Anticipatory Signals of Changes in Corn Demand

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Anticipatory Signals of Changes in Corn Demand

Practitioner's Abstract

This paper analyzes changes in the expected demand for corn in the U.S., and it explores whether anticipatory signals of price jumps can be obtained from simple models. Two main objectives are considered. One is to estimate the relationship between the expected supply of corn and corresponding prices of futures contracts. We argue that such results can provide estimates of demand relationships and their shifts with the passage of time. Moreover, such analysis should allow us to test for possible changes in the structure of demand. A second, related objective is to demonstrate how such historical estimates can allow an analyst to appraise the futures markets' quotes relative to forecasts from the historical model. We argue that the difference in the two prices may contain useful information.

Key Words: Demand estimation; Futures prices; Market expectation; Forecast.

Introduction

The time-series processes for grain and oilseed prices in the U.S. have had occasional jumps in their level (mean) and perhaps shifts in the variability around these levels. These jumps appear to be caused by sudden changes in demand relative to supply. Over the past 50 years, two episodes of structural change are apparent in corn (and other grain) prices. The first one was in 1973, when the ex-USSR opened their market to world grain imports, increasing demand for U.S. grains over a short time period. The national average corn price in the U.S. from 1960 to 1972 was \$1.17/bu., while for 1973 to 2005 was \$2.37/bu. After 2006, corn prices in the U.S. reached record levels (Fig. 1). This last jump seems to be the result of the biofuels policy that increased corn demand for the production of ethanol (De Gorter, Drabik, and Just, 2015).

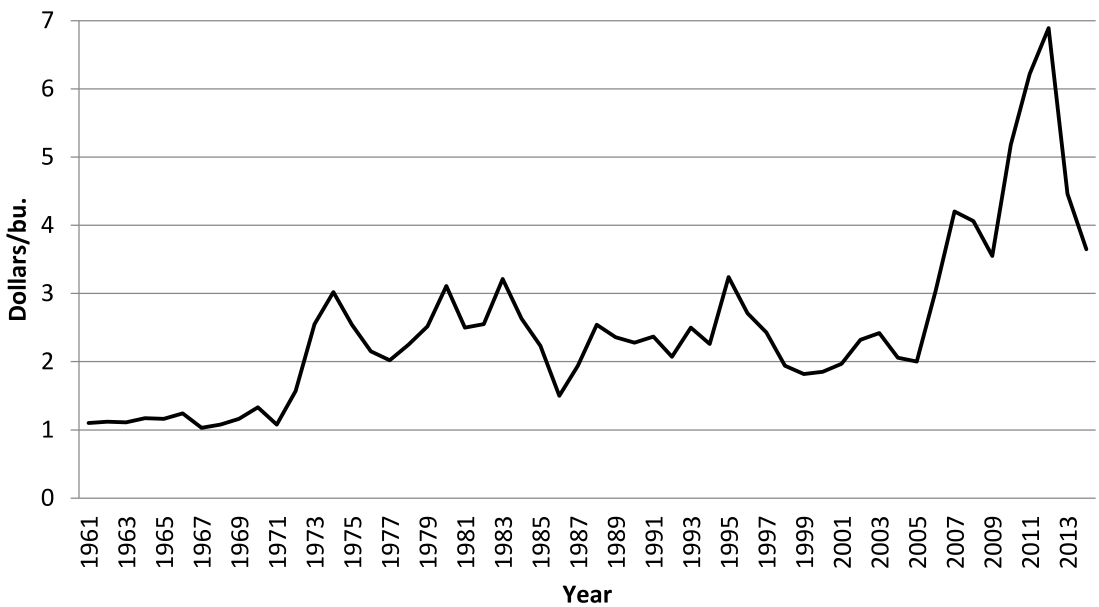

Figure 1. Corn Price, National Yearly Average

Because the statistical properties of prices may change after a jump, models that do not account for such jumps are in danger of providing biased estimates of price responses to production changes (e.g., price flexibilities). Also, increases in volatility that may accompany price jumps (Fig. 2) complicate firms' risk management and operation decisions (Mark et al. 2008). Hedging with options' contracts becomes more expensive as the result of higher volatility. Hence, it would be useful to have a procedure to provide an "early warning" of jumps in price levels, or at a minimum provide a relatively simple way to appraise current price levels relative to historical experience.

Accordingly, this paper analyzes changes in the expected demand for corn in the U.S., and it explores whether anticipatory signals of price jumps can be obtained from simple models. Two main objectives are considered. One is to estimate the relationship between the expected supply of corn and corresponding prices of futures contracts. We argue that such results can provide estimates of demand relationships and their shifts with the passage of time. Moreover, such analysis should allow us to test for possible changes in the structure of demand. A second, related objective is to demonstrate how such historical estimates can allow an analyst to appraise the futures markets' quotes relative to forecasts from the historical model. We argue that the difference in the two prices may contain useful information.

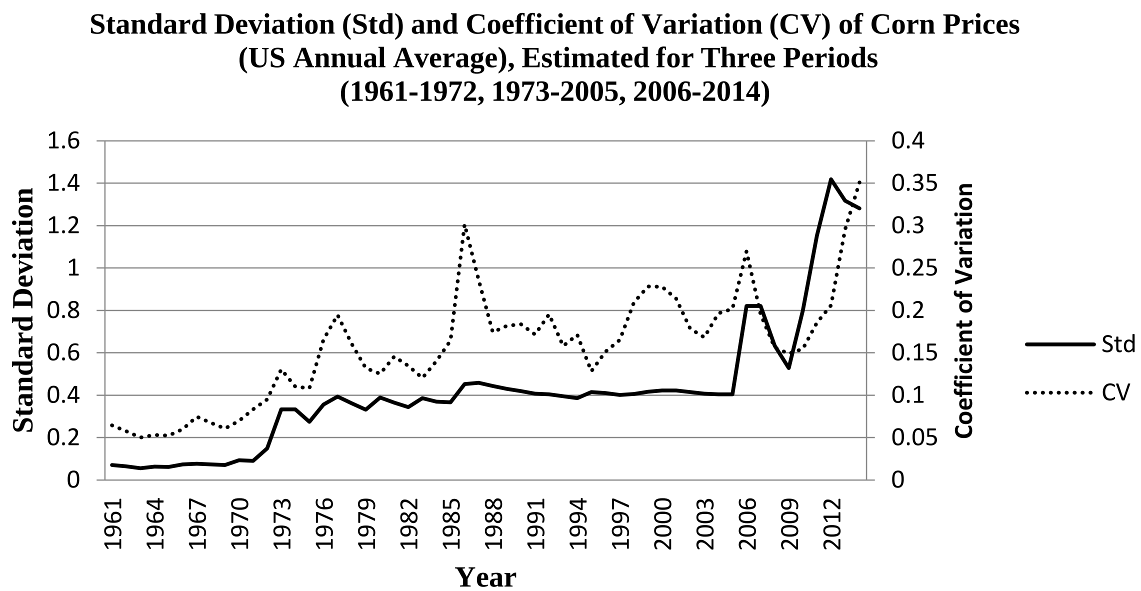

Figure 2. Standard Deviation (Std) and Coefficient of Variation (CV) of U.S. Average Corn Prices

The paper is organized as follows. The next section provides the background and framework for the analysis. We then discuss the data and proposed model specifications for estimating demand relationships and related price flexibility coefficients. Next, empirical estimates are provided, and an application of the results illustrated. Finally, we outline some possible further research opportunities.

Background and Conceptual Framework

Our analysis rests on two well-known assumptions. One is that a current futures price is an unbiased estimate of a conditional mean, i.e., the mean that would prevail at the contract's expiration given current information. Thus, the market is assumed to be at least semi-strong efficient, where market participants act on the same public information. The principal change in observable public information in the months prior to harvest is the WASDE reports of expected supply. Thus, it is possible to observe the changes in expected supply and the corresponding prices for futures contracts for corn.

The second assumption is that changes in expectations about supply can identify demand relationships. This requires that the changes in supply are more variable than are the changes in demand and that the two changes are uncorrelated. (These are the classical identification conditions which were first described by E. Working in 1927 and which may or may not be true in a particular application.) That is, we assume that using the reported expected supply and treating the futures quotes as the expected prices will provide estimates of the market's expected demand for that year (though in practice we find some years in which this is not true because changes in expected supply are small).

In this context, new observations for the forthcoming crop's marketing year—say in August 2015 for the 2015-16 year—can be evaluated relative to the estimates of expected demand in previous years. Examining the new observations relative to historical experience can help us tell if the current futures quote is a consequence of a change in supply, a shift in demand, a combination of the two, and a possible structural change. To elaborate, if futures prices for corn are efficient, anticipatory prices (H. Working, 1962), reflecting market expectations of prices at maturity, and if within a period of a few months, expected demand is less variable than changes in expected supply, estimates of expected demand can be obtained. Under these conditions, estimates of expected demand relationships can provide a basis for estimating changes in flexibility coefficients and **for evaluating current expectations relative to historical evidence.**

The literature contains some precedents for our work (Tomek 1979, and Adjemian and Smith 2012). In particular, this paper expands on Chua and Tomek (2010) by including more recent observations and by analyzing the residuals of new data which incorporates the most recent demand estimates. Particularly, can residuals based on new supply estimates provide anticipatory signals of a shift in demand? For example, could the 2006 price jump have been anticipated from the futures price quotes given the WASDE supply estimates?

Data

The analyses is this paper use two types of data: estimates of expected corn supply for the U.S. and corresponding futures prices of corn observed when the supply estimates are made public. Expected supply of corn in the U.S. is measured as the sum of the production and inventory estimates obtained from the WASDE reports of the USDA, reported in millions of bushels. These reports are released each month. We analyzed WASDE's estimates from July to November (five observations per year). The supply estimates are treated as predetermined in our analysis, although prices in July and August might have tiny effects on carry-in of stocks on September 1.

Settlement prices were obtained for selected delivery months for corn futures contract from Thomson Reuters' Datastream. In this paper, our focus in on prices of December contracts, because it is the closest contract month after harvest. (March and other delivery months will be considered in a future paper.) Prices are in US cents per bushel and are for the same day of the WASDE report release, i.e., the first settlement price after the data release. The release time has varied over the years, and currently is at noon. (Evidence suggests that prices adjust quickly to new information.) The observations used in this paper span from 1995 through 2014. One year, 2013, does not include October, presumably because the USDA was closed because of the federal government "shut down" related to the conflict over passage of the federal budget. Chua and Tomek (2010) and Tomek (1979) contain earlier years.

Identification of possible demand relationships is illustrated in figure 3, which contains observations for the years 1995 through 2005. Each point in a year represents one of the five monthly observations. A very few years include a revised estimate supply estimate. A careful inspection of figure 3 suggests that demand and supply have both been increasing, i.e., shifting to the right, over this 11-year period.

Prices in 1995 and 1996 are the highest in the 11-year sample 1995-2005 and also are high compared to earlier years used in Chua and Tomek. However, starting the analysis in 1995 provides a recent sample which is a good context for an apparent regime change in 2006. That is, the years shown in figure 3 seem to belong to the same demand structure, which appears to change in 2006. This is illustrated in figure 4 that includes observations for 2005 through 2014. Clearly the observations for 2006 lie above those for 2005, and this became more pronounced in 2007 and thereafter, consistent with the plot of annual data in figure 1. Our econometric analyses formalize the relationships shown in figures 3 and 4.

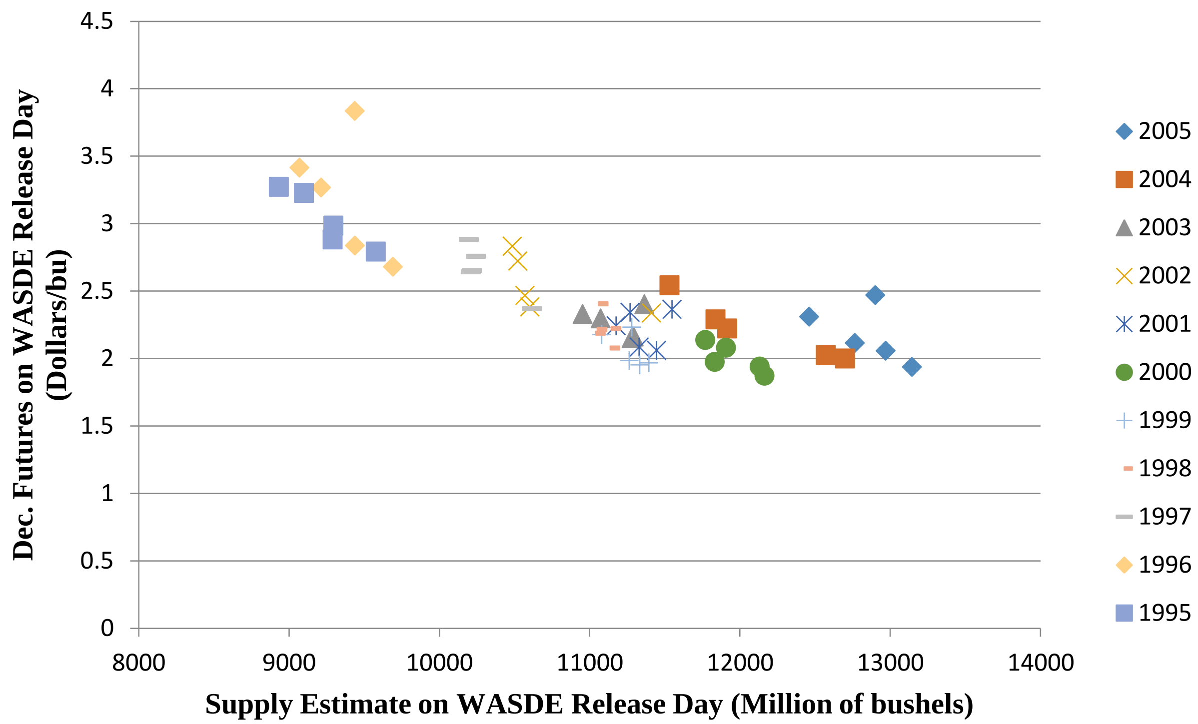

Figure 3. Dec. Futures and Corn Supply Estimates from 1995-2005

Future prices after 2005 behave more erratically than before (see Figure 4). After a seemingly stable demand over the 1995-2005 period (though with some possible increase in expected demand in 2004 and 2005, the observations in 2006 and thereafter have varying slopes, and whether a demand function is identifiable is unclear.

The data from 2006 through 2014 have variable patterns of behavior that clearly differ from the behavior in earlier years. For example, the points in 2008 trace out an almost vertical line, and 2010 has a similar pattern. These are years with little variability in expected supply, but relatively large variability in prices, suggesting that the slope of the demand function is not identifiable. The years 2007 and 2011, on the other hand, appear to have more plausible slopes, with price variability small relative to quantity variability. The sets of yearly observations have different slopes, potentially complicating the analysis of slope changes. Related, the drought in the Midwest in 2012 resulted in highly variable supply estimates, though this may actually help identify a demand relationship.

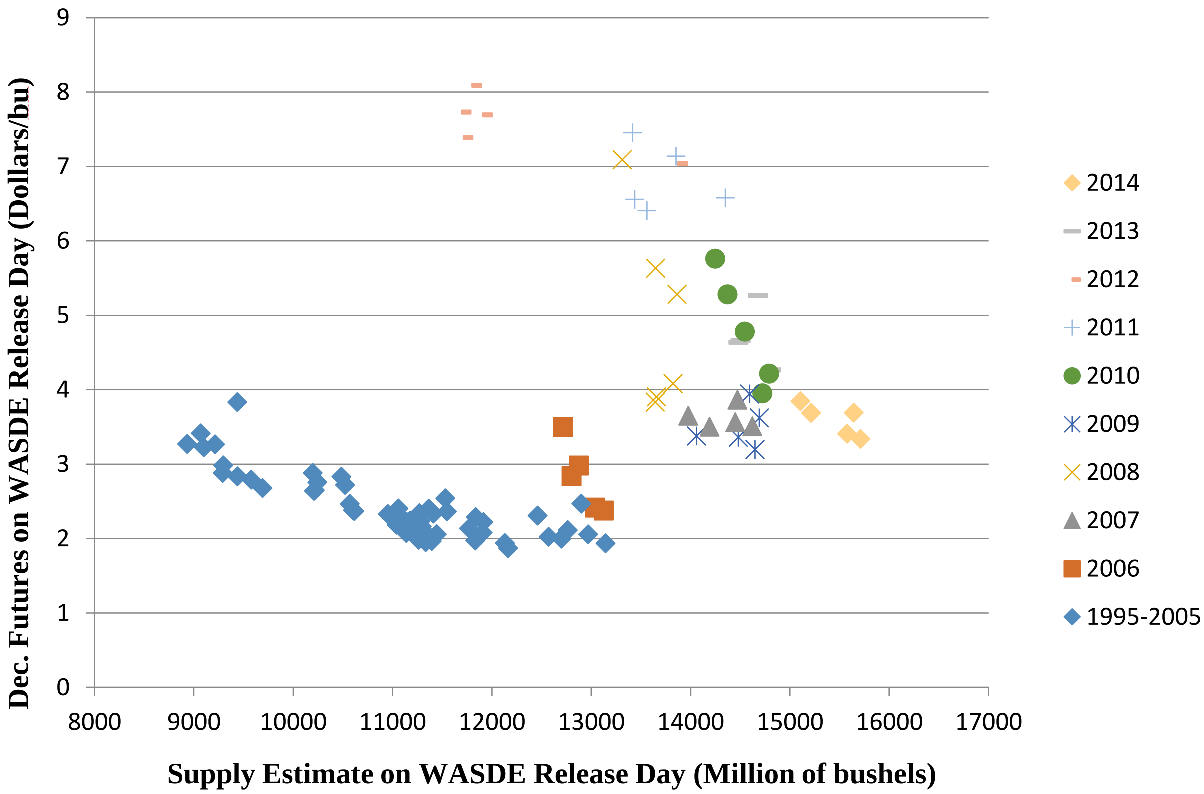

Figure 4. Dec Futures and Corn Supply Estimates from 1995-2014

Model

The basic idea behind this study is that futures prices observed at the time when supply estimates are released should reflect all market information. The new price is an equilibrium point of the expected supply and market conditions. Thus, we specify a simple model where the December futures price is a function of the supply estimate and yearly dummies, and sometimes including interaction terms to allow for slope changes (though these are not reported in this paper). Since Chua and Tomek had found significant month effects, we also considered dummy variables for the month of the year, but these proved to be statistically unimportant in our more recent sample.

The analysis begins with data from 1995 through 2005 as pictured in Figure 3. It would be possible to test whether new observations added to the initial historical sample come from the same structure. The sign of the error term associated with new observations would be important. They potentially signal the direction of change in demand. If the residuals are consistently positive, then the new data implies that the demand curve is shifting to the right.

The model without interaction terms used in this analysis is:

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

Where $P_{m,y}$ are the settlement prices for December futures for corn observed on the day of the WASDE report release on month *m* (July-November) and year *y* (1995-2014). α is the intercept. $S_{m,y}$ is the supply estimate of corn from the WASDE report at month *m* and year *y*. D_y is a dummy variable for years 1996 until 2014, i.e., 1995 is base year, and the gammas represent the shifts in the level after 1995. β and γ_y are the coefficients for the supply estimate and yearly dummies, respectively. $\varepsilon_{m,y}$ denotes the error term for month *m* and year *y*, assumed to be normally distributed with mean 0 and variance σ .

A variety of hypothesis tests are possible. One is simply whether or not individual year effects differ from zero, i.e., whether or not the level of the function has shifted relative to the base period. Rejection of this hypothesis would provide evidence that the observations in the recent years, i.e., after 1995, have shifted to new levels, and also rejection of the null may indicate that the model specification needs to be reevaluated. The foregoing model assumes that the slope of the function, β , is the same for all years, only allowing the intercept to vary across years.

An alternative model from (1) would allow changes in the slope of the function. A potential problem with allowing slope changes across years is that the value for a particular year may not capture the actual demand function's slope, because of the identification problem. As noted above, when the month-to-month variability of supply is relatively small, a demand equation for a year is not identifiable. The data are simply some sort of "hybrid" relationship. This is probably the case in year 2006, where future prices are moving almost vertically, possibly because expected demand is shifting more than expected supply in the five months of 2006. We expect to explore slope changes and other alternative specifications in future research.

Results

The results from estimating equation (1) by Least Squares are presented in Table 1. An interpretation is that we have estimates of the market's expected demand conditional on the information available on the particular dates. The data plotted in Figure 3, and supported by the results in Table 1, imply that equation (1) is likely a reasonable specification for the years 1995 – 2003, that is, these years seem to belong to the same demand function.

Table 1. OLS Regression Result of Model 1 from 1995 to 2014

Variable	Coefficient	Std. Error	P-value
Supply Estimate	-0.055	0.014	0.000
1996	24.658	26.106	0.348
1997	20.685	30.055	0.493
1998	19.909	36.953	0.592
1999	14.090	38.845	0.718
2000	45.612	46.579	0.330
2001	34.247	39.731	0.391
2002	32.470	33.446	0.335
2003	30.451	38.035	0.426
2004	75.319	48.361	0.123
2005	111.776	57.447	0.055
2006	179.833	58.260	0.003
2007	337.658	76.959	0.000
2008	435.533	67.487	0.000
2009	334.168	79.005	0.000
2010	466.186	79.549	0.000
2011	624.721	68.766	0.000
2012	617.422	49.406	0.000
2013	461.798	81.193	0.000
2014	395.764	91.899	0.000
Constant	395.764	91.899	0.000

Adj. R^2 = 0.935, N= 100

The p-values for the coefficients of the yearly dummies are 0.33 or more for the years 1996 through 2003, implying essentially a constant level of demand over that period. But, note, the coefficients are positive numbers implying that the expected demand for the years 1997 through 2003 were larger than in the base year, 1995. In 2004, the intercept increased by 75.31 relative to the baseline level of 1995 and for 2005 is an even larger at 111.77. Both coefficients have p-values below 0.12. Thus, the results depict essentially a constant level of demand that was significantly larger in 2004 and still larger in 2005. The slope, as noted earlier, is constrained to be a constant over the sample (-0.055).

The results presented in Table 2 specify a constant intercept for the years 1995 through 2003 and allow the intercept to shift for each year 2004 through 2014. The slope is still constrained to being a constant. Clearly the results suggest larger price levels that tend to be higher each year from 2004 to 2012 (relative to the base, 1995-2003), but with smaller values in 2013 and 2014 than in 2012. Forcing the slope to be a constant over the entire sample results in the coefficient changing from -0.055 to -0.047, a 14% decline in absolute value.

Table 2. OLS Regression Result of Model 1 from 2004 to 2014

Variable	Coefficient	Std. Error	P-value
Supply Estimate	-0.047	0.006	0.000
2004	39.912	20.633	0.056
2005	70.684	22.867	0.003
2006	138.246	23.093	0.000
2007	285.031	29.070	0.000
2008	388.184	24.977	0.000
2009	280.360	29.791	0.000
2010	412.065	29.984	0.000
2011	576.865	26.296	0.000
2012	581.345	20.859	0.000
2013	407.033	31.665	0.000
2014	334.591	34.522	0.000
Constant	749.930	65.909	0.000

Adj. R^2 = 0.938, N= 100

The values of 2004 and 2005 dummy coefficients, although smaller than those from 2006 onward, indicate that a shift in the expected demand for corn was occurring. Thus, while the jump in the price level became very apparent in 2006, the prices in 2004 were already suggesting a shift in demand, which is consistent with the information available on corn supplied for ethanol production from the WASDE reports as of 2004. To some degree, prices in 2004 and 2005 were starting to anticipate the much larger changes in 2006 and thereafter.

The dummy coefficient for 2012 is the largest year effect, consistent with corn prices hitting a maximum within our sample. The value for 2013 declined, suggesting that expected demand declined in relation to 2012. The pattern of dummy variable coefficients in our simple model gives a measure of changes in the level of demand, conditional on supply expectations, but of course does not provide guidance about possible slope changes. (It is unclear, without further analysis, whether a demand relationship can be identified for the years 2006 onward). One consequence of these demand shifts, besides possible mean and variance changes, is the potential bias in price flexibilities estimates. In a linear model, price flexibilities not only depend on the slope of the demand curve, but also on the ratio of (average) quantity over (average) price. Changes in demand structure affect these values.

Changes in price flexibility coefficients from the baseline years up to 2014 are computed from the estimates reported in Table 3. These coefficients are computed for the mean supply levels and the corresponding price levels, assuming the same slope coefficient. Naturally, these estimates would change if the slope coefficients change. The majority of the estimates are clustered around -2.0, but the values are quite unstable by year; we cannot conclude that a pattern of change exists within our sample.

Table 3. Price Flexibility Estimate for Each Demand Structure

Sample Years	Average December Futures, cents/bu. (P)	Average Supply Estimate, mill. of bu. (S)	S / P	Price Flexibility
1995-2003	246.91	10720.00	43.42	-2.04
2004	221.60	12110.00	54.65	-2.56
2005	217.80	12847.00	58.99	-2.77
2006	282.35	12911.00	45.73	-2.15
2007	362.00	14342.00	39.62	-1.86
2008	497.25	13658.00	27.47	-1.29
2009	350.15	14495.00	41.40	-1.94
2010	479.95	14536.00	30.29	-1.42
2011	682.85	13724.00	20.10	-0.94
2012	758.95	12197.00	16.07	-0.75
2013	471.00	14619.00	31.04	-1.46
2014	359.60	15449.00	42.96	-2.02

How New Information Fits into the Historical Context

Once we have established a demand relationship—or at least a price-quantity relationship—for the historical sample, it can be used to analyze new supply estimates. Specifically, a new WASDE estimate can be inserted into the model and the corresponding December futures price estimated using the model fitted to the sample including the previous year. This estimate—the model's forecast—can be compared with the future's market's quote—also a forecast. The difference is a residual that can provide the user with information. And as new WASDE supply estimates are announced, the procedure creates a set of residuals that provide information about the market's expectations relative to historical expectations.

Using model (1) fitted to data through 2013, we estimated December futures from the WASDE supply estimates of 2014, and compare the estimated future prices with the actual ones. These results are summarized in Table 4.

Table 4. Estimated Dec. 2014 Futures and Their Estimation Error with Model Fitted to 2013 Data

Month	Supply Estimate (Mil. Bu.)	December 2014 Futures (cents/bu.)	Estimated December 2014 Futures (cents/bu.)	Estimation Error (Estimated-Actual)	% Difference on Actual December 2014 Futures
July	15106	384.75	448.26	63.51	16.51%
August	15213	369	443.25	74.25	20.12%
September	15576	341	426.25	85.25	25.00%
October	15643	334	423.11	89.11	26.67%
November	15711	369.25	419.93	50.68	13.72%

The estimated (forecast) 2014 December futures prices, given 2014 supply estimates, are consistently larger than the observed market prices on the dates of release of the WASDE reports. These results suggest that the market expected demand in 2014 to be lower than in 2013. (Another interpretation is that market participants collectively expected supply to be larger than in the WASDE reports; our analysis assumes that the WASDE report on day of release is accepted as an accurate measure of expected supply). From a statistical viewpoint, one could compute a confidence interval around the model's forecast, and determine whether the market price lies outside of the interval. We believe, however, that the differences themselves, whether statistical significant or not can be informative for market analysts. It is potentially another tool to help inform judgments.

Figure 5 depicts the forecast prices and the corresponding market prices for the 2014 supply estimates. The estimated differences are suggestive of a decrease in expected demand in 2014 relative to 2013.

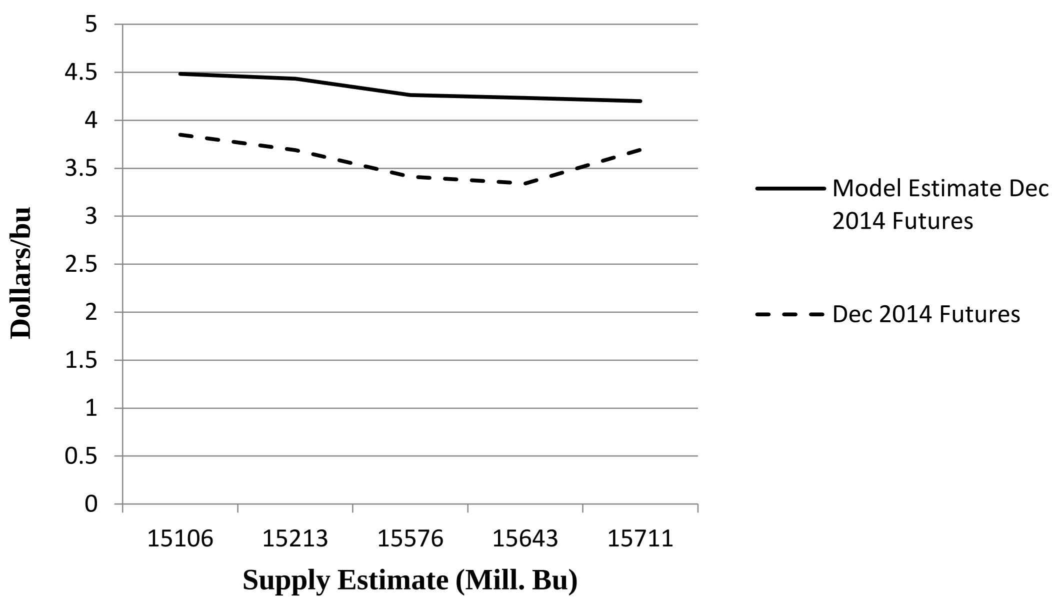

Figure 5. Dec. 2014 Futures and Their Estimated Values

The results of applying the same methodology for the years prior to the 2006 price jump are presented next. In order to establish the context for analysis, we estimate 2003 December futures prices with model (1) fitted to data through 2002. Then we look at the futures estimates of 2004, 2005, and finally 2006 using the same model fitted to data through 2003 (Tables 5, 6, 7 and 8).

Table 5. Estimated Dec. 2003 Futures and Their Estimation Error with Model Fitted to 2002 Data

Month	December 2003 Futures (cents/bu)	Supply Estimate (Mill. of bu)	Estimated December 2003 Futures (cents/bu)	Estimation Error (Estimated-Actual)	% Difference on Actual December 2003 Futures
July	233	10953	242.16	9.16	3.93%
August	229.75	11073	235.17	5.42	2.36%
September	215.25	11279	223.18	7.93	3.69%
October	216.25	11293	222.37	6.12	2.83%
November	240.25	11364	218.24	-22.01	-9.16%

The errors reported in Table 5 are not only small relative to the actual December futures (less than 9.16%), but are not consistently positive for all five months. From July to October, the difference is positive and in the range of 3%. In November, this difference becomes negative and about three times larger than the average of the percentage difference from the four previous months. These results imply that the demand function estimated for the 1994-2002 sample is applicable to 2003. These results are also consistent with the dummy coefficient values for these years from Table 1.

Once the model is fitted to 2003, the estimated 2004, 2005 and 2006 December futures price errors become significantly larger in relative terms. Table 6 shows the results of price estimates for 2004.

Table 6. Estimated Dec. 2004 Futures and Their Estimation Error with Model Fitted to 2003 Data

Month	December 2004 Futures (cents/bu)	Supply Estimate (Mill. bu)	Estimated December 2004 Futures (cents/bu)	Estimation Error (Estimated-Actual)	% Difference on Actual December 2004 Futures
July	254.25	11531	208.45	-45.80	-18.02%
August	229	11837	191.65	-37.35	-16.31%
September	222.25	11915	187.36	-34.89	-15.70%
October	202.5	12571	151.35	-51.15	-25.26%
November	200	12699	144.32	-55.68	-27.84%

The estimation errors shown in Table 6 are much larger than those in Table 5. These differences are now in a range from 15 to 27% less than the actual December 2004 futures. The consistent negative sign in these differences suggest that the market expects demand to increase relative to the base estimates. When estimating the December futures for 2005 these differences become even larger in both absolute and relative terms. The prediction of 2006 has even larger estimation errors than 2005. Table 7 shows the results for the 2005 futures estimates while Table 8 shows the results for the 2006 December futures estimate.

Table 7. Estimated Dec. 2005 Futures and Their Estimation Error with Model Fitted to 2003 Data

Month	December 2004 Futures (cents/bu)	Supply Estimate (Mill. bu)	Estimated December 2004 Futures (cents/bu)	Estimation Error (Estimated-Actual)	% Difference on Actual December 2004 Futures
July	247	12900	133.29	-113.71	-46.04%
August	231	12460	157.44	-73.56	-31.84%
September	211.5	12764	140.75	-70.75	-33.45%
October	205.75	12969	129.50	-76.25	-37.06%
November	193.75	13144	119.89	-73.86	-38.12%

The estimation error as the percentage difference from actual 2005 December futures now range from 31 to 46%. The same difference for 2006 December futures range from 48 to 59%. The magnitude of the estimation errors increase every year, the consistent negative sign suggests the demand increased every year from 2003 to 2006.

Table 8. Estimated Dec. 2006 Futures and Their Estimation Error with Model Fitted to 2003 Data

Month	December 2004 Futures (cents/bu)	Supply Estimate (Mill. bu)	Estimated December 2004 Futures (cents/bu)	Estimation Error (Estimated-Actual)	% Difference on Actual December 2004 Futures
July	284	12802	138.67	-145.33	-51.17%
August	241.75	13038	125.71	-116.04	-48.00%
September	237.75	13126	120.88	-116.87	-49.16%
October	298.25	12876	134.60	-163.65	-54.87%
November	350	12716	143.39	-206.61	-59.03%

The dynamic change of estimated demand curves is illustrated in Figure 6. This figure shows the estimated demand curves for the baseline period (1995-2003), 2006, 2010, 2013, and 2014.

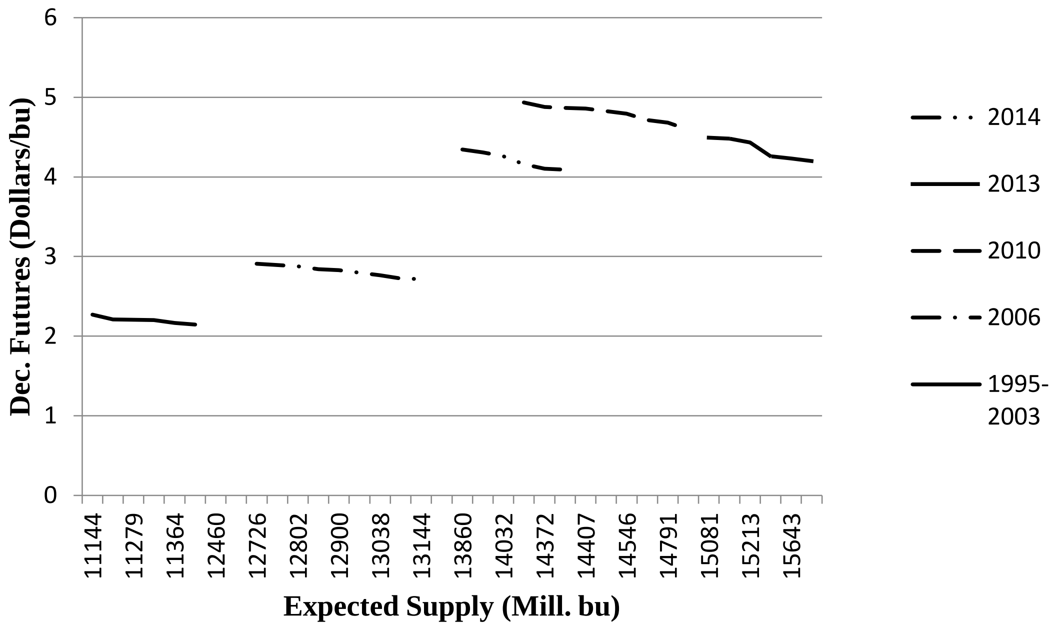

Figure 6. Estimated Demand Curves through Time

The increase in demand from the baseline period can not only be appreciated in Figure 6, but the demand curves for 2010 and 2013 seem to be part of the same curve. This observation is also suggested by the coefficients of these years from Table 1.

Confidence Interval of Futures Price Estimates

Although we believe that the figures and regression results illustrate a useful tool by themselves, it is possible to provide confidence intervals for the point forecasts of the regression model. Then, it is possible to observe whether the market's future quote falls within the confidence interval. Such analyses are and additional type of information. A simple procedure, that uses standard least squares regression software, is summarized in an appendix for those wishing to obtain both the point forecast and its standard error. We emphasize, however, that analysts should not be wedded to arbitrary levels of significance or confidence, such as whether a particular result is significant at the 5% level.

The confidence intervals for each of the monthly forecasts of December futures prices are shown in Table 9.

Table 9. Standard Error and Confidence Interval for 2014 December Futures Estimate with Model Fitted to 2013 data using Dummy Variables.

Month	December 2014 Futures (cents/bu)	Estimated December 2014 Futures (cents/bu)	Standard Error	95% Confidence Interval		P-value ($H_0 = H_a$)
July	384.75	448.26	45.61	357.49	538.95	0.168
August	369	443.25	45.66	352.39	534.04	0.108
September	341	426.25	45.91	334.91	517.52	0.067
October	334	423.11	45.96	331.66	514.50	0.056
November	369.25	419.93	46.02	328.35	511.44	0.274

In this example, all December futures prices—the settlement prices on the date of the WASDE report release—lie within the 95% confidence interval of the price forecasts. However, three months have p-values that are 0.108 or less, and the other p-values are 0.17 and 0.27. Thus, we argue that the differences between the model's forecasts and the market values are likely important; i.e., they suggest that expected demand in 2014 is lower than in 2013.

Similar analyses were done for the price increases that appear to have started in 2004 relative to 2003. These are reported in Table 10. Looking at the last column of Table 10 we see the p-values for the hypothesis test that the estimated futures price is not different than the actual futures price. All estimated futures prices are statistically different from the actual futures prices at p-values of 0.10 or less, except for the September 2004, which has a p-value of 0.132. As we estimate futures prices further in time, the p-values for the null hypothesis tests come closer to zero. However, values as early as July 2004 indicate that the demand relationship for that month does not fit into that of 2003. In other words, the analysis suggests "something" was happening as early as 2004 that is shifting the level of demand relative to expected supply. One can certainly conjecture that the market was anticipating an "ethanol effect."

Table 10. Standard Error and Confidence Interval for 2004-2006 December Futures Estimate with Model Fitted to 2003 Data using Dummy Variables.

Year, Month	December Futures (cents/bu)	Estimated December Futures (cents/bu)	Standard Error	95% Confidence Interval		P-value ($H_0 = H_a$)
2004, July	254.25	208.30	20.74	166.19	250.41	0.033
2004, August	229	191.50	22.22	146.37	236.62	0.100
2004, September	222.25	187.22	22.73	141.07	233.36	0.132
2004, October	202.5	151.19	28.45	93.45	208.94	0.079
2004, November	200	144.16	29.79	83.69	204.64	0.069
2005, July	247	133.13	32.00	68.15	198.11	0.001
2005, August	231	157.30	27.32	101.81	212.77	0.010
2005, September	211.5	140.60	30.49	78.69	202.50	0.026
2005, October	205.75	129.34	32.79	62.76	195.92	0.025
2005, November	193.75	119.73	34.84	48.99	190.46	0.040
2006, July	284	138.51	30.91	75.75	201.26	0.000
2006, August	241.75	125.55	33.59	57.35	193.75	0.001
2006, September	237.75	120.72	34.62	50.42	191.02	0.001
2006, October	298.25	134.45	31.73	70.01	198.88	0.000
2006, November	350	143.23	29.97	82.38	204.08	0.000

Conclusions and Further Analysis

This paper provides estimates of the expected demand for corn by year, assuming demand can be identified from the WASDE supply estimates and corresponding nearby futures (December) prices. We show that expected demand increased for much of the sample period from 1995 onward. A major shift relative to supply changes, appears to have started in 2004, but was especially sharp in 2006 and the years immediately thereafter. Corn production continued to grow and was larger in 2014 than in earlier years, but our model suggests that **conditional on the level of expected supply**, prices in in 2014 were 53 or more cents lower than they would have been in 2013 with the same supply.

We believe that this paper illustrates a relatively simple tool that allows price analysts, especially those doing outlook work, to evaluate futures quotes relative to historical experience. Any analyst still needs to explore potential reasons for the differences between the model's and the market's forecast, but the difference itself formalizes the issues.

Clearly additional research would be useful. This simple model can be expanded to account for slope changes across years, although it is unclear whether demand relationships are identifiable for some of the recent years. (Unfortunately, we did not have the time to explore this issue, but we will do so.) We also think that similar models using March, May and perhaps July futures can be informative about the market's estimates of the prices of storage versus those implied by the model's forecasts. Other refinements include specific hypothesis tests for changes in structure, though we believe the models have value as descriptive devices whatever the tests may show. Further, formal statistical analyses need to consider possible heteroscedasticity in the equation's error term given the likely change in structure over the sample period.

Much additional work is possible and potentially useful, but we think that simple idea illustrated in this paper is by itself useful.

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Appendix

The forecast of the futures price and its standard error can be obtained by an easy-to-use method reviewed in this appendix. The set-up is to fit the model using the sample data and adding one row of data for each forecast, e.g., just one additional row for a single forecast. The additional row sets the dependent variable to zero and includes all explanatory variables. The values of the regressors are those used to make the forecast; for a forecast for July 2014, the WASDE supply estimates for that month would be used; and the 2013 year dummy value would be set to one (all other year dummies are zero). In addition, a dummy variable (an indicator variable) is added to the model that takes the value zero for all of the sample observations and the value -1 for the last row which corresponds to the forecast period. (If more than one forecast is being made, additional indicator variables and rows would be added. In all cases, the indicator variable takes the value -1 just once and all other observations on that variable are zero). The coefficient of this dummy is the forecast level, and its standard error is the estimated standard error of forecast, that can be used to compute a confidence interval, or one can use the associated p-value as a guide to "significance" of the forecast.

As an illustration of this method, confidence intervals for 2014 December futures estimate are obtained by including a new data row (one for each forecast month) in the regression function. These new rows include the WASDE supply estimates for the respective months of 2014, the yearly dummy variables used in the original model, and a new dummy variable that takes the value of -1 for the month and year, say for July 2014, and 0 otherwise. The dependent variable (December futures prices vector) is set to zero for the forecast periods. Using this technique, the coefficients of the new dummy variables provide the forecasts of the December futures prices that are conditional on the WASDE supply estimates for the respective months, and the standard errors associated with these forecasts can be used to construct confidence intervals. In this example all of the year dummies, except 2013, are zero.

In the text, we have provided intervals for the set of forecasts for all months of 2014 (Table 9); in practice, the analyst would have one, then two, then three forecasts, etc. as the WASDE estimates evolve over the months. Also, note, in the set-up described, the forecasts for 2014 are made with the equation that uses the sample 2004 through 2013, and the forecast of expected price can be viewed as relative to 2013. That is, the forecast is made—conditioned on—with the use of the 2013 yearly dummy variables combined with the new WASDE supply estimates for 2014.

The equation is:

$$P_{m,y} = \alpha + \beta S_{m,y} + \sum_{y=2004}^{j-1} \gamma_y D_y + \delta_{m,j} F_{m,j} + \varepsilon_{m,y} \qquad (2)$$

All variables correspond to those as in model in the text, with the exception of $F_{m,j}$, which takes value -1 if the predicted month is *m* for year *j*, and 0 otherwise. Its corresponding dependent variable, $P_{m,y}$, is set to 0 and $S_{m,y}$ is the estimated supply of the forecasted future price. D_y is set to 1 if the forecasting model is fit to year i. This is usually the year prior to the forecast. For instance, when calculating the confidence interval for July 2014 based on the model for 2013 we would add a new row of data where $P_{m,y}$ is 0, $S_{m,y}$ is 15106, D_y is 1 for y = 2013 and 0 otherwise. $F_{m,j}$ is -1 and $\delta_{m,j}$ its estimated coefficient. The distribution of $\delta_{m,j}$ allows us to obtain a standard error corresponding to that of the forecasted futures price.