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Anticipatory Signals of Changes in Corn Demand

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Anticipatory Signals of Changes in Corn Demand

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Abstract: Contemporaneous observations on expected supply and on prices of post-harvest futures contracts for corn are used to estimate expected demand relationships. These equations are used to forecast the prices of the post-harvest contracts based on new supply estimates. Each forecast can be compared with a corresponding futures price, i.e., the market's forecast. The differences help discern the market's expectations about the expected demand for the new crop relative to historical experience, which can help support outlook analyses. The discussion also deepens understanding of the term "anticipatory prices," as used by H. Working (1958).

Key words: anticipatory prices, expected prices, futures prices, expected demand

JEL code: Q02, Q11

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Introduction

Commodity prices have complex time-series processes, including occasional jumps in their means and in the magnitude of the variability about the respective means. This is apparent in the behavior in the average price of corn in the United States over the past 55 years (Figure 1). The jumps were likely caused by large changes in demand relative to supply. The shift in 1973 occurred when the ex-USSR opened their market to world grain imports, and the jump in 2006 likely is the result of the U.S. biofuels policy that increased the demand for corn and soybeans to produce biofuels (DeGorter, Drabik, and Just 2015). The farm price of corn averaged $1.17 per bushel from 1960 through 1972 (when price support programs were effective), $2.36 from 1973 through 2005, and $4.49 from 2006 through 2015. The standard deviations for the three periods were $0.15, $0.40, and $1.24, respectively.

Specifying useful models for such time-series processes is difficult, while increases in volatility complicate firms' risk management and operation decisions (Mark et al. 2008). For example, increased volatility *ceteris paribus* increases the prices of options contracts and the expense (e.g., margins) of using futures and options contracts. Thus, when having accurate forecasts would be especially valuable, modeling and forecasting are likely more difficult. In this context, we propose a simple procedure to appraise expected (anticipatory) prices generated in futures markets relative to forecasts from models of historical experience. The U.S. corn market is used as an example.

This paper has two objectives. One is to demonstrate the relationship between the expected supply of corn and corresponding prices of futures contracts. Such results can, under some circumstances, show how expected demand relationships have changed with the passage of time. Thus, this paper contributes to the literature on interpreting futures prices as anticipatory prices. A second objective is to demonstrate that such estimates can assist outlook analysts, as the newest information and prices can be compared with past expectations.

The next section provides the background and framework for our analysis. We then discuss the data and proposed model specifications for estimating what we call expected demand relationships based on the price of December futures contracts. The use of other contract prices, specifically May corn, is also briefly discussed. Empirical results are estimated and applications of the results illustrated, and finally some conclusions are drawn.

Background and Conceptual Framework

This paper grows out of Holbrook Working's classic paper (1958) on futures contract prices as anticipatory prices. As he wrote (1958, 191), "Prices of such commodities, as potatoes and wheat … must be formed under the influence of expectations. … We are dealing with prices that must be anticipatory." Thus, price changes reflect changes in information, but as Working (1958, 195) also noted, "The information on which these predictions are made … is itself unpredictable … [hence] price changes generated by [this information] are unpredictable price changes." In essence, he described a random walk-type model subsequently popularized in the general finance literature. In addition, he showed (1958, Table 1) that the estimated supply of corn had negative correlations with various price series including those for July futures contracts.

Holbrook Working was perhaps the first person to discuss the seeming paradox that today's futures price is a prediction of the contract's maturity price, but is not predictive of price changes. We emphasize that it is precisely because information changes that prices observed on different dates can be combined with information observable on those same dates to estimate the relationship of prices to the information, which we call expected demand. Specifically, our analysis uses settlement prices for corn futures contracts observed on the dates of release of the monthly *World Agricultural Supply and Demand Estimates* (WASDE) reports (e.g., USDA 2015); i.e., the prices are observed at approximately one-month intervals on dates that coincide with the release of potentially important new information. The current, time t, price for a futures contract is viewed as an estimate of the price at contract maturity, time T, conditional on the information available at t.

If the corn market is pricing efficient, each futures quote is an unbiased estimate of a corresponding maturity price. It is sometimes not sufficiently emphasized, however, that the maturity price being forecast also changes as the conditioning information changes. The idea advanced in this paper is to take advantage of the potential variability in the anticipatory prices associated with varying information. (Forecasts from econometric models are also conditional on the information that is used to make the forecasts, which is important to remember in comparing forecasts from econometric models with futures prices. Both futures quotes and forecasts from structural models can be considered rationally expected prices.)

The variation in futures prices, related to changes in the estimates of expected supply and demand, can provide valuable insights. Each price combined with the quantity estimate from the WASDE reports provides a point of equilibrium associated with the expectations observable on the date of release of the reports. A set of monthly observations becomes available on the points of equilibrium for each marketing year.

If expected supply varies more than expect demand and if the two changes are uncorrelated, then an expected demand relationship is identified. These are the classical identification conditions described by E. J. Working (Holbrook's brother) in 1927, which are illustrated in Figure 2. Estimates of expected supply (production and inventory carry-in) are shown as predetermined (perfectly price inelastic) and as varying along a stable expected demand relation. In practice, expected demand can also change, but if supply varies more than demand and if the two have little or no correlation, one can estimate the effect of changes in supply on prices. There are years in which the monthly estimates of expected production vary more than demand, but not in every year.

Nonetheless, the expected supply estimates and corresponding futures prices for a sample of marketing years demonstrate how the price-quantity observations have shifted with the passage of time and also possibly provide evidence—an early warning—about structural changes in the price-quantity relationship. In particular, the observations on quantity and price, as they become available for the forthcoming marketing year, can be compared with the historical relationships. Even if a slope coefficient is not identifiable for each year, current expectations can be evaluated relative to the historical evidence.

We note, as an aside, that our approach supplements a well-documented outlook method that makes season average farm prices a function of the ratios of ending inventories to total use (inventory/use) for each marketing year (e.g., Staehr 2012; Tomek and Kaiser 2014, 378-382; Westcott and Hoffman 1999). These data are available from WASDE reports, and when a new estimate of the expected year-end ratio is released, the season average price can be forecast. This approach assumes, of course, that the historical relationship is applicable to the forthcoming year. The effect of a jump in the price level becomes estimable only after the accumulation of more than one year's observation.

Some research suggests that composite forecasts, that combine futures quotes with other forecasts, reduce the root mean square error of that forecast relative to the individual forecasts

(Colino and Irwin 2010). This result presumably occurs because the individual forecasts contain some different information. It is especially likely that the individual forecasts are based on information obtained on different dates, and therefore the composite forecast can have a time-based "diversification effect." Since, as already noted, different conditioning information means that different conditional means are being forecast, an average of forecasts is implicitly an average of different "target" maturity prices.

This paper does not contradict such results. Rather, we use the relationship of futures prices to the information available **on fixed dates**. The emphasis is on the value of relatively simple models as a context for outlook and in general as a foundation for modeling the time series of commodity prices, including possible early warning signs of a structural change. Hence, those doing outlook have a base to build on—add to—the information contained in WASDE reports. This could indeed reduce the mean square error, creating a composite forecast.

In addition to building on H. Working (1958), this paper extends other work. Tomek (1979) was perhaps the first to emphasize the possibility of estimating demand relations and price flexibility coefficients by marketing year; his paper also illustrated the shift in demand associated with entry of the (then existing) Soviet Union into the world grain market. Chua and Tomek (2010) updated the earlier work and used a somewhat different modeling framework that permitted pooling of the monthly observations for groups of years. Their work also suggested a further jump in the level of demand for corn starting with the 2006-2007 marketing year, with 2005-2006 perhaps being a transition year. Adjemian and Smith (2012) specify a more complex model to estimate price flexibility coefficients *inter alia* by time horizon and demand composition.

Data

As stated above, this paper's analysis uses a measure of the expected supply of corn in the U.S., which is defined as the sum of production and of September 1 inventory estimates, obtained from WASDE reports in million bushels (e.g., USDA 2015). We use five monthly observations per year—those estimates released from July through November (before and during harvest)—where the marketing year is September 1 through August 31.

The supply estimates are treated as predetermined, although prices in July and August might have tiny effects on the carry-in of stocks on September 1. The October and November WASDE reports contain the updated estimate of September 1 inventory. By July, production is fixed in the sense that the crop has been planted and inputs, such as fertilizer, committed. June and earlier months' supply estimates have the potential to be endogenous to future prices, and are therefore excluded from the analysis. The month-to-month variability in the production estimates is largely related to growing conditions. The WASDE reports are assumed to accurately reflect market expectations on the date of the report.

The measure of anticipatory prices is settlement quotations for futures contracts, and as noted above, they (in cents per bushel obtained from Thomson Reuters' Datastream) are for the dates of release of the WASDE reports. The analysis focuses on prices of the December contract, the first post-harvest delivery month, but we briefly discuss the use of more distant contract months, for the same marketing year. The release time of day has varied over the years, and currently is at noon. The evidence suggests that prices adjust quickly to new information, so that settlement prices do reflect noontime information (Lehecka, Wang, and Garcia 2014).

The prices are not deflated, since this paper is about the response of market prices to changes in information about expected supply. If the emphasis were solely on estimating price flexibilities of demand, then deflating prices and using more complex models might be appropriate (e.g., see Adjemian and Smith 2012).

Our sample spans the marketing years 1995-1996 through 2014-2015. Thus, the analyses are based on a 20-year period, with five observations per year, with the exceptions of six observations in 2008 and four observations in 2013. (No WASDE report was published for October 2013, because the USDA was closed as a federal budget had not been passed, and October 2008 had two observations because of a data error revision.) An application considers the case of using WASDE estimates of expected supply in 2015 to forecast prices for the December 2015 contract and to compare them with settlement prices for that contract.

The data, using December futures prices, for the years 1995 through 2005 are plotted in Figure 3. Starting the analysis in 1995 provides a relatively recent sample which provides a context for an apparent regime change. An inspection of the Figure suggests that both demand and supply increased over that 11-year period. In 1995, supply was expected to be about nine billion bushels, while in 2005 it was expected to be almost 13 billion bushels. Futures prices were near three dollars bushel in 1995 and a little above two dollars per bushel in 2005. The slopes of expected demand appear to be similar for these years, but our econometric analysis will formalize the relationships.

The data for years 2006 through 2014 are plotted in Figure 4, and clearly prices behave differently than in the previous years. The observations for 2006 have a relatively steep slope while those for 2007 are essentially flat. The mean in 2006 was 282.25 cents per bushel, up from 217.8 in 2005; the mean of the five December futures prices peaked in 2012 at 758.9 cents. It is unclear from the data plots alone whether or not plausible estimates of slope coefficients can be obtained. One of the “problems” may be the relative lack of intra-year variability in the supply estimates, which makes identifying expected demand difficult or impossible. Nonetheless, the data provide a foundation for evaluating new data points as they arise, and we formally evaluate simple models of expected demand in the next section, including those that pool observations from different years.

Models

The conceptual model is that $P_t = E[P_T|I_t] + e_t$, where P is a price of a futures contract, I is the conditioning information, E = the expectation operator, t = the current date, T = the maturity date of the contract, and e is an error term. That is, P_t is viewed as an estimate of an unknown conditional mean; P_t is the market-determined price given the expected supply and demand conditions at the point in time, t. This notation makes clear that anticipatory prices are equivalent to rationally expected prices, assuming the information set is complete. Since the prices are observed by months and years, we adopt the notation $P_{m,y}$. Most models are fitted to the prices of the December contract, and the text will make clear if other maturity month's prices are used.

The initial specification of the statistical model makes price a linear function of expected supply, year effect dummy variables that permit a shift in the level of price-quantity relationship, and interaction terms that permit the slope coefficient to change by year. (A month effect was found not to be statistical important.) Thus, consistent with the simple model depicted in Figure 2, futures prices are a linear function of expected supply and the level of demand accommodated by year-effect dummy variables. It is clear from Figures 3 and 4 and from statistical tests (discussed in the results section) that a substantial change in price behavior occurred starting in 2006, and we estimate equations for the full sample and for the two sub-periods separately (before 2006 and starting from 2006). The initial specification with interaction variables is:

$$P_{m,y} = \alpha + \beta S_{m,y} + \sum_{y=1996}^{2014} \beta_y S_{m,y} D_y + \sum_{y=1996}^{2014} \gamma_y D_y + \varepsilon_{m,y} \qquad (1)$$

where $P_{m,y}$ is a futures price of corn observed in month m and year y. $S_{m,y}$ is the corn supply estimate observed at month m and year y. D_y is a dummy variable that takes value 1 for year y, α is the estimated intercept, β is the slope coefficient, while β_y captures a slope change for year y. γ_y is the year effect coefficient. $\varepsilon_{m,y}$ is the error term with distribution $N \sim (0, \sigma_\varepsilon)$.

This model can be simplified to restrict the slope to a constant over various time periods. We use statistical tests and judgment to arrive at the models which we report. Because pre-testing was done with the fixed data set, the t and F statistics associated with the results should not be associated with specific levels of type I error (Wallace 1977). It is clear however, that the behavior of prices is different in the two sub-periods depicted in Figures 3 and 4.

Results

The results from fitting equation (1) by Least Squares, using the full 100 observations, are presented in Table 1. These results are equivalent to fitting 20 individual equations, one for each year. The 20 slope coefficients, relating price to the expected supply, vary from -0.105 to near zero, often exhibiting considerable percentage changes from year to year. Since expected supply varies little relative to expected demand in some years, it is difficult to claim that expected demand relations have been identified for each year. Moreover, although the R^2 is 0.947, each of the slope coefficients is effectively dependent on five observations and can be importantly influenced by one observation.

Thus, for the purposes of this paper, we believe that it is appropriate to use a model that restricts the slope to a constant over longer periods than one year, thereby allowing the slope estimates to depend on a larger range of supply changes. While expected demand has also grown, it clearly has some variability that is unrelated to changes in expected supply. Thus, we interpret the equations that use longer samples as estimates of expected demand. Also, we believe that an "average" slope coefficient is preferable for simulating the price effects of changes in expected supply.

The restricted model for the full sample is also reported in Table 1. For the full 20-year sample, the estimated slope coefficient is -0.055, and the coefficients of the dummy variables suggest a larger demand for corn in recent years, relative to the 1995-1996 base year. This result is supported by the behavior of the average prices for the December contracts for each year. This average was 303.2 cents per bushel in 1995, declined over the years through 2006, but was significantly higher in subsequent years. Specifically, the five-observation average for 2012 December futures was 759 cents per bushel, and although the average price decreased to 359.6 cents in 2014, it was still significantly larger (t = 4.31) than the 303.2 value in 1995.

The prices for December futures contracts are associated with higher levels of expected demand relative to supply from 2004 onward (to be discussed) and is especially clear in 2006 and thereafter. From the viewpoint of outlook work, it seems preferable to split the sample, using a recent period to analyze new information, and thus we fit the restricted model to two periods 1995 – 2005 and 2006 - 2014 (Table 2). The slopes are -0.0495 and -0.0573, respectively, and the coefficients of the year effects are significantly different from the base years (1995 and 2006) in the respective equations.

Given our interest in applications to outlook work, we also fit the full and restricted models to the nine observations (only four available in 2013) for the two most recent years in the sample, 2013 and 2014 (Table 3). In this case, the interaction estimate is not statistical important, and the slope estimate for the restricted model is -0.059. The models that restrict the slope coefficient to a constant over the entire sample and over various sub-samples have an internal consistency, with estimates ranging from approximately -0.05 to -0.06. Also, as noted above, supply estimates seem sufficiently variable relative to demand that the fitted models can be viewed as estimates of expected demand. It certainly is appropriate to view each observation as an equilibrium point based on expectations that existed at particular points in time.

The estimates suggest that a 100 million bushel change in expected supply resulted, on average, in about a five-cent price change in the earlier period and nearly a six-cent price change (each in the opposite direction) in the later period. Estimates of price flexibilities will vary, of course, depending on the point on a linear equation that is used to estimate them, and while we do not emphasize estimating price flexibility coefficients, it is interesting to note that the shift in demand relative to supply is such that prices are more flexible in the earlier than in the later period. The price flexibilities are -2.26 and -1.70, at the respective points of means for the 1995 - 2005 and 2006 – 2014 periods. This difference reflects the fact that the quantity-price ratio was 45.63 in the first period and only 25.59 in the second period; i.e., the price of corn was significantly larger relative to quantity in the recent period.

Application: How New Information Fits into the Historical Context

Once an expected demand relationship has been estimated, it can be used to forecast futures contract prices for corn for December delivery based on new WASDE supply estimates, and the forecasts can be compared with the market's prices. The differences are a measure of the market's belief about how much prices will be above or below those suggested by historical experience. The differences can be partitioned into expected supply and demand effects. For example, using the model fitted to the 1995-2005 sample, the forecast of the December 2006 futures price, based on the July 2006 WASDE supply estimate (12,802 million bushels), would have been 220.07 cents. The market's settlement price on the day of the release of the expected supply estimate was 284 cents (Table 4 Panel D).

These forecasts use the 2005 intercept estimate (760.53 + 93.24 = 853.77), and the changes in level of expected supply affect price through the estimate slope (-0.0495). In this example, the expected supply in 2006 is little different than in 2005, and consequently the higher market prices, relative to the forecasts, imply a large increase in expected demand in 2006 relative to 2005. Such numerical results can be combined with estimates for other delivery months (see below), basis estimates, and/or judgment for outlook work. A knowledgeable analyst can discuss possible reasons for changes in expectations.

The results reported in Panels A, B, and C of Table 4 help clarify that price changes are influenced by changes in both expected supply and demand. As an example, we compare August prices for the December 2003 futures contract (Panel A) with August prices for December 2004 contract (Panel B). The two market prices are about the same (229.75 cents and 229 cents), although supply was expected to be 810 million bushels larger in 2004. Not surprisingly, the forecast price, using the model fitted through 2003, results in a large decline in the forecast price (about 43 cents); this is the decline in price associated with an increase in supply along the level of demand estimated for 2003. Since prices are essentially unchanged, the results suggest that the market expects an increase in demand that offsets the expected increase in supply.

The historical record (contained in the four panels of Table 4) also suggests that by 2004, the market was anticipating higher prices for given levels of supply. Supply was growing, but prices were not declining. One needs to go back to 2003 when the model, fitted through 2002, provided forecasts slightly above the market price in four of the five months of 2003 (Panel A). By October of 2006 (Panel D), market prices were much higher than those predicted from the model fitted through 2005. The regression models quantify a record of expected demand outpacing the growth in supply starting in 2004, which became obvious by 2006. The results for subsequent years imply that a shift in demand relative to the level of supply has persisted.

Other applications are possible. Our examples use one-step (year) ahead forecasts, i.e., provide a comparison of new expectations with the most recent level in the sample, but it is also possible to make two or more steps (years) ahead forecasts. Another approach is to fit the model to the full sample, and use this equation to provide a historical perspective on changes in expected demand and supply. The latter case merely requires using the appropriate intercept estimate for a past year to compute prices for the supply levels corresponding to (say) the current year. For example, using the year 2000 intercept, from the equation fitted to the 1995 – 2005 sample, and the October 2006 expected supply, the forecast price for the December 2006 futures contract is about 155 cents per bushel while the settlement price was 298.25 cents. The much higher market price occurred notwithstanding an increase in supply of about three billion bushels from 2000 to 2006. In sum, the relatively simple model specification permits flexible uses, and an analyst is free to add judgment, modify the model's specification, and/or use different sample periods.

Forecasts for 2015 with Confidence Intervals

Confidence intervals can, of course, be computed for the point forecasts (for a convenient way to do so, see Salkever 1976). If market prices fall within the interval, it is a statistical base for saying that no significant changes in prices have occurred relative to historical experience.

But, confidence intervals based on standard errors of forecast tend to be large and not, in our judgment, very informative. One reason for the wide intervals in this application is the growth in supply. Consequently, forecasts for the forthcoming marketing year are often based on supply estimates that are as large as, or larger than, those in the sample. As expected supply increases relative to the sample mean, the standard error of forecast gets larger *ceteris paribus*.

Nonetheless, we illustrate the forecasts for the December 2015 corn futures contract using the equation fitted to the 2006 – 2014 sample (see Table 2). These are the kind of results that an analyst could have obtained as the WASDE reports were released in July through November 2015. The forecasts, their confidence intervals, and market prices for the December 2015 contract are reported in Table 5. The forecasts use the 2014 estimated intercept (1,244.65) and slope (-0.0573), i.e., assume the 2014 level of demand. Since the forecasts use the WASDE estimates of expected supply, the analyst does not have to make ancillary estimates of the right-hand side variables.

In interpreting results, we again disentangle the effects of a change in supply and a shift in demand. The estimates of expected supply for the 2015 – 2016 marketing year varied in a relatively narrow range of 15,286 to 15,458 million bushels from July through November, and these numbers were approximately 200 million bushels below the 2014 – 2015 values, though much larger than the supply estimates in 2013 – 2014 and earlier years. The slightly smaller supply with a constant demand is estimated to have increased price 11 to 12 cents relative to 2014, but the actual market prices were still above the forecasts. This implies that the expected demand for corn as of July – November 2015 was larger than in 2014. This is illustrated in Figure 5. Nonetheless, it is true that the market prices in 2015 were within the confidence intervals estimated for the forecasts, which can be interpreted as no significant increase in expected demand. Ultimately, analysts must bring judgment to their outlook analyses.

Extension to Prices for Other Maturities

The foregoing analysis can be extended to the prices of contracts for other maturity months. We illustrate this alternative using the prices of the May contract. Two dependent variables are considered: one is the price level for the May futures; and the other is the difference between the May and December prices, a price of storage between the two months. The model specification is the same as for the December prices.

The results for the price-level equation for May are very similar to those for the December contract. This result is not surprising for an annually produced, continuously storable commodity like corn, because the prices for the different maturity dates are linked by the price of storage (the cost of carry) and hence are highly correlated. They move in a near lock-step form. Related, the more distant contract prices should not exceed the December contract's prices by more than the cost of storage. Fitting separate equations does not take account of this restriction, but the prices in the sample presumably reflect this restriction.

An alternative specification, that uses the price differences (in our case, May minus December prices) as the dependent variable, has the virtue of directly forecasting the price of storage. If the equations are linear, the two price-level equations provide forecasts that are identical to those based on a price-level equation and a price difference equation. But, we wanted to explore a possible curvilinear functional relationship between the price of storage and expected supply, since the relationship between the price of storage and inventories is curvilinear (see Joseph, Irwin, and Garcia 2016 and their references and for a conceptual model see Tomek and Kaiser 2014, 258-262).

Our specification continues to use the WASDE supply estimates and year-effect dummy variables. Three functional forms—linear, reciprocal of expected supply, and logarithm of expected supply—are presented for the 2006 – 2014 sample period in Table 6. The three alternatives have almost identical explanatory power, and in each case the t-ratio for the coefficient of expected supply is larger than 3.3. The marginal effect of a revision in expected supply is estimated to be 0.003 cent in the linear specification, i.e., a 100 million bushel increase in expected supply is estimated to increase the price of storage 0.3 cent. The relatively large negative coefficient associated with the 2012 dummy variable (year effect) reflects a negative carrying charge in that year, which is possibly due to the decrease in expected supply caused by a drought.

Forecasts of carrying charges, the price differences between May and December futures, for the five months in 2015 are provided in Table 7. The functional forms made essentially no difference in the forecasts. The functional form could make a difference in the magnitudes of the forecasts if expected supply was unusually large or small relative to the observations in the sample. But, the main lesson from our exploration is that variation in expected supply has a small, though statistically important effect on carrying charges. Changes in expected supply alone do not account for much of the variation in the price of storage, which varied from 14.75 to 18.25 cents in the five months, July to November 2015.

Clearly better explanations of changes in the price differences among contracts requires additional analysis, but it is unclear whether models can be found that would improve forecasts of the price of storage. One would need high quality measures of expectations about variables like interest rates and crop size for future years.

Concluding Observations

Prices of futures contracts are anticipatory, and for corn a systematic relationship exists between a measure of expected supply and corresponding futures prices. The quantitative content of new information may not be predictable, but the historical relationship between information and prices can be estimated and used to demonstrate how changes in expectations affect prices. That is, the price-quantity observations can be viewed as estimates of points of equilibrium that identify expected demand relationships.

This paper proposes a relatively simple model that relates prices for post-harvest futures contracts for corn to pre-harvest estimates of supply. The slope coefficient tells how prices vary as expected supply varies, *ceteris paribus*. The year-effect dummy variables provide estimates of the level of expected demand for each year and give a historical perspective on how demand has shifted, given the expected supply. This allows the analyst to partition the price effects between shifts in expected supply and expected demand, and permits one to compare the price effects of new information for the next marketing year with past experience. The model also has the virtue of using explanatory variables that can be treated as predetermined.

The same approach can be used to forecast the expect prices of storage conditional on the new information on expected supply, and again the forecasts can be compared with the market's price differences among different contract maturity months. The models for the price level (December contract) have large R^2's, though the confidence intervals for forecasts are large. We believe, however, that it is the differences between the equation's forecasts and the market's prices that are of interest for outlook work. Also, the models provide estimates of the marginal effect of possible changes in expected supply.

While the simplicity of our approach is a benefit, other models may be worth exploring. For outlook work, the modeling question is, is it possible to obtain observable variables of expectations that are predetermined and don't have to be obtained by ancillary forecasts? Other grain and oilseed markets presumably can be analyzed by analogy with the corn market. Livestock markets are likely to be more challenging. But in the United States, the USDA does provide measures of expected supply for products, like hogs, on a systematic basis, and it may be worth exploring the relationship between measures of expected supply and anticipatory prices.

On the technical side, we tested for heteroskedasticty, and the null of homoskedasticty was rejected for the equations fit to the early part of the sample, but not for the recent portion of the sample. Given our emphasis on outlook applications and forecasting, however, we report results only for the ordinary least squares estimates. Feasible generalized least squares results do not change the basic characteristics of the results.

It is not surprising that changes in futures prices reflect changes in information. What we show is that it is possible to estimate and use the relationship between new information and futures prices precisely because futures price are anticipatory prices.

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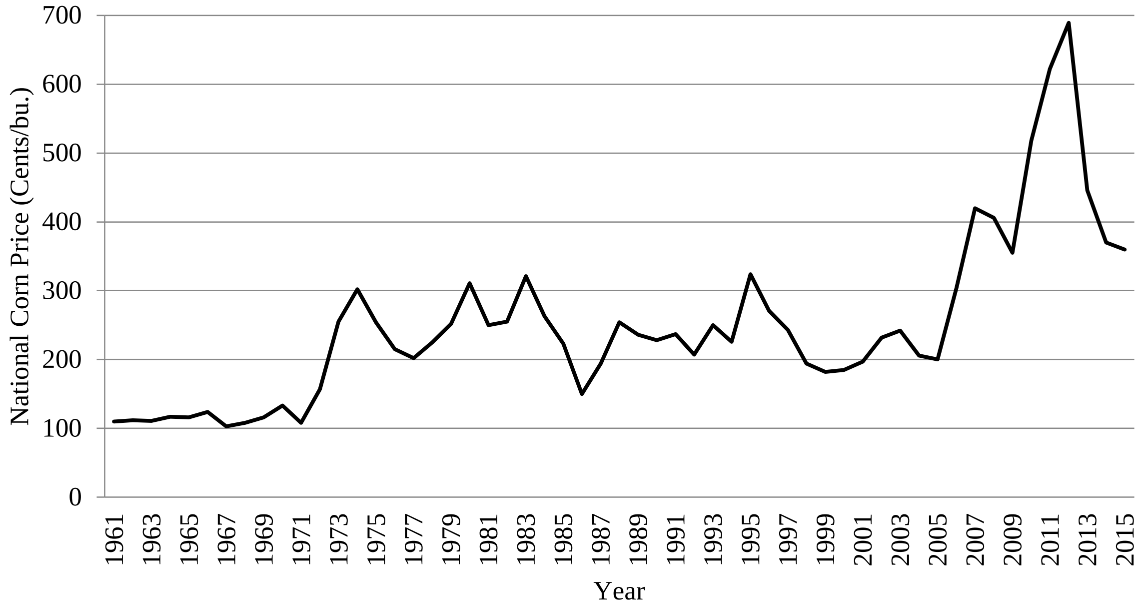

Figure 1. Weighted National Annual Average Farm Price of Corn, U.S., 1960-61 – 2014-15

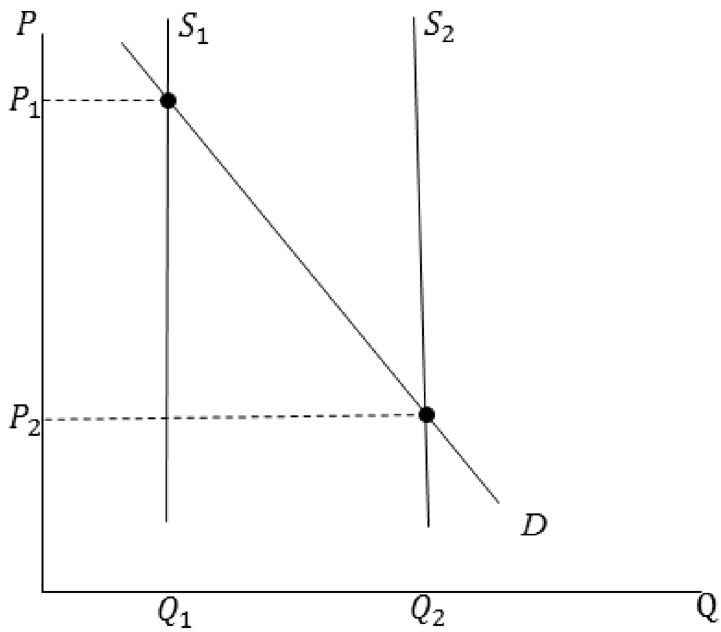

Figure 2. An Illustration of Supply Shifts Identifying a Demand Relation.

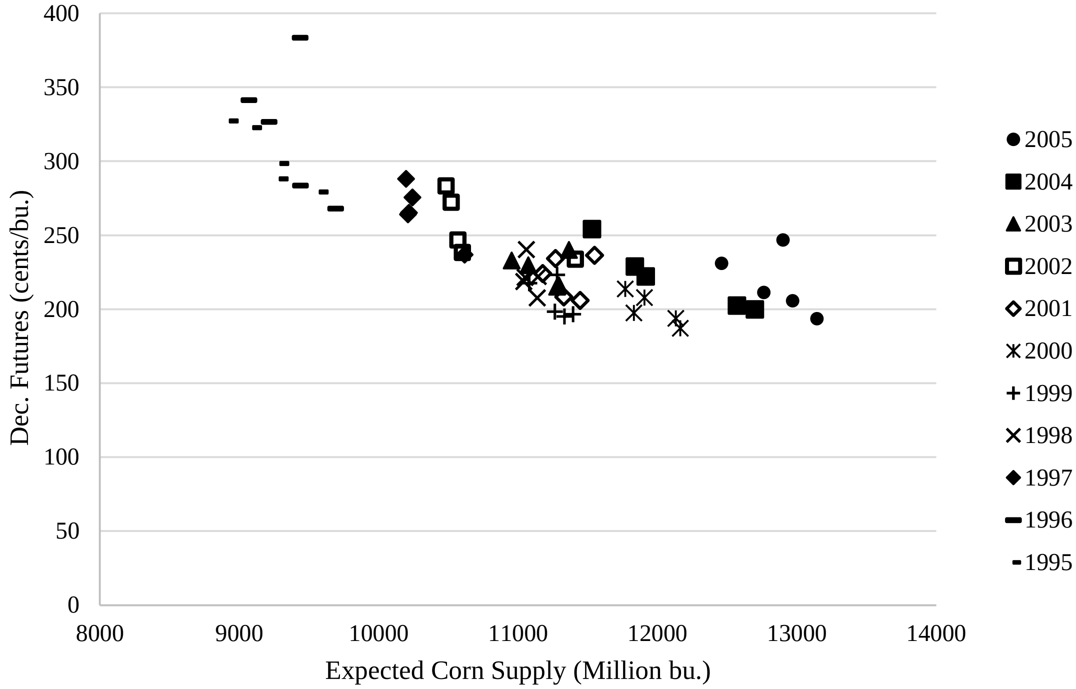

Figure 3. December Futures and Corn Supply Expectations (1995-2005)

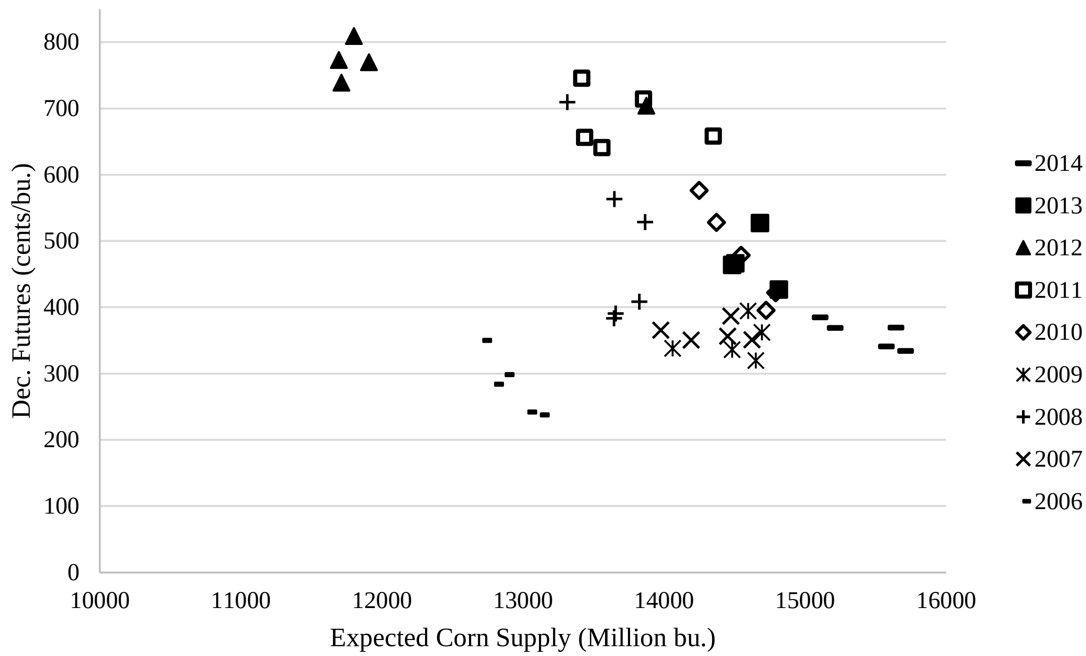

Figure 4. December Futures and Corn Supply Expectations (2006-2014)

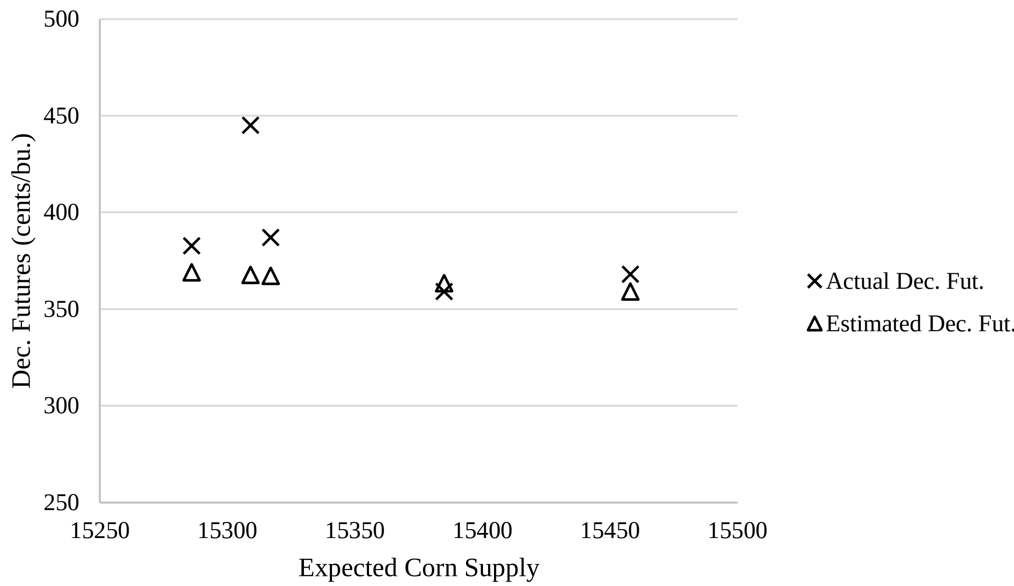

Figure 5. Actual and Estimated December 2015 Futures Prices.

Table 1. OLS Regression Results of Equation 1 with and without Year Interactions, 1995 – 2014

	Full Model	t-ratio	Restricted Slope	t-ratio
Supplyest	-0.0823	(-1.07)	-0.0546	(-3.85)
D1996	181.6	(0.18)	24.66	(0.94)
D1997	145.2	(0.11)	20.68	(0.69)
D1998	327.6	(0.08)	19.91	(0.54)
D1999	-80.35	(-0.04)	14.09	(0.36)
D2000	-261.6	(-0.18)	45.61	(0.98)
D2001	-875.1	(-0.55)	34.25	(0.86)
D2002	-429.6	(-0.49)	32.47	(0.97)
D2003	-686.5	(-0.49)	30.45	(0.80)
D2004	-329.9	(-0.39)	75.32	(1.56)
D2005	-275.5	(-0.24)	111.8	(1.95)
D2006	2481.3	(1.56)	179.8	(3.09)
D2007	-706.5	(-0.56)	337.7	(4.39)
D2008	5237.1	(3.84)	435.5	(6.45)
D2009	-1134.8	(-0.90)	334.2	(4.23)
D2010	4010.8	(2.92)	466.2	(5.86)
D2011	-16.95	(-0.02)	624.7	(9.08)
D2012	83.56	(0.11)	617.4	(12.50)
D2013	150.1	(0.07)	461.8	(5.69)
D2014	238.7	(0.19)	395.8	(4.31)
D1996S	-0.0164	(-0.15)		

D1997S	-0.00925	(-0.07)		
D1998S	-0.0231	(-0.06)		
D1999S	0.0134	(0.08)		
D2000S	0.0320	(0.25)		
D2001S	0.0852	(0.58)		
D2002S	0.0469	(0.52)		
D2003S	0.0689	(0.52)		
D2004S	0.0400	(0.47)		
D2005S	0.0379	(0.36)		
D2006S	-0.170	(-1.27)		
D2007S	0.0826	(0.78)		
D2008S	-0.343	(-2.99)		
D2009S	0.111	(1.06)		
D2010S	-0.234	(-2.10)		
D2011S	0.0558	(0.62)		
D2012S	0.0505	(0.64)		
D2013S	0.0315	(0.20)		
D2014S	0.0213	(0.21)		
Constant	1063.4	(1.50)	808.0	(6.10)
N	100		100	
Adj. R^2	0.947		0.935	
AIC	1035.3		1045.8	

Table 2. OLS Regression Results of Restricted Model for subsamples 1995-2005 and 2006-2014

	First Period (1995-2005)	t-ratio	Second Period (2006-2014)	t-ratio
Supplyest	-0.0495	(-4.75)	-0.0573	(-2.30)
D1996	23.98	(2.13)		
D1997	15.25	(0.97)		
D1998	10.42	(0.47)		
D1999	3.658	(0.15)		
D2000	31.63	(1.04)		
D2001	23.39	(0.95)		
D2002	24.87	(1.31)		
D2003	20.42	(0.88)		
D2004	60.57	(1.90)		
D2005	93.24	(2.38)		
D2007			161.6	(3.14)
D2008			257.7	(6.43)
D2009			158.5	(2.93)
D2010			290.7	(5.30)
D2011			447.0	(10.58)
D2012			435.7	(10.59)
D2013			286.5	(4.95)
D2014			222.7	(3.04)
Constant	760.5	(7.87)	1022.0	(3.17)
N	55		45	

Adj. R^2	0.831	0.870
AIC	482.2	502.9

Table 3. OLS Regression Results of Full and Restricted Models for subsample 2013-2014

	Full Model	t-ratio	Restricted Slope	t-ratio
Supplyest	-0.0508	(-0.41)	-0.059	(-1.16)
D2014	88.59	(0.04)	-62.43	(-1.33)
D2014S	-0.0102	(-0.07)		
Constant	1213.5	(0.67)	1333.2	(1.80)
N	9		9	
Adj. R^2	0.736		0.78	
AIC	91.59		89.60	

N= 45.

Table 4. Dec. Futures Price Forecasts, Actual Prices and their Differences, cents per bushel

	Actual			Estimation	
A. Model through 2002	Dec. Fut. 2003	Supply Est. (mil. bu.)	Estimated Dec. Fut.	Error (Actual-Estimated)	% Difference on Actual Dec. Fut.
July	215.25	11279	222.16	-6.91	-3.21%
August	229.75	11073	234.16	-4.41	-1.92%
Sept	233	10953	241.15	-8.15	-3.50%
Oct	216.25	11293	221.35	-5.10	-2.36%
Nov	240.25	11364	217.21	23.04	9.59%
B. Model through 2003	Dec Fut. 2004				
July	254.25	11531	208.31	45.94	18.07%
August	229	11837	191.51	37.49	16.37%
Sept	222.25	11915	187.22	35.03	15.76%
Oct	202.5	12571	151.20	51.30	25.33%
Nov	200	12699	144.17	55.83	27.91%
C. Model through 2004	Dec Fut. 2005				
July	247	12900	182.12	64.88	26.27%
August	231	12460	204.13	26.87	11.63%
Sept	211.5	12764	188.92	22.58	10.68%
Oct	205.75	12969	178.67	27.08	13.16%
Nov	193.75	13144	169.91	23.84	12.30%

D. Model through 2005	Dec Fut. 2006				
July	284	12802	220.07	63.93	22.51%
August	241.75	13038	208.39	33.36	13.80%
Sept	237.75	13126	204.03	33.72	14.18%
Oct	298.25	12876	216.41	81.84	27.44%
Nov	350	12716	224.33	125.67	35.91%

Table 5. Dec. Futures Price and their Forecasts for 2015, cents per bushel

	Dec Fut. 2015	Estimated Dec Fut.	Standard Error	95% Confidence Interval		P-value Ho=Ha
July	445	367.67	64.35	237.02	498.31	0.237
Aug	368	359.13	64.26	228.68	489.58	0.891
Sept	387	367.21	64.34	236.58	497.83	0.760
Oct	382.75	368.98	64.39	238.27	499.70	0.832
Nov	359	363.31	64.28	232.82	493.80	0.947

Table 6. OLS Regression Results on May-December Futures Price Differences for 2006-2014.

	Linear		Reciprocal of Supply		Logarithm of Supply	
	Coefficient	t-ratio	Coefficient	t-ratio	Coefficient	t-ratio
Supplyest	0.00298	(3.32)	-527436	(-3.39)	39.864	(3.36)
D2007	0.733	(0.39)	0.929	(0.52)	0.813	(0.44)
D2008	7.240	(5.00)	7.234	(5.04)	7.226	(5.01)
D2009	-2.473	(-1.27)	-2.210	(-1.18)	-2.360	(-1.23)
D2010	-6.844	(-3.45)	-6.563	(-3.46)	-6.723	(-3.47)
D2011	-4.573	(-3.00)	-4.549	(-3.01)	-4.572	(-3.01)
D2012	-18.521	(-12.47)	-18.077	(-11.78)	-18.296	(-12.13)
D2013	-5.043	(-2.41)	-4.725	(-2.37)	-4.903	(-2.4)
D2014	-7.019	(-2.65)	-6.158	(-2.58)	-6.602	(-2.63)
Constant	-18.054	(-1.55)	61.305	(5.07)	-356.891	(-3.18)
Adj. R^2	0.9353		0.9360		0.9357	

N= 45.

Table 7. May-December Futures Differences Forecasts, cents per bushel.

	Dec 2015 Futures	May 2016 Futures	May 2016-Dec 2015	Forecast May 2016-Dec2015 (Linear Model)	Supply Estimates (mil. bu.)
July	445	459.75	14.75	20.58	15309
Aug	368	386.25	18.25	21.02	15458
Sept	387	405.25	18.25	20.60	15317
Oct	382.75	400	17.25	20.51	15286
Nov	359	374.5	15.5	20.81	15385

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