Quantile Regression Estimates of Confidence Intervals for WASDE Price Forecasts

by

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Abstract

This study uses quantile regressions to estimate historical forecast error distributions for WASDE forecasts of corn, soybean, and wheat prices and then compute confidence limits for the forecasts based on the empirical distributions. Quantile regressions with fit errors expressed as a function of forecast lead time are consistent with theoretical forecast variance expressions while avoiding assumptions of normality and optimality. Based on out-of-sample accuracy tests over 1995/96 through 2006/07, quantile regression methods produced intervals consistent with the target confidence level. Overall, this study demonstrates that empirical approaches may be used to construct accurate confidence intervals for WASDE corn, soybean, and wheat price forecasts.

Keywords: Commodity, Evaluating forecasts, Government forecasting, Judgemental forecasting, Prediction intervals, Price forecasting

Quantile Regression Estimates of Confidence Intervals for WASDE Price Forecasts

Price volatility causes many agricultural firms to rely on forecasts in decision-making. Consequently, the U.S. Department of Agriculture (USDA) devotes substantial resources to agricultural situation and outlook programs. A prominent example of USDA forecasting efforts is the WASDE (World Agricultural Supply and Demand Estimates) program, which provides monthly forecasts for major crops, both for the U.S. and the world. WASDE price forecasts (unlike all other WASDE estimates) are published in the form of an interval. Interval forecasts, in contrast to point estimates, represent a range of values in which the realized value of the series is expected to fall with some pre-specified probability (Diebold ,1998, p. 41). WASDE price forecasts are generated using a balance sheet approach, with published intervals reflecting uncertainty associated with prices in the future (Vogel and Bange, 1999). For example, the October 2007 WASDE forecast of the 2007/08 marketing year average farm price was \$2.90-\$3.50/bushel for corn, \$7.85-\$8.85/bushel for soybeans and \$5.80-\$6.40/bushel for wheat. However, the confidence level associated with the published interval is not revealed. One of the challenges in calculating the forecast intervals and specifying an associated confidence level is the fact that these are consensus forecasts, and therefore, cannot be described by a formal statistical model.[1]

Bayesian learning models emphasize the important role that precision of information plays in market participants' interpretation and reaction to information releases (e.g., Kandel and Pearson, 1995; Hautsch and Hess, 2007). This is consistent with repeated calls in the agricultural economics literature for increased use of interval and probability forecasting (e.g., Timm, 1966; Teigen and Bell, 1978; Bessler and Kling, 1989). However, application and analysis of interval and probability forecasts has received relatively little attention. Sanders and Manfredo (2003) examined one-quarter ahead WASDE interval forecasts of livestock prices from 1982 through 2002 and found hit rates (the proportion of time the interval contains the subsequent actual price) ranging from 48% for broilers to only 35% for hogs. Isengildina, Irwin, and Good (2004) showed that monthly WASDE interval forecasts of corn and soybean prices during the 1980/81 through 2001/02 marketing years also had relatively low hit rates, ranging from 36% to 82% for corn and from 59% to 89% for soybeans depending on the forecast month. In addition, actual prices were more likely to be above the forecast intervals, suggesting that observed symmetric USDA forecast intervals did not reflect the true asymmetry in the distribution of underlying prices. The authors also argued that specific confidence levels should accompany forecast intervals in order to minimize confusion and misunderstanding in forecast interpretation.

While numerous procedures have been proposed to calculate confidence limits generated by statistical forecasting models (e.g., Chatfield, 1993, Prescott and Stengos, 1987; Bessler and Kling, 1989), these procedures provide little guidance for forecasts based on a combination or a consensus process rather than formal models, as is the case with WASDE forecasts. In reviewing the prediction interval literature, Chatfield (1993) observes that, when theoretical formulae are not available or there are doubts about model assumptions, the use of empirically-based methods should be considered as a general purpose alternative. Chatfield also notes that the empirical method, "…is attractive in principle, however, it seems to have been little used in practice, presumably because of the heavy computational demands (p. 127)." He suggests that since computational demands have become much less of a burden, this method should be re-examined.

Empirical methods are based on the notion that confidence limits for future forecasts may be estimated by evaluating historical forecast errors. An empirical method was first applied to construction of confidence limits for economic forecasts by Williams and Goodman (1971). Their approach consisted of splitting the data in two parts and fitting the method or model to the first part in order to find forecast errors. The model was then refitted each year adding an additional observation in the first part and increasing the part of the sample used to estimate forecast errors. The key assumption of this method is that future forecast errors belong to approximately the same distribution as past forecast errors.[2] Williams and Goodman (1971) argued that this assumption is less restrictive than the standard assumption that a forecasting model describes the series adequately in the future. Therefore, by accumulating forecast errors through time one can obtain an empirical distribution of forecast errors and determine confidence limits for future forecasts by using the percentage points of the empirical distribution generated from past errors. The benefit of this method is that it can be applied in a straightforward manner to any type of error distribution, including fat-tailed and/or asymmetric distributions.

Empirical methods of constructing forecast confidence intervals have been used successfully in a variety of fields (e.g., Murphy and Winkler, 1977; Stoto, 1983; Keilman, 1990; Zarnowitz, 1992; Shlyakhter et al., 1994; Jorgensen and Sjoberg, 2003). One of the main limitations of empirical methods is the heavy data requirement. That is, a reasonably large sample of forecasts is needed to reliably estimate confidence intervals. Therefore, empirical methods have been most widely-used in areas where data limitations are less common, such as weather, population, and software development forecasting.

Taylor and Bunn (1999a, 1999b) suggested a new approach to empirical interval estimation that addresses the small sample problem by pooling data across time and forecasting horizons and estimating forecast error distributions via quantile regression. The authors develop forecast error quantile models that are functions of lead time, *k*, as suggested by theoretically derived variance expressions. The use of quantile regression avoids the normality and optimality assumptions underlying theoretical forecast variance expressions. Another benefit of this approach is that it relaxes the assumption that error distributions for each forecasting month are independent, since forecast errors tend to decline from the beginning to the end of the forecasting cycle as more information becomes available.

The purpose of this paper is to investigate the use of quantile regression for estimation of empirical confidence limits for WASDE forecasts of corn, soybean, and wheat prices. WASDE price interval forecasts for corn, soybean, and wheat during the period from 1980/81 to 2006/07 are included in the analysis. Within each marketing year, 19 monthly forecasts of average marketing year farm price are available for corn and soybeans, and 17 for wheat. In the first part of the analysis, descriptive statistics for published WASDE interval forecasts are presented and discussed. In the second part of the analysis, quantile regression models are estimated and evaluated for the entire sample period. Model specifications include forecast horizon and stock/use ratios as independent variables. In the third part of the analysis, out-of-sample performance of empirical confidence intervals is evaluated, where the first 15 observations (1980/81-1994/95) are used to generate confidence limits for the 16th year (1995/96); the first 16 observations are used to generate confidence limits for the 17th year (1996/97) and so on. Statistical significance of the differences of hit rates from a target confidence level is assessed using an unconditional coverage test developed by Christoffersen (1998). The results of this research will provide valuable information that can be used to accurately estimate confidence limits for WASDE price interval forecasts.

Data and Descriptive Analysis

Corn, soybean, and wheat interval price forecasts in WASDE reports are released monthly by the USDA, usually between the 9th and 12th of the month. The first price forecast for a marketing year is released in May preceding the U.S. marketing year (September through August for corn and soybeans and June through May for wheat). Estimates are typically finalized by September (for wheat), and November (for corn and soybeans) of the following marketing year. Thus, 18 forecast updates of marketing year average corn and soybean prices and 16 forecast updates of marketing year average wheat prices are generated in the WASDE forecasting cycle. While the forecasts are published in the form of an interval, the probability with which the realized price is expected to fall within the forecast interval is not specified.

Descriptive statistics for WASDE interval price forecasts for corn, soybeans, and wheat over the 1980/81 through 2006/07 marketing years are presented in Tables 1-3.[3] During the study period, the first (May prior to harvest) forecast intervals averaged $0.39/bushel for corn, $1.27/bushel for soybeans, and $0.46/bushel for wheat. In relative terms, May forecast intervals for wheat were the narrowest representing about 14% of the average forecast price, compared to 17% for corn and 22% for soybeans.[4] By November after harvest these average intervals narrowed to $0.36/bushel for corn, $0.90/bushel for soybeans, and $0.25/bushel for wheat. The relative magnitude of post-harvest wheat forecast intervals was about half the size of corn and soybean price intervals, with a November average of 7% and 15%, respectively. These forecast intervals usually collapsed to point estimates in May after harvest for wheat and soybeans and in August after harvest for corn. No trends in the magnitude of interval forecasts over time were detected. Thus, intervals in the same months did not become smaller (or larger) from the beginning to the end of the sample period.

Interval forecast accuracy is typically described in terms of the hit rate; i.e., the proportion of time the forecast interval included the final value. Tables 1-3 indicate that hit rates for individual months ranged from 30 to 85 percent for corn, 26 to 81 percent for soybeans, and 37 to 89 percent for wheat. Prior to harvest, hit rates for corn and wheat price forecast intervals were lower, both averaging 46 percent, compared to 67 percent for soybeans. This implies that, on average, corn and wheat price interval forecasts prior to harvest contained the final price estimate only 46 percent of the time. After harvest, the hit rates for all commodities increased, averaging 71 percent for corn, 65 percent for soybeans, and 67 percent for wheat price interval forecasts. All three commodities demonstrated some very low hit rates late in the forecasting cycle. For example, hit rates for corn price interval forecasts averaged 44 and 48 percent in August and September after harvest; soybean hit rates averaged 26, 41, and 48 percent from May through July after harvest, and wheat hit rates averaged 41 and 37 percent in May and June after harvest. This loss in accuracy late in the forecasting cycle is associated with prematurely collapsing forecast intervals to point estimates.

Another issue is whether forecast intervals accurately reflect the shape of the underlying price distribution. Statistics on the proportion of misses above and below the forecast interval reported in Tables 1-3 provide insight on this issue. If the forecast intervals accurately reflected the shape of the underlying price distribution, one would expect equal probability of misses above and below the forecast interval. Table 2 demonstrates that for soybean price forecast intervals the proportion of misses above the interval was 2 times greater than the proportion of misses below the interval prior to harvest and 2.9 times greater after harvest. Furthermore, the magnitude of misses in soybean forecast intervals tended to be much greater on the upside then the downside, averaging $0.71/bushel and $0.28/bushel, respectively, prior to harvest and

$0.17/bushel and $0.10/bushel, respectively, after harvest. The other two commodities do not exhibit such persistent tendencies.

An important basic assumption of the empirical approach to estimating confidence limits is that the distribution of forecast errors remains stable over time. The validity of this assumption for corn, soybean and wheat price forecast errors is tested by dividing the sample in two parts, from 1980/81 through 1994/95 and from 1995/96 through 2006/07 and examining whether the first two moments of forecast error distributions differed between two sub-periods. Analysis was conducted for both unit errors, calculated as the difference between the final (November for corn and soybeans and September for wheat) estimate and the midpoint of the forecast interval, and percentage errors, calculated as the difference between the final (November for corn and soybeans and September for wheat) estimate and the midpoint of the forecast interval divided by the midpoint of the forecast interval.

Based on independent sample t-tests (not shown) there is no consistent evidence of statistically significant differences in the means of errors and percentage errors of price forecasts between the two sub-periods (except July through September after harvest in corn). Test results based on Levene's F-statistic (not shown) indicated no statistically significant difference in the variances of errors and percentage errors for each forecasting month between the two sub-periods (except September after harvest in corn and May and June prior to harvest in wheat). This evidence suggests that forecast error distributions of monthly WASDE corn, soybean, and wheat price forecasts were generally stable over time. Even though in most cases results were consistent across both types of errors, percentage errors typically demonstrated smaller differences between the two sub-periods. The use of percentage errors may be preferred to unit errors when price levels change (as they did for all three commodities after 2006). In this case, intervals based on unit errors will be understated relative to intervals based on percentage errors. Therefore, the remainder of this paper uses percentage errors to calculate empirical forecast intervals.

Quantile Regression Models

Quantile regression was developed by Koenker and Bassett (1978) as an extension of the linear model for estimating rates of change in not just the mean but all parts of the distribution of a response variable. Consider the simple case of the constant only model $y_t = \beta_0 + e_t$, where β_0 is a constant parameter and e_t is an *i.i.d*. random error term. Koenker and Basset note that the τ^{th} quantile of y_t can be derived from a sample of observations, as the solution $\beta_0(\tau)$ to the following minimization problem: $\min \beta_0 \left[\sum_{t|y_t \geq \beta_0} \tau |y_t - \beta_0| + \sum_{t|y_t < \beta_0} (1-\tau)|y_t - \beta_0| \right]$. This minimization problem, as a means for finding the τ^{th} sample quantile, readily extends for the more general case where y_t is a linear function of explanatory variables (X). The estimates are semi-parametric in the sense that no parametric distributional form is assumed for the random part of the model, although a parametric form is assumed for the deterministic part of the model. The conditional quantiles denoted by $Q_y(\tau|X)$ are the inverse of the conditional cumulative distribution function of the response variable, $F_y^{-1}(\tau|X)$, where $\tau \in [0,1]$ denotes the quantiles (Koenker and Machado, 1999). As an example, for $\tau = 0.90$, $Q_y(0.90|X)$ is the 90th percentile of the distribution of y conditional on the values of X. An approximation of the full probability distribution can be produced from the quantile estimates corresponding to a range of values of τ ($0< \tau<1$). For symmetric distributions, the 0.50 quantile (or median) is equal to the mean μ.

Taylor and Bunn (1999a, 1999b) suggested the use of quantile regressions for generating prediction intervals of forecasts based on exponential smoothing. The authors show that quantile regressions with fit errors expressed as a function of forecast lead time are consistent with theoretical forecast variance formulas. In the present context, quantile regression models based on this approach can be specified for a given commodity as follows:

$$(1) \qquad Q_{tk}(\tau) = \beta_0 + \beta_1 k_t + \beta_2 k_t^2 + \varepsilon_{tk}$$

where $Q_{tk}(\tau)$ is the τ^{th} conditional quantile of the distribution of WASDE forecast errors in marketing year *t* and forecast month *k* and *k* is indexed from 1 to 16 for corn and soybeans and 1 to 14 for wheat (see Tables 1-3).[5] Both heteroskedasticity and autocorrelation are likely to be estimation issues. Heteroskedasticity is likely present since the variance of forecast errors will undoubtedly be higher earlier in the forecasting cycle rather than later. Autocorrelation is present due to the overlapping nature of forecast horizons for a given marketing year. Five covariance estimators were considered to test the sensitivity of estimation results to alternative assumptions about the error distributions: Huber sandwich (valid for independent but non-identical errors), residual bootstrap, XY-pair bootstrap (valid when errors and explanatory variables are not independent), Markov chain marginal bootstrap, and modified Markov chain marginal bootstrap (robust to heteroskedasticity). While there was little difference in the quantile estimation results across the covariance estimators, we present results using the XY-pair bootstrap with 100 replications as it was the most conservative method (largest standard errors for hypothesis testing). [6]

Another benefit of the quantile regression approach is that other factors that impact forecast error distributions may be included in the analysis. Economic theory indicates that the size of the forecast error in each marketing year may be related to the “tightness” of underlying supply and demand conditions. These supply and demand conditions are often summarized by the stocks/use ratio (e.g., Westcott and Hoffman, 1999). For example, historical stocks/use ratio estimates during the period of study for corn ranged from 5% in 1995 to 66% in 1985. It is reasonable to hypothesize that forecast errors are larger during periods of low stocks/use ratios and vice versa.[7] The expanded quantile regression model is specified as follows,

(2) $$Q_{tk}(\tau) = \beta_0 + \beta_1 k_t + \beta_2 k_t^2 + SU_{tk} + \varepsilon_{tk}$$

where SU_{tk} is the WASDE stocks/use estimate for marketing year *t* and forecast month *k*.

Detailed estimation results are presented only for particular quantiles in order to conserve space.[8] As noted earlier, confidence levels associated with WASDE interval price forecasts are not published. Isengildina, Irwin, and Good (2004) conducted a survey of USDA analysts involved in compiling WASDE corn and soybean price interval forecasts to determine confidence levels associated with the forecasts. Analyst responses were variable across respondents (by as much as 30% in the beginning of the season) and over the forecasting cycle (from 65% in May prior to harvest to 95% in April after harvest). The average confidence level prior to harvest was 81% for corn and 78% for soybeans; the average confidence level after harvest was 91% for corn and 87% for soybeans. Based on this information, and assuming that wheat analysts provide interval forecasts for similar confidence levels, $\tau = 0.10$ and $\tau = 0.90$ quantiles are estimated prior to harvest and $\tau = 0.05$ and $\tau = 0.95$ quantiles after harvest. These quantile estimates are then used to generate upper and lower bounds of 80% and 90% confidence intervals pre- and post- harvest, respectively, for each commodity. All quantile regressions were estimated using *Eviews 6.0* econometric software.

In-Sample Results

Table 4 presents quantile regression estimation results for models based only on forecast month for corn, soybeans and wheat over the 1980/81 through 2006/07 marketing years. The quantile regression approach offers the benefit of pooling data across months and years, and thus substantially increasing the statistical power of the empirical approach to forecast interval estimation. Specifically, quantile regressions estimated over the 1980/81 through 2006/07 marketing years use 459 observations for corn and soybeans, and 378 observations for wheat, while standard empirical methods would use only 27 observations (one per marketing year) to estimate distributions of forecast errors. Note that all but two of the estimated coefficients (k^2 for 0.95 quantile in corn and soybeans) are significant at conventional levels. The constants for different quantiles describe the shape of the forecast error distribution by indicating the distance from the forecast midpoint to the respective quantile, thus the sign is negative for $\tau < 0.5$ and positive for $\tau > 0.5$. The coefficient on the forecast month k describes an inverse relationship between forecast month and forecast error, i.e. forecast errors become smaller as more information becomes available over the forecasting cycle (k becomes larger), thus the sign is positive for $\tau < 0.5$ and negative for $\tau > 0.5$. The coefficient on k^2 describes the nonlinearity in the relationship between forecast error and forecast month k. The negative sign of k^2 coefficient for $\tau < 0.5$ and positive for $\tau > 0.5$ indicates that forecast errors are decreasing at an increasing rate as forecast month k increases. This pattern is illustrated in Figure 1 which shows forecast errors for all forecast months over 1980/81 through 2006/07 marketing years as well as quantile regression estimates for the 0.10 and 0.90 quantiles based on the same data. Figure 1 demonstrates how forecast errors become smaller over the forecasting cycle in a non-linear fashion and the ability of the quantile regression to capture this pattern in its estimated coefficients.

The interpretation of the pseudo R-squared is similar to the interpretation of the traditional R-squared. Results in Table 4 indicate that using only forecast month as an explanatory variable explains from 25% to 34% percent of the variation in forecast errors at the identified quantiles in corn and soybeans and from 33% to 49% of the variation in wheat. Quasi-likelihood ratio statistics indicate that the explanatory power of all estimated models is statistically significant.

Figures 2-4 present estimated coefficients and 95% confidence bounds for regression model (1) across the full range of quantiles $(\tau \in [0,1])$. These figures demonstrate the different impact of the quantile regression variables on various quantiles of the forecast error distribution. Thus, we observe the positive relationship with the constant and k^2 and the negative relationship with k. The impact of k and k^2 is different for all quantiles except for the upper quantiles in corn and wheat, where the 0.80 and the 0.90 quantiles are affected in about the same way. The fact that the magnitude of the coefficients on k and k^2 is greater for the tails and zero for the median indicates changes in the variability but not the expected value of the error as the forecasts move through the forecasting cycle. This may be tested formally by comparing estimated slopes at different points of the error distributions. Wald tests (Koenker and Bassett, 1982) at the 0.05, 0.10, 0.90, and 0.95 quantile levels reject the null hypothesis of slope equality, and thus conditional quantiles are not identical.

Figures 2-4 also suggest that the right tail of the error distributions appears slightly longer than the left, which was also noted in the data section. This observation is consistent with theory as spot prices of storable commodities are expected to have skewed distributions with a long tail toward high prices (Williams and Wright, 1991, p. 105). Asymmetry in forecast error distributions reflects the inability of symmetric intervals published by USDA to reflect the asymmetric distribution of the underlying commodity prices. Conditional symmetry across quantiles is formally tested using a test suggested by Newey and Powell (1987). The test computes a Wald statistic of whether the two sets of coefficients for symmetric quantiles around the median will equal the value of the coefficients at the median. The null hypothesis for this test is that the distribution is symmetric. The results of the symmetry tests across $\tau = 0.05, 0.95$ and $\tau=0.10, 0.90$ significant evidence of asymmetry in quantiles for corn, soybean, and wheat forecast errors. Asymmetry is most prevalent in wheat forecast errors and less prevalent in corn forecast errors. Thus, empirical confidence intervals calculated using quantile regression approach should be able to reflect the asymmetry of the underlying commodity prices.

The in-sample results for the expanded quantile regression models that include the stocks-to-use ratio (equation 2) are presented in table 5. Overall, the results for the expanded quantile regression (equation 2) in table 5 are similar to the results for quantile regression (equation 1) in table 4 because the estimated coefficient on the stocks-to-use ratio is statistically different from zero in only a few cases: upper quantiles ($\tau = 0.95$, $\tau = 0.90$) for corn and lower quantiles ($\tau = 0.05$, $\tau = 0.10$) for soybeans. As discussed in the methods section, an inverse relationship is expected between forecast error and the stocks-to-use ratio. This inverse relationship would result in a positive coefficient estimate for $\tau < 0.5$ and a negative coefficient for $\tau > 0.5$. Our results are consistent with these expectations in soybeans but not in corn. The value of the coefficient of 0.14 for $\tau = 0.05$ in soybeans suggests that if the stocks-to-use ratio increases by 1%, the 5th percentile will become 0.14 percentage points closer to the forecast midpoint, and vice versa. In general the results in table 5 indicate that stocks-to-use ratios contribute relatively little to explaining changes in corn, soybean and wheat price forecast error distributions.

Out-of-Sample Results

Results presented in the previous section suggest that quantile regression is a useful tool for generating empirical confidence intervals for WASDE corn, soybean and wheat price forecasts. In order to rigorously assess the potential of the quantile regression approach to improve upon published WASDE price forecasts, out-of-sample performance is evaluated, where the first 15 observations (1980/81-1994/ 95) were used to generate confidence limits for the 16th year (1995/96); the first 16 observations were used to generate confidence limits for the 17th year (1996/97) and so on. The target confidence level prior to harvest is 80% and after harvest is 90%. For example, the out-of-sample confidence intervals for 2007/08 forecasts can be constructed using the estimates based on the 1980/81-2006/07 marketing years presented in table 4. The 80% confidence limits for May prior to harvest (k = 1) corn price forecasts are -0.267+0.030*1-0.001*1^2 = -0.24 (for τ = 0.10), and is 0.236-0.025*1+0.001*1^2 = 0.21 (for τ = 0.90). This result means that 24% of the forecast midpoint should be subtracted and 21% of the midpoint should be added to the midpoint to construct an 80% confidence interval. For a $3.40/bu. average price, the estimated interval would be $2.59 - $4.12/bu. Forecast intervals based on quantile regression with stocks/use ratios are calculated in a similar manner and include the coefficient and the value of stocks/use estimates released in respective months.

Hit rates describe the proportion of times forecast intervals contain the final or "true" value (y_t) and may be defined as an indicator variable, I_t^k ,

(4) $$I_t^k = \begin{cases} 1, & \text{if } \; y_t \in \left[l_{t/k}(\alpha), u_{t/k}(\alpha) \right] \\ 0, & \text{if } \; y_t \notin \left[l_{t/k}(\alpha), u_{t/k}(\alpha) \right] \end{cases}$$

where $\left[l_{t/k}(\alpha), u_{t/k}(\alpha) \right]$ are the lower and upper limits of the interval forecast for y_t made at time k with confidence level α. The closer the hit rate to the stated confidence level, the more accurate is the forecast. Forecast coverage is based on the expectation of the indicator variable, I_t^k and examines whether the proportion of times the forecast interval includes the true value is equal to the target (stated) confidence level. Thus, forecast coverage may be examined by testing the hypothesis H_0: $E(I_t^k)=\alpha$ against H_1: $E(I_t^k)\neq\alpha$. If H_0 is not rejected and the interval hit rate is equal to the stated confidence level, forecasts are said to be calibrated. Since the indicator variable I_t^k has a binomial distribution (Christoffersen, 1998), the likelihood function under the null hypothesis is,

(5) $$L(\alpha) = (1-\alpha)^{n_0} \alpha^{n_1} .$$

where L is a likelihood function. Under the alternative hypothesis, the likelihood function is,

(6) $$L(p) = (1-p)^{n_0} p^{n_1}$$

where n_1 and n_0 are the number of times an interval was "hit" (1) or "missed" (0) in the indicator sequence I_t^k. Then, forecast coverage may be tested via the likelihood ratio test,

(7) $$LR_c = -2\ln\left(\frac{L(\alpha)}{L(\hat{p})}\right) \xrightarrow{asy} \chi^2(1)$$

where $\hat{p} = n_1/(n_0+n_1)$ is the maximum likelihood estimator of p. This test is described by Christoffersen (1998) as an unconditional coverage test.[9]

Results of the accuracy tests for out-of-sample forecast intervals computed using quantile regression are shown in Tables 6-8. As was observed in Tables 1-3 for the entire sample, published forecasts had relatively low hit rates in the prediction sub-sample, 1995/96-2006/07, although significant improvement in forecast accuracy was observed in corn price forecast intervals after harvest. The hit rates for published intervals averaged 53% for corn, 67% for soybeans, and 44% for wheat prior to harvest. Empirical confidence intervals had much higher hit rates averaging 75%-78% for corn, 80%-82% for soybeans and 53%-56% for wheat prior to harvest. These hit rates were statistically different from the target confidence level of 80% in 4 out of 30 cases, or about 13% of the time. For comparison, published intervals' hit rates were statistically different from the assumed target level in 9 out of 15 cases, or 60% of the time.

After harvest the hit rates for published intervals averaged 79% for corn, 56% for soybeans, and 71% for wheat. After harvest hit rates for empirical confidence intervals averaged 83% - 92% for corn, 83% - 84%% for soybeans, and 92% for wheat. These hit rates were statistically different from the target level of 90% in 6 out of 66 cases, or about 9% of the time. Published confidence intervals' hit rates were statistically different from the assumed target level in 12 out of 33 cases, or 40% of the time.

The accuracy of empirical confidence intervals did not differ much between those generated with quantile regression (equation 1) and quantile regression with stocks-to-use ratios (equation 2). It appears that the introduction of the stocks-to-use ratios did not improve the accuracy of the forecast intervals in any of the three commodities included in this analysis. This finding is consistent with a lack of statistical significance of the stocks-to-use coefficient estimates. Table 6 shows that confidence intervals generated with quantile regressions with stocks-to-use ratios in corn were actually less accurate than those generated with quantile regressions without stocks-to-use ratios. This result is likely due to the fact that the estimated coefficient on the stocks-to-use variable in corn had a sign which was not consistent with expectations. These findings demonstrate that one should be careful about adding additional variables in quantile regressions used for confidence interval estimation. Overall, these results demonstrate a dramatic improvement in accuracy for empirical confidence intervals relative to published intervals.

Summary and Conclusions

A prominent example of USDA forecasting efforts is the WASDE (World Agricultural Supply and Demand Estimates) program, which provides monthly forecasts for major crops, both for the U.S. and the world. WASDE price forecasts (unlike all other WASDE estimates) are published in the form of an interval. WASDE price forecasts (unlike all other WASDE estimates) are published in the form of an interval to reflect uncertainty associated with prices in the future. However, the confidence level associated with the published interval is not revealed. One of the challenges in calculating WASDE price forecast intervals and specifying an associated confidence level is the fact that these are consensus forecasts that cannot be described by a formal statistical model. Such forecasts cannot use the confidence interval formulas derived for statistical models, but may instead rely on empirically-based methods.

The basic empirical method was first introduced by Williams and Goodman (1971), and is based on the notion that by accumulating forecast errors through time one can obtain an empirical distribution of forecast errors. One of the main limitations of the empirical method is the heavy data requirement for forecast error distribution estimation. Recently, this limitation has become less of an issue as Taylor and Bunn (1999a, 1999b) suggested a new approach to empirical interval estimation that addresses the small sample problem by pooling data across time and forecasting horizons and estimating forecast error distributions. The authors then develop forecast error quantile models that are functions of lead time, *k*, as suggested by theoretically derived variance expressions. This paper explores the use of quantile regression for estimation of empirical confidence limits for WASDE forecasts of corn, soybean, and wheat prices.

Following Taylor and Bunn, quantile regressions for corn, soybean, and wheat forecast errors over 1980/81 through 2006/07 were specified as a function of forecast lead time measured as the forecast month from the beginning to the end of the forecasting cycle. The estimated coefficients indicate the distance from the forecast midpoint to a particular point of error distribution. One of the benefits of quantile regression approach is that other factors that impact forecast error distribution may be included in analysis. This study hypothesized that during the periods of low stocks/use ratios, which reflect the underlying supply and demand conditions, forecast errors may be larger than during the periods of high stocks/use ratios. However, very little impact of stocks/use variable on the forecast error distributions was found.

The quantile regression approach to calculating forecast intervals was evaluated based on out-of-sample performance, where the first 15 observations (1980/81-1994/ 95) were used to generate confidence limits for the 16th year (1995/96); the first 16 observations were used to generate confidence limits for the 17th year (1996/97) and so on. Empirical confidence intervals averaged 75%-78% for corn, 80%-82% for soybeans and 53%-56% for wheat prior to harvest. These hit rates were statistically different from the target confidence level of 80% in 4 out of 30 cases, or about 13% of the time. After harvest hit rates for empirical confidence intervals averaged 83% - 92% for corn, 83% - 84%% for soybeans, and 92% for wheat. These hit rates were statistically different from the target level of 90% in 6 out of 66 cases, or about 9% of the time. Overall, these results demonstrate a dramatic improvement in accuracy for empirical confidence intervals relative to published intervals.

Overall, this study demonstrates how quantile regression may be used to construct empirical confidence intervals for WASDE corn, soybean, and wheat price forecasts. The findings suggest that empirical confidence intervals calculated using quantile regressions may significantly improve the accuracy of WASDE corn, soybean, and wheat price forecasts. The results of this study may be extended to calculation of confidence intervals for price forecasts associated with other WASDE commodities. Furthermore, quantile regression approach to calculating empirical confidence intervals discussed in this study may be used to generate confidence intervals for non-price WASDE categories, such as export forecasts, that are not currently published in interval form.

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Table 1. Descriptive and Accuracy Statistics for WASDE Corn Price Interval Forecasts, 1980/81-2006/07 Marketing Years.

k =Month of Forecasting Cycle	Mean Forecast Price ($/bu.)	Average Interval ($/bu.)	Minimum Interval ($/bu.)	Maximum Interval ($/bu.)	Hit Rate (%)	Misses Below (%)	Misses Above (%)	Avg. Miss Below ($/bu.)	Avg. Miss Above ($/bu.)
Prior to harvest									
1 (May)	2.29	0.39	0.20	0.60	37	19	44	0.27	0.24
2 (June)	2.31	0.39	0.20	0.60	30	26	44	0.23	0.22
3 (July)	2.35	0.39	0.20	0.50	44	22	33	0.26	0.19
4 (August)	2.39	0.38	0.20	0.50	56	26	19	0.15	0.22
5 (September)	2.39	0.37	0.20	0.50	56	26	19	0.14	0.23
6 (October)	2.38	0.37	0.20	0.40	56	22	22	0.11	0.13
Average	2.35	0.38	0.20	0.52	46	23	30	0.19	0.21
After harvest									
7 (November)	2.38	0.36	0.20	0.40	74	11	15	0.18	0.13
8 (December)	2.37	0.34	0.20	0.40	81	7	11	0.15	0.14
9 (January)	2.38	0.30	0.15	0.40	85	7	7	0.10	0.20
10 (February)	2.38	0.25	0.15	0.40	81	7	11	0.10	0.10
11 (March)	2.38	0.20	0.10	0.40	74	11	15	0.05	0.06
12 (April)	2.39	0.14	0.00	0.30	74	11	15	0.04	0.06
13 (May)	2.39	0.10	0.00	0.25	70	19	11	0.06	0.05
14 (June)	2.38	0.07	0.00	0.20	70	19	11	0.05	0.05
15 (July)	2.38	0.04	0.00	0.10	74	19	7	0.04	0.06
16 (August)	2.38	0.01	0.00	0.10	44	30	26	0.03	0.03
17 (September)	2.38	0.00	0.00	0.10	48	30	22	0.02	0.02
Average	2.38	0.17	0.07	0.28	71	15	14	0.07	0.08

Note: Mean forecast price is calculated by averaging the midpoints of forecast intervals. Hit rate is the proportion of times the interval contained the final (September) estimate. Misses above and below describe cases when the final estimate fell above or below the forecast interval. N=27

Table 2. Descriptive and Accuracy Statistics for WASDE Soybean Price Interval Forecasts, 1980/81-2006/07 Marketing Years.

k =Month of Forecasting Cycle	Mean Forecast Price ($/bu.)	Average Interval ($/bu.)	Minimum Interval ($/bu.)	Maximum Interval ($/bu.)	Hit Rate (%)	Misses Below (%)	Misses Above (%)	Avg. Miss Below ($/bu.)	Avg. Miss Above ($/bu.)
Prior to harvest									
1 (May)	5.72	1.27	0.40	2.50	52	19	30	0.31	0.71
2 (June)	5.73	1.22	0.40	2.50	56	15	30	0.36	0.71
3 (July)	5.77	1.19	0.30	2.50	67	7	26	0.29	0.70
4 (August)	5.89	1.19	0.30	2.50	81	4	15	0.05	0.91
5 (September)	5.96	1.07	0.30	2.50	78	7	15	0.39	0.79
6 (October)	5.93	0.97	0.30	2.50	70	11	19	0.30	0.44
Average	5.83	1.15	0.33	2.50	67	10	22	0.28	0.71
After harvest									
7 (November)	5.93	0.90	0.30	2.50	70	11	19	0.35	0.39
8 (December)	5.94	0.79	0.30	2.50	81	7	11	0.15	0.42
9 (January)	5.92	0.68	0.20	1.25	78	4	19	0.10	0.20
10 (February)	5.91	0.59	0.15	1.25	81	0	19	0.00	0.19
11 (March)	5.89	0.44	0.15	1.00	81	0	19	0.00	0.17
12 (April)	5.91	0.26	0.00	0.50	78	4	19	0.06	0.14
13 (May)	5.93	0.00	0.00	0.00	26	22	52	0.11	0.09
14 (June)	5.94	0.00	0.00	0.00	41	15	44	0.14	0.08
15 (July)	5.95	0.00	0.00	0.00	48	15	37	0.09	0.06
16 (August)	5.63	0.00	0.00	0.00	63	15	22	0.05	0.04
17 (September)	5.95	0.00	0.00	0.00	67	11	22	0.01	0.03
Average	5.90	0.33	0.10	0.82	65	9	26	0.10	0.17

Note: Mean forecast price is calculated by averaging the midpoints of forecast intervals. Hit rate is the proportion of times the interval contained the final (September) estimate. Misses above and below describe cases when the final estimate fell above or below the forecast interval. N=27

Table 3. Descriptive and Accuracy Statistics for WASDE Wheat Price Interval Forecasts, 1980/81-2006/07 Marketing Years.

k =Month of Forecasting Cycle	Mean Forecast Price ($/bu.)	Average Interval ($/bu.)	Minimum Interval ($/bu.)	Maximum Interval ($/bu.)	Hit Rate (%)	Misses Below (%)	Misses Above (%)	Avg. Miss Below ($/bu.)	Avg. Miss Above ($/bu.)
Prior to harvest									
1 (May)	3.31	0.46	0.20	0.70	41	33	26	0.19	0.40
2 (June)	3.32	0.46	0.20	0.70	37	37	26	0.15	0.32
3 (July)	3.28	0.44	0.20	0.60	59	22	19	0.07	0.33
Average	3.30	0.45	0.20	0.67	46	31	23	0.14	0.35
After harvest									
4 (August)	3.30	0.43	0.20	0.60	67	15	19	0.07	0.19
5 (September)	3.30	0.36	0.20	0.60	74	7	19	0.09	0.15
6 (October)	3.33	0.31	0.15	0.60	78	7	15	0.12	0.12
7 (November)	3.34	0.25	0.10	0.40	67	15	19	0.10	0.06
8 (December)	3.34	0.21	0.10	0.30	70	15	15	0.06	0.05
9 (January)	3.34	0.17	0.10	0.30	70	15	15	0.04	0.03
10 (February)	3.34	0.12	0.10	0.20	70	15	15	0.03	0.03
11 (March)	3.33	0.10	0.00	0.20	78	7	15	0.04	0.03
12 (April)	3.33	0.07	0.00	0.20	67	11	22	0.03	0.03
13 (May)	3.34	0.00	0.00	0.05	41	33	26	0.03	0.03
14 (June)	3.34	0.00	0.00	0.00	37	37	26	0.03	0.03
Average	3.33	0.18	0.09	0.31	65	16	19	0.06	0.07

Note: Mean forecast price is calculated by averaging the midpoints of forecast intervals. Hit rate is the proportion of times the interval contained the final (September) estimate. Misses above and below describe cases when the final estimate fell above or below the forecast interval. N=27

Table 4. Quantile Regression Estimation Results for Corn, Soybeans, and Wheat WASDE Price Forecast Errors, Forecast Month Only, 1980/81-2006/07 Marketing Years.

	Quantile			
Commodity/Estimate	0.05	0.10	0.90	0.95
Corn				
Constant	-0.318 ***	-0.267 ***	0.236 ***	0.249 ***
k	0.035 ***	0.030 ***	-0.025 ***	-0.019 ***
k^2	-0.001 ***	-0.001 ***	0.001 ***	0.000
Pseudo R-squared	0.357	0.260	0.285	0.300
Quasi-LR statistic	329.735 ***	238.440 ***	257.263 ***	183.603 ***
Soybeans				
Constant	-0.307 ***	-0.204 ***	0.225 ***	0.290 ***
k	0.036 ***	0.023 ***	-0.022 ***	-0.025 ***
k^2	-0.001 ***	-0.001 ***	0.001 ***	0.000
Pseudo R-squared	0.302	0.235	0.275	0.316
Quasi-LR statistic	253.164 ***	236.240 ***	266.222 ***	225.015 ***
Wheat				
Constant	-0.218 ***	-0.174 ***	0.226 ***	0.248 ***
k	0.032 ***	0.025 ***	-0.033 ***	-0.036 ***
k^2	-0.001 ***	-0.001 ***	0.001 ***	0.001 ***
Pseudo R-squared	0.420	0.316	0.318	0.438
Quasi-LR statistic	327.255 ***	248.856 ***	229.637 ***	331.868 ***

Note: *k* is month of the forecasting cycle. Number of observations is 459 for corn and soybeans, and 378 for wheat. One asterisk indicates significance at 10% level, two asterisks indicate significance at 5% level, and three asterisks indicate significance at 1% level.

Table 5. Quantile Regression Estimation Results for Corn, Soybeans, and Wheat WASDE Price Forecast Error, Forecast Month and Stocks-to-Use Ratio, 1980/81-2006/07 Marketing Years.

	Quantile			
Commodity/Estimate	0.05	0.10	0.90	0.95
Corn				
Constant	-0.318 ***	-0.267 ***	0.206 ***	0.249 ***
k	0.035 ***	0.031 ***	-0.025 ***	-0.028 ***
k^2	-0.001 ***	-0.001 ***	0.001 ***	0.001 ***
Stocks-to-Use	0.001	-0.013	0.131 **	0.142 ***
Pseudo R-squared	0.357	0.260	0.308	0.352
Quasi-LR statistic	327.978 ***	237.578 ***	233.797 ***	231.510 ***
Soybeans				
Constant	-0.325 ***	-0.224 ***	0.225 ***	0.297 ***
k	0.038 ***	0.025 ***	-0.022 ***	-0.026 **
k^2	-0.001 ***	-0.001 ***	0.001 ***	0.001
Stocks-to-Use	0.140 ***	0.111 ***	-0.015	0.006
Pseudo R-squared	0.321	0.249	0.275	0.316
Quasi-LR statistic	279.345 ***	259.245 ***	263.186 ***	225.154 ***
Wheat				
Constant	-0.229 ***	-0.191 ***	0.224 ***	0.262 ***
k	0.033 ***	0.026 ***	-0.035 ***	-0.040 ***
k^2	-0.001 ***	-0.001 ***	0.001 ***	0.002 ***
Stocks-to-Use	0.037	0.046	0.011	0.015
Pseudo R-squared	0.431	0.331	0.319	0.441
Quasi-LR statistic	328.201 ***	246.255 ***	237.039 ***	330.615 ***

Note: k is month of the forecasting cycle. Stocks-to-use is the WASDE estimate of stocks divided by total use. Number of observations is 459 for corn and soybeans, and 378 for wheat. One asterisk indicates significance at 10% level, two asterisks indicate significance at 5% level, and three asterisks indicate significance at 1% level.

Table 6. Out-of-Sample Accuracy Statistics for Empirical Confidence Intervals for WASDE Corn Price Forecasts, 1995/96-2006/07 Marketing Years.

Month of the Forecasting Cycle	Published Intervals		Quantile Regression Intervals		Quantile Regression with Stocks/Use Intervals	
	Hit Rate (%)	Unconditional Coverage Test	Hit Rate (%)	Unconditional Coverage Test	Hit Rate (%)	Unconditional Coverage Test
Prior to harvest						
1 (May)	42	8.46 ***	75	0.18	75	0.18
2 (June)	33	12.26 ***	75	0.18	75	0.18
3 (July)	50	5.36 **	83	0.09	67	1.17
4 (August)	58	2.92 *	75	0.18	75	0.18
5 (September)	67	1.17	75	0.18	75	0.18
6 (October)	58	2.92 *	83	0.09	75	0.18
Average	51		78		75	
After harvest						
7 (November)	92	0.04	92	0.04	83	0.50
8 (December)	92	0.04	100	n/a	83	0.50
9 (January)	100	n/a	100	n/a	100	n/a
10 (February)	92	0.04	100	n/a	92	0.04
11 (March)	92	0.04	100	n/a	92	0.04
12 (April)	67	4.83 **	83	0.50	75	2.22
13 (May)	75	2.22	92	0.04	75	2.22
14 (June)	75	2.22	83	0.50	67	4.83 **
15 (July)	83	0.50	83	0.50	75	2.22
16 (August)	42	16.99 ***	92	0.04	75	2.22
17 (September)	58	8.20 ***	100	n/a	92	0.04
Average	79		93		83	

Note: Empirical price forecast intervals were calculated using percentage errors from the 1980/81 marketing year forward. Target confidence level is 80% prior to harvest and 90% after harvest. One asterisk indicates significance at 10% level, two asterisks indicate significance at 5% level, three asterisks indicate significance at 1% level.

Table 7. Out-of-Sample Accuracy Statistics for Empirical Confidence Intervals for WASDE Soybean Price Forecasts, 1995/96-2006/07 Marketing Years.

Month of the Forecasting Cycle	Published Intervals		Quantile Regression Intervals		Quantile Regression with Stocks/Use Intervals	
	Hit Rate (%)	Unconditional Coverage Test	Hit Rate (%)	Unconditional Coverage Test	Hit Rate (%)	Unconditional Coverage Test
Prior to harvest						
1 (May)	58	2.92 *	75	0.18	75	0.18
2 (June)	67	1.17	75	0.18	75	0.18
3 (July)	67	1.17	75	0.18	75	0.18
4 (August)	75	0.18	75	0.18	75	0.18
5 (September)	67	1.17	75	0.18	75	0.18
6 (October)	58	2.92 *	75	0.18	75	0.18
Average	65		75		75	
After harvest						
7 (November)	67	4.83 **	83	0.50	83	0.50
8 (December)	75	2.22	92	0.04	75	2.22
9 (January)	75	2.22	92	0.04	75	2.22
10 (February)	83	0.50	92	0.04	92	0.04
11 (March)	83	0.50	92	0.04	92	0.04
12 (April)	83	0.50	83	0.50	83	0.50
13 (May)	17	35.66 ***	92	0.04	92	0.04
14 (June)	25	28.58 ***	92	0.04	92	0.04
15 (July)	25	28.58 ***	75	2.22	83	0.50
16 (August)	42	16.99 ***	67	4.83 **	92	0.04
17 (September)	42	16.99 ***	75	2.22	58	8.20 ***
Average	56		85		83	

Note: Empirical price forecast intervals were calculated using percentage errors from the 1980/81 marketing year forward. Target confidence level is 80% prior to harvest and 90% after harvest. One asterisk indicates significance at 10% level, two asterisks indicate significance at 5% level, three asterisks indicate significance at 1% level.

Table 8. Out-of-Sample Accuracy Statistics for Empirical Confidence Intervals for WASDE Wheat Price Forecasts, 1995/96-2006/07 Marketing Years.

Month of the Forecasting Cycle	Published Intervals		Quantile Regression Intervals		Quantile Regression with Stocks/Use Intervals	
	Hit Rate (%)	Unconditional Coverage Test	Hit Rate (%)	Unconditional Coverage Test	Hit Rate (%)	Unconditional Coverage Test
Prior to harvest						
1 (May)	33	12.26 ***	50	5.36 **	50	5.36 **
2 (June)	33	12.26 ***	50	5.36 **	42	8.46 ***
3 (July)	67	1.17	75	0.18	75	0.18
Average	44		58		56	
After harvest						
4 (August)	75	2.22	92	0.04	92	0.04
5 (September)	83	0.50	92	0.04	92	0.04
6 (October)	92	0.04	100	n/a	100	n/a
7 (November)	75	2.22	92	0.04	92	0.04
8 (December)	75	2.22	83	0.50	83	0.50
9 (January)	75	2.22	100	n/a	92	0.04
10 (February)	75	2.22	92	0.04	92	0.04
11 (March)	83	0.50	92	0.04	92	0.04
12 (April)	67	4.83 **	92	0.04	92	0.04
13 (May)	42	16.99 ***	100	n/a	100	n/a
14 (June)	42	16.99 ***	100	n/a	100	n/a
Average	71		94		93	

Note: Empirical price forecast intervals were calculated using percentage errors from the 1980/81 marketing year forward. Target confidence level is 80% prior to harvest and 90% after harvest. One asterisk indicates significance at 10% level, two asterisks indicate significance at 5% level, three asterisks indicate significance at 1% level.

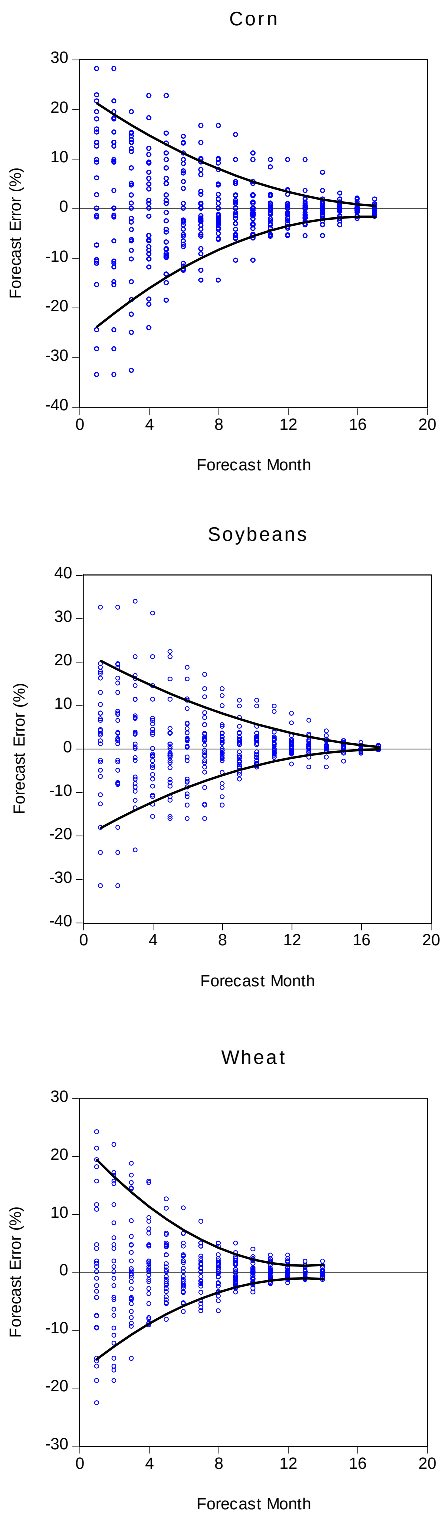

Figure 1. Errors by Forecast Month and Estimated 0.10 and 0.90 Quantiles for WASDE Corn, Soybean, and Wheat Price Forecasts, 1980/81-2006/07 Marketing Years

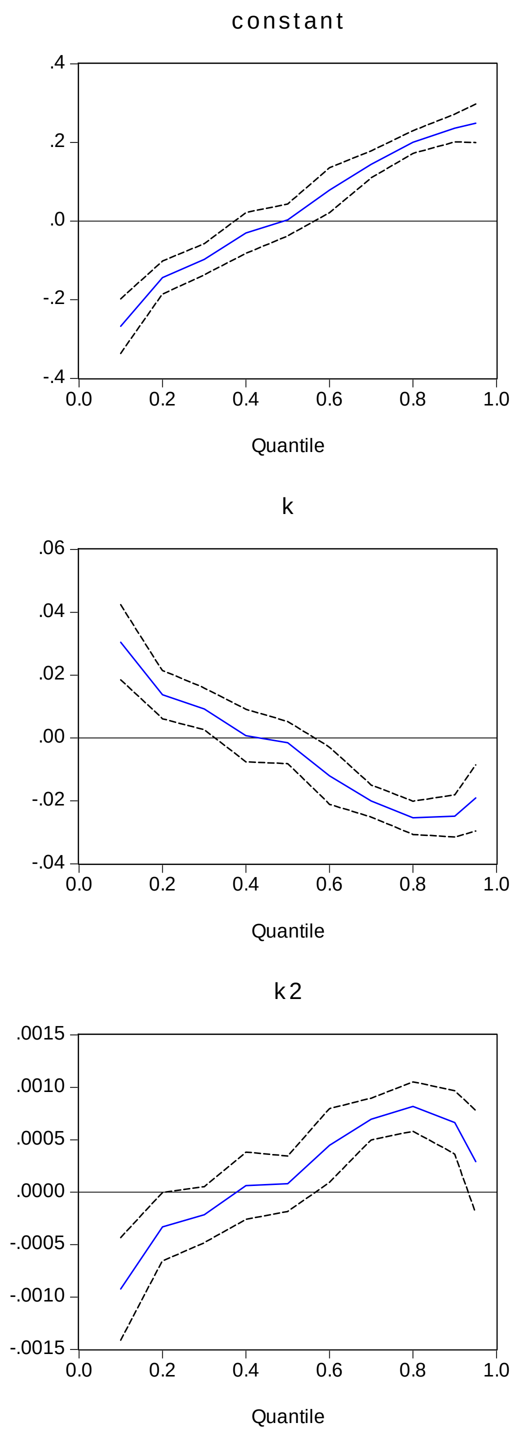

Figure 2. Quantile Regression Coefficient Estimates and 95% Confidence Bounds for WASDE Corn Price Forecast Errors, 1980/81-2006/07 Marketing Years

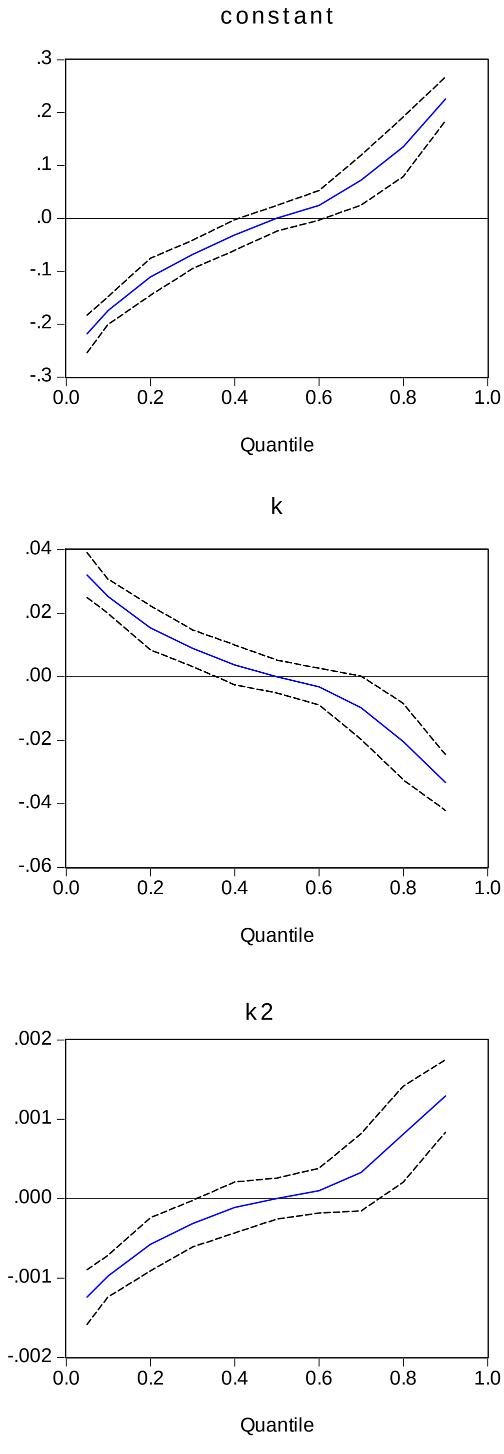

Figure 3. Quantile Regression Coefficient Estimates and 95% Confidence Bounds for WASDE Soybean Price Forecast Errors, 1980/81-2006/07 Marketing Years

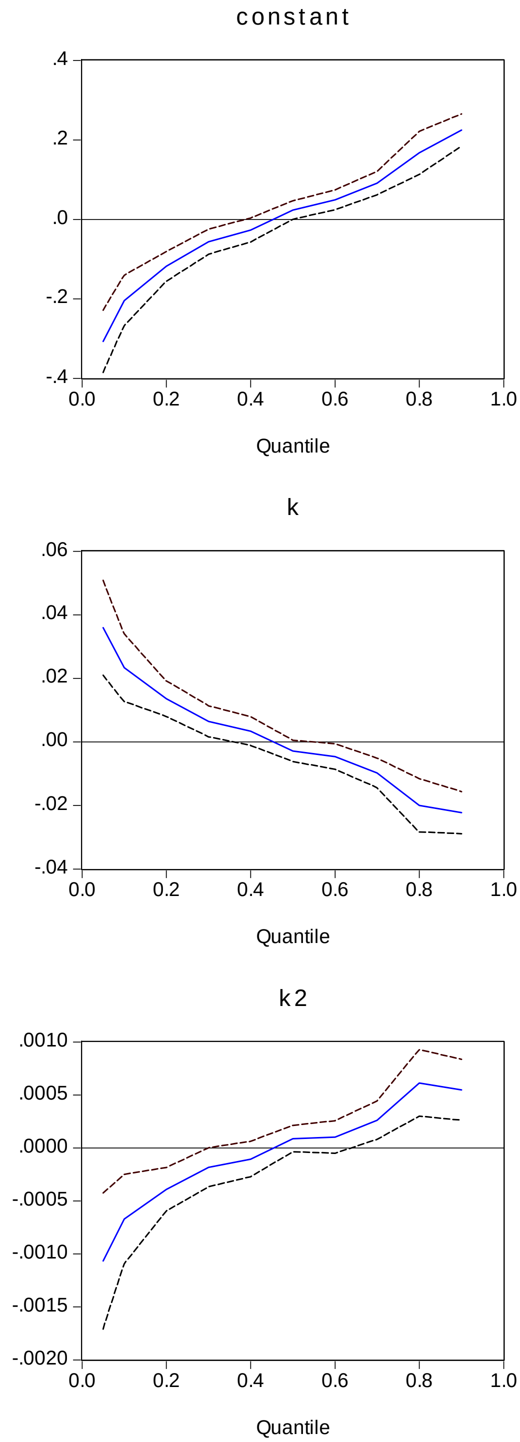

Figure 4. Quantile Regression Coefficient Estimates and 95% Confidence Bounds for WASDE Wheat Price Forecast Errors, 1980/81-2006/07 Marketing Years

Endnotes

[1] According to Vogel and Bange (1999), "The process of forecasting price and balance sheet items is a complex one involving the interaction of expert judgment, commodity models, and in-depth research by Department analysts on key domestic and international issues" (p. 10).

[2] It is worth noting that most theoretical variance expressions are based on the same assumption.

[3] Tables 1-2 present descriptive statistics for 17 monthly forecasts of corn and soybean prices and Table 3 presents descriptive statistics for 14 monthly forecasts of wheat prices because the last "forecast" provides the final estimate for each commodity.

[4] Isengildina, Irwin, and Good (2004) provide survey evidence that WASDE price intervals are symmetric. That is, a midpoint is forecast and then an equal interval is added to each side of the midpoint. Therefore, the average forecast price is computed in this study by taking an average of the midpoint of forecast prices for each month.

[5] The last several months (17 and 18 for corn and soybeans and 15 and 16 for wheat) were not included in the analysis because the errors were usually zero, so the distributions were impossible to estimate.

[6] Note that only quantile regression parameter estimates are used for computing empirical confidence intervals, thus unbiasedness of estimated coefficients is the most important assumption for this approach. Koenker (2005, p74) argues that parameter estimates of the quantile regression are unbiased even in cases when the IID assumption is not satisfied. Therefore, the potential impact of heteroskedasticity and autocorrelation in the errors will likely be limited to efficiency issues for hypothesis testing.

[7] Other model specifications were also explored. The price level and a measure of volatility, calculated as an absolute value of percentage difference of the forecasted price from the average

of the previous five years' prices, were considered. However, these alternative specifications failed to improve model performance. The results for the additional alternative specifications are not presented here but are available from the authors upon request.

[8] The complete set of quantile estimation results is available from the authors upon request.

[9] Christoffersen (1998) also proposed additional tests that examine interval forecast independence and forecast coverage conditional on independence. However, due to a small number of observations, these tests cannot be applied reliably to the prediction part of the sample (1995/96-2004/05).