimated supply and price expectations models (equation 6 and equation 9, respectively). The corn price elasticity rises from a very low 0.002 in the typical corn supply model to 0.013 and 0.01 for the jointly estimated models (equation 6 and equation 9, respectively).

Notice in table 3 that long run elasticties for wheat are quite high, while that of corn quite low. This may reflect the fact that corn often is rotated with soybeans and that factors other than price dominate the decision to plant corn. The long run elasticities for wheat are quite high. However, readers should be reminded that long run elasticities represent the long run supply response to a price change, and which stays at the new level year after year after year, decade after decade.

Table 2 provides estimates of the elasticity of supply response with respect to a previous period's forecasting error (equation 9a). For both wheat and corn, this elasticity is above 0.04 (in absolute value). For example, a 100% rise in a positive forecast error (from the previous period) would reduce wheat supply 4.4% and corn supply 5.3%. The corn model reveals a greater sensitivity to past price forecasting errors than to the expected price itself.

Finally, an attempt was made to estimate a soybean supply model. Forecasted prices generated in a similar fashion to that of wheat and corn performed poorly. Forecasts of the soybean price were improved by adding additional price lags to the price expectation equation. A variable accounting for corn/soybean rotation variable also was included in the soybean supply equation. Despite this, estimation the soybean supply equation alone, and as a system, yielded a wrong sign elasticity estimate. An attempt was made to estimate wheat, corn and soybean models jointly. While we were able to obtain convergent estimates of this highly nonlinear models parameters, soybean price elasticities came out the wrong sign.

Estimates of Expected Prices

Table 5 compares estimates of expected prices calculated from a single price equation and compares those with price expectations calculated from estimates of the two equation system. The first column lists the wheat price. The second column provides an out-of-sample price forecast generated from estimates of a single equation. In estimating this price equation data, each period, was cut off one year prior to the forecast, a forecast made, and then a new regression was estimated and cut off prior to the next forecast. Thus the coefficients of this model were constantly changing. The third column lists within sample forecasts generated from the same price forecasting model estimated from 1985-2007. The fourth and fifth columns present forecasts generated from price expectation equations whose coefficients were estimated jointly with the supply equation in (6) and (9), respectively. The expected prices reported in column four and five were generated by models which allow for regional difference in expectations; though the coefficients on regional expectation variables were significantly different from zero, they were not significantly different from each other.

There is no guarantee that the predicted harvest price will be more accurate when price expectations are jointly estimated along with the supply equation. That is, employing information on producer supply response to assist in the estimation of producer price expectations only does just that. Farmers may or may not more accurately forecast prices than do economists. Even so, when estimating supply response, it is preferable to have an accurate depiction of producer expectations than an accurate depiction of the harvest price itself.

In any case, the sum of squared forecast errors reported on the bottom of table 5 indicates that when price expectations are jointly estimated along with the wheat supply equation, forecasts are more accurate than the out-of-sample price predictions from a rolling single equation model. However, they are less accurate than the within sample predictions of the same estimated equation. Table 5 also shows that the jointly estimated supply and price equations, produced price forecasts which performed worse in terms of accuracy and in terms of predicting the direction of a price change than the within sample forecasts of the single equation price equation.

Table 6 compares expected corn prices estimated from a single price equation against those estimated jointly with the supply equation. As with wheat, the first column lists the actual corn price, the second column the out-of-sample price forecast and the third column the within-sample forecasts. The one substitution model and two substitution model (fourth and fifth columns) presents forecast generated the two jointly estimated two equation systems. Unlike with wheat, the expected corn price generated from the joint model preformed significantly worse, in terms of accuracy, than both the out-of-sample and within- sample models. Yet again, we must remind readers our goal is not to produce the best forecast but to produce a more accurate depiction of producer expectations. Note however, the forecast of the corn price generated from the two-equation model preformed slightly better than the single equation out-of-sample forecasts in predicting the expected direction of the price change.

In summary, jointly estimating supply and price expectation equations together significantly changed the estimate of the supply response for wheat and corn. The inclusion of past price forecasting errors also influenced producer supply response. However, by jointly estimating the price equation alongside the supply equation, we produced price forecasts which were less accurate than those obtained from a single forecast equation. That is, taking revealed producer behavior and using it to estimate the parameters of the price expectation equation caused wheat forecasts, and more so, corn price forecasts, to be less accurate. However, this result may reflect the reality of the real world. Producers, who must operate in real time, and deal with a multitude of factors that may affect planting and production decisions, may not be able forecast prices as well as modelers who can evaluate their data after the fact, and whose sole focus is to develop more accurate forecast of producer's expected prices.

Conclusion

Over the past fifty years, considerable effort has gone into using econometric methods to estimate the response of agricultural producer to changes in the expected output price. However, parameter estimates of supply response are biased in that the modeler's depiction of expected price is sure to deviate from the producer's expected price. Typically, economists use theory, or reasoned logic, to postulate a producer price expectation scheme. This paper takes a different approach by assuming little as possible about the producer's output price expectations, and estimates the producer price expectation equation and producer supply response equation in a two equation system. A key feature of our model is that we force information from the supply response equation to assist in the estimation of price expectation equation. Therefore, revealed producer behavior is used to help estimates producer's price expectations.

This paper also allows lagged price forecasting errors to influence supply, which provides a second route for allowing observed producer behavior to aid in the estimation of price expectations. Using county specific data, two different systems of equations of supply and price expectation equations are estimated for wheat and corn. One system allows for lagged forecasting error to influence supply and one does not. Taking into account that preferences for price expectations may differ across producers and regions, we allow representative producers for each county to form heterogenous price expectations.

We find that estimation of the two equation model significantly changes the estimate of the wheat price response parameter but had a minor effect on the corn supply response parameter. We also found that lagged price forecasting errors have a negative and significant effect on supply. This result suggest that following a season where the output price was over-predicted, producers supply less than they otherwise would have given their current prediction. That is, over-prediction of price leads to caution in planting in the subsequent year. We did not find that the two equation estimates dramatically changed the estimate of producers' predicted price. But when it did change the prediction, the producer assisted forecast was less accurate than the within sample forecast estimated with a stand alone price equation. However, our goal is to use he price expectation that best represents what producers use in making their supply decisions. Future refinements of our approach can include applying it towards estimating a system of several supply equations; and testing restrictions implied by economic theory. .

References

Arnade, C. and J. Copper, "Acreage Decision When Risk Preferences Vary" Journal of Agriculture and Resource Economics, 37,(2012): 399-414.

Askari, H. and John Cummings "Estimating Supply Response with a Nerlove Model: A Survey" *International Economic Review*, 18, (1977):257-292.

Ball, V. E. "Modeling Supply Response in a Multiproduct Framework." *American Journal of Agricultural Economics* 70(1988):813-25.

Brorsen, W, J.C. Chavas, and W. Grant "A Market Equilibrium Analysis of the Impact of Risk on the U.S. Rice Industry. American Journal of Agricultural Economics, 69, (1987):733-739.

Coyle, B. 1992. "Risk Aversion and Price Risk in Duality Models of Production: A linear Mean-Variance Approach", *American Journal of Agricultural Economics* 74(1992):849-59.

B.S. Fisher, and Carol Tanner "The Formulation of Price Expectations: An Empirical Test of Theoretical Models" *American. Journal of Agricultural Economics.* 60 (1978):245-248

Gardner, B. "Futures Prices In Supply Analysis" *American Journal of Agricultural Economics* 58(1976):80-84.

Griliches Z. "Estimates of the Aggregate U.S. Farm Supply Function. *Journal of Farm Economics*, 40(1958):282-293.

Just R. and R. Pope 1991. "On Testing the Structure of Risk Preferences in the Agricultural Supply Analysis," *American Journal of Agricultural Economics* 73(1991):743-48

Lin, William and R. Dismukes. "Risk Considerations in Supply Response: Implications for Counter-Cyclical Payments' Production Impact," Selected paper American Agricultural Economics Association Annual Meeting, July 2005, Providence, R.I.

Lucas "An Equilibrium Model of the Business Cycle", *Journal of Political Economy,* 83(1975):1113–1144

McIntosh, C. and R, Shumway Multiproduct Production Choices and Policy Response *Western Journal of Agricultural Economics,* 16(1991): 291-303.

Muth, J.F. "Rational Expectations and the Theory of Price Movements" *Econometrica* 29 (1961):315-35.

Nerlove, Mark, Adpative Expecations and the Cobweb Phenomena, *Quarterly Journal of Economics*, 73(1958):227-240.

Nerlove, M. *The Dynamics of Supply, Estimate of Farmers Response to Price*, John Hopkins Unversity Press, 1958

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

Seale, J. and S. Shonkwiler "Rationality, Price Risk, and Response", *Southern Journal of Agricultural Economics* 19(1987):111-118.

Sheffrin, S. *Rational Expectations*, Cambridge University Press, New York. 1983

Shumway, C. R., and W. P. Alexander. "Agricultural Product Supplies and Input Demands: Regional Comparisons." *American Journal of Agricultural Economics* 70(1988): 154-61.

Shumway, C. R., and A.A. Chang. "Supply Response of Texas Field Crops: An Evaluation of The CET Linear Supply Model." *Western Journal of Agricultural Economics 5* (1980): 149-154.

Tweeten and Quance. "The Supply Function in Agriculture Revisted", *American Journal of Agricultural Economics*, 51(1969): 342-352.

Turnovsky, Stephen. "Empirical Evidence on the Formation of Price Expectations", *Journal Of the American Statistical Association*, 65(1970):1141-1154

Wallis, K. F. "Econometric Implications of the Rational Expectations Hypothesis", *Econometrica* (48)1980: 49-73.

Table 1 Estimated Supply Equation for Wheat.

	OLS[1]			SUR System		
Variable	*Coeff*	*Estimate*	*T-stat*	*Coeff*	*Estimate*	*T-stat*
Lag WHT[2]	A2	0.8966	191.40	A2	0.898	193.22
PPE	B1	26537	6.02	B1	108740	18.27
FFUEL	B2	803.27	2.85	B2	802.5	2.98
FFERT	B3	-1409.3	-6.99	B3	-1404.4	-7.08
WINDX	B4	-308.29	-0.58	B4	-521.7	-1.05
EPF				N1	-92750	-0.88
Regional Cost Coefficients						
NWC1[3]	B9	-3.4095	-0.02		-96.9	-0.63
NWC2	B10	20.301	0.11		-74.7	-0.60
NWC3	B11	139.53	0.77		39.8	0.27
NWC4	B12	4.6741	0.03		90.16	0.54
NWC5	B13	422.3	2.15		332.2	1.71
NWC6	B14	224.39	1.53		113.65	0.82
.						
.						
.						
NWC49	B57	-69.825	-0.27		55.64	0.22
NWC50	B58	273.82	1.70		396.59	2.55
NWC51	B59	-46.721	-0.13		78.92	0.23
NWC52	B60	153.78	0.91		276.96	1.68
CONST	A1	58537	3.00		-129450	-0.81
		R^{+} = 0.896			Log. Like Stat. = -109,149	

1/ The first reported supply equation was estimated by OLS. The expected price was generated by an out-of- sample forecast from a price equation estimated prior to estimating the supply equation. The second supply equation was estimated jointly with a price expectation equation, and the variables of the expectation price equation were substituted in for expected price. This version of the supply equation, also contains a lagged price error, variable, is equivalent to that described in equation 9a.

2/*Lag WHT* represents lag wheat supply. *PPE* represents expected price. *FFUEL, FFERT*, *WINDX* represent fuel price, fertilizer price, and an index of other input costs, respectively. *EPF* is the lag price forecasting error of equation 9.

3/ The *NWC* variables are dummy /input price interaction terms for 53 crop reporting districts. These represent regional differences in production costs. This table only reports ten of the 52 terms.

Table 2: Price Expectation Equation

		OLS		SUR System Cross		
Variable	Coef	Estimate	T-stat		Estimate	T-stat
G1PW	V1	0.61	3.15	V1	0.943	78.61
G2PW	V2	0.31	1.43	V2	-0.484	-37.71
G1PCHS	V3	0.52	2.13	V3	0.065	5.00
PCH4M	V4	0.55	4.89	V4	0.335	37.04
Constant	Z0	0.287	1.73	Z0	1.49	57.0
PE1E	V5	N.A		V5	0.27	4.84
PE52E	V52	N.A		V52	0.27	3.22
		R^2 = 0.81				

1/ The reported OLS model was estimated from 1964 to 2006, using time series data.

2/The second price equation was estimated jointly with the general supply equation (9a of the text) and cross equation restrictions imposed on the equations parameters

3/ G1(2) pw represents harvest prices lagged 1(2) years. G1pchs, represent the previous year's change in price from planting to harvest, pch4m, represents the change in wheat prices, over the 4 months prior to planting. PEiE—represent dummy*lag price interaction terms, for each 53 different crop reporting districts. This variable, which is meant to capture regional differences in price expectations and serves as a proxy for idiosyncratic expectation variable, $Z_{1,}$ of the text. Two of the 52 PEiE parameter estimates are reported in this table.

Table 3: Output Price Elasticities

	Wheat Short-run	Wheat Long-run		Corn Short-run	Corn Long run
Typ sup	0.116	1.123	Typ sup	0.022	0.037
One-sub	0.461	4.603	One-sub	0.168	0.288
Two –sub	0.464	4.654	Two-sub	0.129	0.241

Price Error Elasticities

Error Price Elasticities	Wheat Short-run	Wheat Long-run		Corn Short-run	Corn Long-run
Two-sub	-0.044	-0.430	Two-sub	-0.053	-0.089

1/ Typ supply, a typical supply equation where expected prices were generate prior to estimation of the supply equation
2/One sub (two)-the elasticities for the supply equation in model in 6a (9a).
3/Price Error elasticites. The elasticities were calculated suing the average of the absolute value of (Pe-pt-1).
4/Note a positive price error elas right sign is the right sign for an ecm model but wrong sign for our model

Table 4: Testing the Parameters of the General Supply Equation:

$\underline{\beta_1 = 0}$

Wheat: 304*** Implies Expected Price belong in model

Corn: 12*** Implies Expect Price belong in model

$\underline{\eta_1 = 0}$

Wheat: 206*** implies lagged price surprise belong in model

Corn: 60*** implies lagged price surprise belong in model

No Regional PE's Dummies Model

Wheat: 68**: implies regional differences in expectation significant

Corn: 11.8 Implies regional differences in expectations not significant

---

1/Likehihood ratio tests, were applied to test the above parameter restrictions. Test statistics are χ^2 distributed with degrees of freedom equal to the number of restrictions.

2/ *** significant at the .01 level, ** significant at the .05 level, .1 significant at the .1 level.

Table 5. Price Forecasts (Wheat)

	Price Wheat	Priorxx Out of sample	Priorxx In sample	Epc One-sub	Epc Two-sub
1985	2.897	2.868	2.882	2.746	2.729
1986	2.327	2.459	2.516	2.407	2.376
1987	2.397	2.474	2.361	2.251	2.220
1988	3.443	2.982	3.045	2.898	2.890
1989	3.75	3.404	3.791	3.595	3.646
1990	2.88	2.92	3.201	3.059	3.050
1991	2.573	3.213	2.641	2.517	2.446
1992	3.17	2.891	2.643	2.495	2.499
1993	2.727	2.712	3.246	3.107	3.115
1994	3.023	3.124	2.817	2.675	2.642
1995	3.797	3.697	3.505	3.315	3.324
1996	4.23	2.957	3.455	3.301	3.319
1997	3.31	3.876	3.682	3.502	3.495
1998	2.393	3.115	2.518	2.386	2.333
1999	2.107	2.203	2.203	2.117	2.048
2000	2.08	2.205	2.398	2.290	2.277
2001	2.407	2.281	2.610	2.498	2.490
2002	3.047	3.233	3.282	3.111	3.127
2003	3.123	3.311	3.445	3.269	3.300
2004	3.23	2.191	2.760	2.676	2.631
2005	3.187	3.11	3.128	2.979	2.968
2006	3.223	3.436	3.158	2.976	2.985
2007	5.097	4.772	4.109	3.846	3.852
Sum of Squared Errors[3]					
	--	4.570	2.274	2.750	2.812
	--	4.674	3.25	4.291	4.335
% correct sign on change[4]					
	--	77.2	77.2	68.18	68.180

1/PM-Price from outside model. Out of sample forecast for a model cutoff before the prediction, and within sample forecast from model estimated over whole period. In sample from model estimate 1984 to 2006, the same years as price equation in joint models 2/PPE-Forecast for price expectation equation jointly estimated with supply equation. Cross equation restrictions from supply equation and price expectation equation applied. 3/ Sum of forecast errors over the all but the last year (2007) and over the whole period. 4/ Percent of time the direction of price change is correctly forecasted.

Table 6: Price Forecasts Corn

	Price Corn	Prior EPC out of sample	Prior EPC in-sample	EPC One sub	EPC Two sub
1985	2.230	2.645	2.310	2.745	2.748
1986	1.410	1.820	1.400	1.769	1.771
1987	1.630	1.630	1.967	1.430	1.431
1988	2.640	2.540	2.611	1.361	1.362
1989	2.300	2.960	2.582	2.624	2.626
1990	2.210	2.300	1.920	2.746	2.749
1991	2.400	2.410	2.152	2.303	2.305
1992	2.040	2.430	2.300	2.321	2.323
1993	2.370	2.040	1.975	2.301	2.303
1994	2.010	2.240	2.180	2.179	2.181
1995	3.060	2.570	2.553	2.199	2.201
1996	2.940	3.900	3.070	2.744	2.747
1997	2.660	3.180	2.828	3.975	3.978
1998	1.940	1.750	2.044	1.666	1.668
1999	1.780	1.930	1.742	1.753	1.755
2000	1.780	2.290	2.040	1.692	1.694
2001	1.890	1.900	1.845	2.129	2.130
2002	2.450	2.310	2.598	1.804	1.805
2003	2.210	2.400	2.207	2.310	2.312
2004	1.850	2.460	2.055	2.588	2.590
2005	1.720	1.850	1.640	2.655	2.657
2006	2.820	2.290	2.812	1.630	1.631
2007	3.360	2.750	2.838	2.782	2.784
sum sq error		3.97	1.43	8.83	8.84
%correct		57.0	87.7	65.0	65.0

1/ Same interpretation as table 1