Quantile Regression Methods of Estimating Confidence Intervals for WASDE Price Forecasts

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Introduction

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 cannot be described by a formal statistical model. 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).

The need for probability and interval forecasting has been repeatedly expressed in the agricultural economics literature (e.g., Timm, 1966; Teigen and Bell, 1978; Bessler and Kling, 1989; Bessler, 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. They find that actual market prices fall in the forecasted ranges a relatively small proportion of the time, about 48% of the time for broilers and only 35% of the time 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 (the proportion of time the interval contains the subsequent actual price) 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 further argue 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 for forecasts generated by statistical 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.[1] 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. The importance of empirical control of a model's probability assessments has been also recognized in engineering applications (e.g., Mahadevan, 2006).

Taylor and Bunn (1999a, 1999b) suggested a new approach to empirical interval estimation that overcomes 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 forecast updates are available for corn and soybeans, and 15 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. Models 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 more accurately estimate confidence limits for WASDE price interval forecasts.

Data

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 August (for wheat), October (for corn) and November (for soybeans) of the following marketing year. Thus, 19 forecast updates of soybean, 18 forecast updates of corn and 16 forecast updates of wheat prices are generated in the WASDE forecasting cycle each marketing year. 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.[2] 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.[3] 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 demonstrate 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 empirical approaches to estimating confidence limits is that the distribution of forecast errors remains stable over time. Previous studies (e.g., Stoto, 1983; Smith and Sincich, 1988) have evaluated this assumption and found that the distribution of population forecast errors remained relatively stable over time and data on past forecast errors provided very useful predictions of future forecast errors. In the present study 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. Results of this analysis are presented in Tables 4-6. 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. Independent sample t-tests showed no statistically significant difference at the 1% level in mean forecast errors for each forecasting month between the two sub-periods (except July and August after harvest in corn, and May and June prior to harvest in wheat). Levene's F-statistic showed no statistically significant difference in forecast error variances at the 1% level for each forecasting month between the two sub-periods (except 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 of the cases results were consistent across both types of errors, percentage errors demonstrate smaller differences between two sub-periods. The use of percentage errors may be preferred to unit errors when mean 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.

The evidence presented in this section describes several major concerns regarding WASDE interval forecasts of corn, soybeans, and wheat prices: 1) these intervals are characterized by relatively low hit rates; 2) in soybeans, symmetric forecast intervals do not accurately reflect the shape of the underlying price distribution; and 3) confidence levels associated with these forecast intervals are not specified. The remainder of this paper applies quantile regression to calculation of empirical confidence limits for WASDE price 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 τ=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 where fit errors Q_t are expressed as a function of forecast lead time k are consistent with theoretical forecast variance formulas. Assuming lead time k corresponds to the forecast error series for k-step ahead forecasts, the following quantile regression for a given level of τ is specified:

(1) $$Q_t(\tau) = \beta_0 + \beta_1 k + \beta_2 k^2 + \varepsilon_t .$$

In the present application, k is substituted for its reverse, *FM,* the forecast month from the beginning to the end of the forecast cycle (1 through 16 for corn and soybeans and 1 through 14 for wheat, as shown in Tables 1-3),[4]

$$Q_t(\tau) = \beta_0 + \beta_1 FM + \beta_2 FM^2 + \varepsilon_t \,. \qquad (2)$$

Additionally, while Taylor and Bunn rely on fit errors as a proxy for post sample errors; our study uses observed forecast errors as the dependent variable in quantile regressions. Following Taylor and Bunn, standard errors were estimated by bootstrap resampling in order to correct for heteroscedasticity. Bootstrap resampling used the *XY*-pair method with 100 replications and samples the same size as the original data.

Calculation of empirical confidence intervals using quantile regression requires specification of target confidence levels (τ). As mentioned in the data section, confidence levels associated with published WASDE interval price forecasts are not specified. Isengildina, Irwin, and Good (2004) conducted a survey of USDA officials involved in compiling WASDE corn and soybean price interval forecasts inquiring about the confidence levels associated with published 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, the present study uses an 80% confidence level prior to harvest and a 90% confidence level after harvest. Equation (2), was used to generate upper (τ=0.90) and lower (τ=0.10) bounds of the 80% confidence interval and upper (τ=0.95) and lower (τ=0.05) bounds of the 90% confidence interval pre- and post- harvest, respectively, for each commodity. All quantile regressions were estimated using *Eviews* econometric software.

In-Sample Results

Table 7 presents quantile regression results for τ=0.05, 0.10, 0.90, and 0.95 for corn, soybeans and wheat over 1980/81 through 2006/07 marketing years. Estimated coefficients indicate the distance from the forecast midpoint to a particular point of the error distribution. For example, the construction of an 80% confidence interval will include calculation of τ=0.10 and τ=0.90. Thus, its value in May prior to harvest (FM=1) for corn for τ=0.10 is -0.212+0.020*1+0*1^2 = -0.19, and for τ=0.90 is 0.274-0.029*1+0.001*1^2 = 0.25. This result means that 19% of the forecast midpoint should be subtracted and 25% 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 $2.75 - $4.25/bu.

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. Specifically, quantile regressions estimated over the 1980/81 through 2006/07 marketing years uses 513 for corn observations, while standard empirical methods would use only 27 observations (one per marketing year and forecast horizon) to estimate distributions of forecast errors. The interpretation of the pseudo R-squared is similar to the interpretation of the traditional R-squared. Results indicate that using only forecast month as an explanatory variable explains from 29% to 38% percent of the variation in identified quantiles of corn forecast errors, from 27% to 37% of the variation in identified quantiles of soybean forecast errors, and from 37% to 53% of the variation in identified quantiles of wheat forecast errors.

One of the benefits of quantile regression approach is that other factors that impact forecast error distribution 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 in 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 may be hypothesized that during the periods of low stocks/use ratios, forecast errors may be larger than during the periods of high stocks/use ratios. This hypothesis is tested using an omitted variable test, which examines whether the additional variable makes a significant contribution to explaining the variation in the dependent variable. The null hypothesis of the omitted variable test is that the additional regressor is not significant. This test is performed by computing a QLR test of the null hypothesis (Koenker and Machado, 1999). The results of the omitted variable tests presented in table 8 demonstrate that the stocks/use ratio makes a significant contribution to explaining the variation in forecast error only for the upper quantiles in corn and the lower quantiles in soybeans and the lowest quantile in wheat.

Figures 1-3 show the estimated coefficients and their 95% confidence bounds for corn, soybean and wheat forecast errors, respectively. These figures indicate that stocks/use ratios have a very limited impact on the shape of the forecast error distributions. The fact that the coefficients on FM and FM^2 differ across different quantiles demonstrates that the tails of the error distributions are changing faster than their center as we move through the forecasting cycle. This argument may be tested formally by comparing estimated slopes at different points of distribution. Koenker and Bassett (1982) proposed to use the Wald test to analyze slope equality. Results of the slope equality tests presented in table 8 indicate that the slope coefficients differ across quantiles, thus conditional quantiles are not identical and quantile regression provides estimates superior to estimation procedures that assume that forecast errors are i.i.d.

Figures 1-3 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 highly skewed distributions with a long tail toward high prices (Williams and Wright, 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 Newey and Powell (1987) test:

$$\frac{\beta(\tau)+\beta(1-\tau)}{2}=\beta(1/2) \tag{3}$$

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 τ=0.05,0.95 and τ=0.10, 0.90 presented in table 8 demonstrate significant evidence of asymmetry in soybean and wheat forecast errors, but not 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.

Out-of-Sample Results

Results presented in the previous section indicate that quantile regression is a potentially powerful tool for generating empirical confidence intervals for WASDE corn, soybean and wheat price forecasts. The use of quantile regression may help resolve the problems currently associated with WASDE corn, soybean and wheat price forecasts, namely, low hit rates, inability to reflect asymmetry of underlying price distributions, and unspecified confidence levels. In order to 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%. The accuracy of the out of sample performance is evaluated using hit rates and an unconditional coverage test described below.

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,

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

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.[5]

Results of the accuracy tests for out-of-sample forecast intervals computed using quantile regression are shown in tables 9-11. 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 through 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. Overall, these results demonstrate a dramatic improvement in accuracy for empirical confidence intervals relative to published intervals.

Conclusions

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. Several major concerns regarding WASDE forecast intervals of corn, soybeans, and wheat prices include: 1) forecast intervals have relatively low hit rates; 2) forecast intervals do not necessarily reflect the shape of the underlying price distribution; and 3) confidence levels associated with these forecast intervals are not specified. One of the challenges in calculating WASDE price forecast intervals and specifying an associated confidence level is the fact that these are consensus forecasts and 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 overcomes 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 tests of the equality of slopes on the estimated coefficients demonstrated that slope coefficients differed across quantiles. This finding reflects the fact that the tails of the error distributions are changing faster than centers moving through the forecasting cycle. This study also tested symmetry in error distributions and found that soybean and wheat forecast error distributions were asymmetric with long right tails. This finding is consistent with theory as spot prices of storable commodities are expected to have highly skewed distributions with a long tail toward high prices (Williams and Wright, p. 105). Thus, empirical confidence intervals calculated using quantile regression approach should be able to reflect the asymmetry of the underlying commodity prices

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.

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 (November) estimate. Misses above and below describe cases when the final estimate fell above or below the forecast interval.

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

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 (November) estimate. Misses above and below describe cases when the final estimate fell above or below the forecast interval.

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

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 (November) estimate. Misses above and below describe cases when the final estimate fell above or below the forecast interval.

Table 4. Comparison of the First Two Moments of Unit and Percentage Error Distributions for WASDE Corn Price Interval Forecasts, 1980/81-1994/95, and 1995/96-2006/07 Marketing Years.

	Unit Errors ($/bu)						Percentage Errors (%)					
Month of the Forecasting Cycle	1980/81-1994/95 Mean	1995/96-2005/06 Mean	*t*-test	1980/81-1994/95 Variance	1995/96-2005/06 Variance	Levene's *F*-statistic	1980/81-1994/95 Mean	1995/96-2005/06 Mean	*t*-test	1980/81-1994/95 Variance	1995/96-2005/06 Variance	Levene's *F*-statistic
Prior to harvest												
1 (May)	0.08	0.09	-0.05	0.15	0.16	0.02	0.05	0.05	0.02	0.03	0.03	0.11
2 (June)	0.08	0.04	0.28	0.15	0.15	0.07	0.05	0.02	0.38	0.03	0.02	0.36
3 (July)	-0.02	0.07	-0.67	0.12	0.11	0.08	0.00	0.04	-0.70	0.02	0.02	0.02
4 (August)	-0.03	0.00	-0.26	0.05	0.14	2.32	-0.01	0.01	-0.35	0.01	0.02	3.07 *
5 (September)	-0.04	0.01	-0.49	0.05	0.11	1.15	-0.01	0.01	-0.39	0.01	0.02	1.59
6 (October)	-0.04	0.03	-0.69	0.04	0.06	0.30	-0.01	0.01	-0.54	0.01	0.01	0.28
After harvest												
7 (November)	-0.03	0.03	-0.83	0.05	0.02	1.99	0.00	0.02	-0.54	0.01	0.00	1.00
8 (December)	-0.02	0.03	-0.79	0.04	0.01	0.81	0.00	0.02	-0.57	0.01	0.00	0.45
9 (January)	-0.01	-0.01	-0.07	0.03	0.01	1.38	0.00	0.00	0.14	0.00	0.00	1.22
10 (February)	-0.01	-0.01	0.05	0.02	0.01	0.83	0.00	0.00	0.25	0.00	0.00	0.71
11 (March)	0.00	-0.02	0.46	0.01	0.01	0.41	0.00	-0.01	0.69	0.00	0.00	0.61
12 (April)	-0.01	-0.03	0.71	0.01	0.00	0.18	0.00	-0.01	0.95	0.00	0.00	0.08
13 (May)	-0.01	-0.02	0.35	0.00	0.00	0.00	0.00	-0.01	0.50	0.00	0.00	0.00
14 (June)	-0.01	-0.01	0.18	0.00	0.00	0.00	0.00	0.00	0.35	0.00	0.00	0.00
15 (July)	-0.02	0.01	-2.07 **	0.00	0.00	0.27	-0.01	0.00	-1.99 *	0.00	0.00	0.02
16 (August)	-0.01	0.01	-2.31 **	0.00	0.00	0.48	0.00	0.00	-2.47 **	0.00	0.00	0.13

Note: Forecast error is calculated as the unit or percentage difference between the final (November) estimate and the midpoint of the forecast interval. One asterisk indicates significance at 10% level, two asterisks indicate significance at 5% level, three asterisks indicate significance at 1% level.

Table 5. Comparison of the First Two Moments of Unit and Percentage Error Distributions for WASDE Soybean Price Interval Forecasts, 1980/81-1994/95, and 1995/96-2006/07 Marketing Years.

	Unit Errors ($/bu)						Percentage Errors (%)					
Month of the Forecasting Cycle	1980/81-1994/95 Mean	1995/96-2005/06 Mean	*t*-test	1980/81-1994/95 Variance	1995/96-2005/06 Variance	Levene's *F*-statistic	1980/81-1994/95 Mean	1995/96-2005/06 Mean	*t*-test	1980/81-1994/95 Variance	1995/96-2005/06 Variance	Levene's *F*-statistic
Prior to harvest												
1 (May)	-0.01	0.53	-1.55	0.92	0.61	0.77	0.01	0.10	-1.66	0.02	0.02	0.03
2 (June)	0.00	0.50	-1.47	0.92	0.58	0.59	0.01	0.10	-1.55	0.02	0.02	0.01
3 (July)	-0.04	0.46	-1.67	0.58	0.62	0.02	0.00	0.09	-1.66	0.02	0.03	0.17
4 (August)	-0.10	0.27	-1.42	0.34	0.60	0.63	-0.01	0.05	-1.24	0.01	0.02	0.99
5 (September)	-0.20	0.22	-1.75 *	0.38	0.38	0.03	-0.02	0.04	-1.35	0.01	0.01	0.43
6 (October)	-0.12	0.20	-1.52	0.38	0.21	0.77	-0.01	0.03	-1.10	0.01	0.01	0.11
After harvest												
7 (November)	-0.10	0.18	-1.45	0.33	0.16	0.62	0.00	0.03	-1.08	0.01	0.01	0.16
8 (December)	-0.07	0.12	-1.21	0.18	0.14	0.03	0.00	0.02	-0.92	0.00	0.00	0.13
9 (January)	-0.01	0.08	-0.83	0.07	0.09	0.12	0.00	0.01	-0.60	0.00	0.00	0.40
10 (February)	0.01	0.09	-0.81	0.05	0.06	0.02	0.01	0.01	-0.61	0.00	0.00	0.13
11 (March)	0.05	0.08	-0.43	0.03	0.03	0.01	0.01	0.01	-0.28	0.00	0.00	0.02
12 (April)	0.05	0.04	0.31	0.02	0.02	0.34	0.01	0.01	0.22	0.00	0.00	0.27
13 (May)	0.03	0.02	0.38	0.01	0.01	0.08	0.01	0.00	0.19	0.00	0.00	0.15
14 (June)	0.02	0.01	0.31	0.01	0.01	0.09	0.00	0.00	0.06	0.00	0.00	0.16
15 (July)	0.01	0.00	0.72	0.00	0.01	1.63	0.00	0.00	0.44	0.00	0.00	1.70
16 (August)	0.01	-0.01	1.77 *	0.00	0.00	1.43	0.00	0.00	1.56	0.00	0.00	1.36

Note: Forecast error is calculated as the unit or percentage difference between the final (November) estimate and the midpoint of the forecast interval. One asterisk indicates significance at 10% level, two asterisks indicate significance at 5% level, three asterisks indicate significance at 1% level.

Table 6. Comparison of the First Two Moments of Unit and Percentage Error Distributions for WASDE Wheat Price Interval Forecasts, 1980/81-1994/95, and 1995/96-2006/07 Marketing Years.

	Unit Errors ($/bu)						Percentage Errors (%)					
Month of the Forecasting Cycle	1980/81-1994/95 Mean	1995/96-2005/06 Mean	*t* -test	1980/81-1994/95 Variance	1995/96-2005/06 Variance	Levene's *F* -statistic	1980/81-1994/95 Mean	1995/96-2005/06 Mean	*t* -test	1980/81-1994/95 Variance	1995/96-2005/06 Variance	Levene's *F* -statistic
Prior to harvest												
1 (May)	0.02	0.03	-0.06	0.11	0.34	5.18 **	0.01	0.02	-0.10	0.01	0.03	4.60 **
2 (June)	0.00	0.03	-0.15	0.10	0.26	4.13 *	0.01	0.01	-0.11	0.01	0.02	3.61 *
3 (July)	0.01	0.12	-0.94	0.07	0.12	2.69	0.01	0.04	-0.72	0.01	0.01	1.72
After harvest												
4 (August)	0.03	0.05	-0.18	0.05	0.08	0.14	0.02	0.01	0.08	0.01	0.01	0.00
5 (September)	0.02	0.05	-0.38	0.03	0.04	0.11	0.01	0.01	-0.04	0.00	0.00	0.00
6 (October)	0.01	0.00	0.08	0.02	0.02	0.06	0.01	0.00	0.36	0.00	0.00	0.41
7 (November)	0.01	-0.01	0.36	0.02	0.01	0.26	0.01	0.00	0.67	0.00	0.00	0.74
8 (December)	0.00	-0.01	0.46	0.01	0.01	0.29	0.00	0.00	0.79	0.00	0.00	0.17
9 (January)	-0.01	-0.01	-0.05	0.01	0.00	0.33	0.00	0.00	0.37	0.00	0.00	0.59
10 (February)	-0.01	-0.01	-0.06	0.00	0.00	0.55	0.00	0.00	0.39	0.00	0.00	0.70
11 (March)	0.01	0.00	0.66	0.00	0.00	0.07	0.00	0.00	1.03	0.00	0.00	0.33
12 (April)	0.01	-0.01	1.51	0.00	0.00	0.27	0.01	0.00	1.89	0.00	0.00	1.05
13 (May)	0.00	0.00	0.44	0.00	0.00	0.46	0.00	0.00	0.72	0.00	0.00	1.23
14 (June)	0.00	0.00	0.41	0.00	0.00	0.50	0.00	0.00	0.67	0.00	0.00	1.28

Note: Forecast error is calculated as the unit or percentage difference between the final (November) estimate and the midpoint of the forecast interval. One asterisk indicates significance at 10% level, two asterisks indicate significance at 5% level, three asterisks indicate significance at 1% level.

Table 7. Quantile Regression Results for Corn, Soybeans, and Wheat, 1980/81-2006/07 Marketing Years.

	Quantiles			
	5th	10th	90th	95th
Panel A: Corn				
Constant	-0.243	-0.212	0.274	0.326
	(-13.799) ***	(-7.098) ***	(10.17) ***	(9.881) ***
FM	0.022	0.020	-0.029	-0.030
	(7.471) ***	(4.471) ***	(-6.594) ***	(-5.267) ***
FM^2	-0.001	0.000	0.001	0.001
	(-3.951) ***	(-2.955) ***	(4.530) ***	(3.043) ***
Pseudo R-squared	0.374	0.291	0.344	0.375
Adjusted R-squared	0.372	0.289	0.341	0.372
Quasi-LR statistic	424.795	348.522	436.133	379.487
Panel B: Soy				
Constant	-0.241	-0.172	0.270	0.395
	(-8.740) ***	(-7.781) ***	(8.198) ***	(4.292) ***
FM	0.026	0.019	-0.028	-0.040
	(5.742) ***	(5.775) ***	(-6.512) ***	(-3.005) ***
FM^2	-0.001	-0.001	0.001	0.001
	(-4.097) ***	(-4.459) ***	(5.084) ***	(2.210) **
Pseudo R-squared	0.334	0.267	0.313	0.367
Adjusted R-squared	0.332	0.265	0.310	0.364
Quasi-LR statistic	365.173	347.122	427.364	410.825
Panel C: Wheat				
Constant	-0.166 ***	-0.141 ***	0.243 ***	0.273 ***
	(-12.282)	(-12.662)	(6.992)	(11.587)
FM	0.019 ***	0.017 ***	-0.031 ***	-0.033 ***
	(8.600)	(9.839)	(-6.170)	(-9.170)
FM^2	-0.001 ***	0.000 ***	0.001 ***	0.001 ***
	(-5.988)	(-7.939)	(5.463)	(7.468)
Pseudo R-squared	0.477	0.381	0.371	0.532
Adjusted R-squared	0.474	0.378	0.369	0.530
Quasi-LR statistic	733.577	634.494	529.355	840.047

Note: FM is month of the forecasting cycle. Bootstrap t-statistics are in parentheses. N= 513. One asterisk indicates significance at 10% level, two asterisks indicate significance at 5% level, three asterisks indicate significance at 1% level.

Table 8. Diagnostic Test Results for Quantile Regression Models of Corn, Soybean, and Wheat Forecast Errors, 1980/81-2006/07 Marketing Years.

Test/Commodity	Quantiles			
	5^{th}	10^{th}	90^{th}	95^{th}
Omitted Variable Test [a]				
Corn	0.452	0.079	11.275 ***	33.192 ***
Soybeans	10.448 ***	9.570 ***	0.000	0.000
Wheat	4.472 **	0.453	0.000	0.000
Slope Equality Test [b]				
Corn	334.106 ***	337.139 ***	337.139 ***	334.106 ***
Soybeans	302.232 ***	275.267 ***	275.267 ***	302.232 ***
Wheat	192.634 ***	243.532 ***	243.532 ***	192.634 ***
Symmetry Test [b]				
Corn	6.147	2.372	2.372	6.147
Soybeans	10.103 **	6.579 *	6.579 *	10.103 **
Wheat	21.829 ***	10.806 **	10.806 **	21.829 ***

Notes: [a] QLR L-statistic for stocks/use variable, [b] Wald test. N=513. One asterisk indicates significance at 10% level, two asterisks indicate significance at 5% level, three asterisks indicate significance at 1% level.

Table 9. Accuracy Statistics for Empirical Confidence Intervals for WASDE Corn Price Forecasts, 1995/96-2006/07 Marketing Years.

	Published Intervals		Quantile Regression Intervals		Quantile Regression with Stocks/Use Intervals	
Month of the Forecasting Cycle	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	75	0.18
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	53		78		75	
After harvest						
7 (November)	92	0.04	92	0.04	92	0.04
8 (December)	92	0.04	100	n/a	92	0.04
9 (January)	100	n/a	100	n/a	100	n/a
10 (February)	92	0.04	100	n/a	100	n/a
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	75	2.22	67	4.83 **
15 (July)	83	0.50	83	0.50	75	2.22
16 (August)	42	16.99 ***	92	0.04	67	4.83 **
17 (September)	58	8.20 ***	100	n/a	83	0.50
Average	79		92		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 10. 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 *	83	0.09	83	0.09
2 (June)	67	1.17	83	0.09	83	0.09
3 (July)	67	1.17	83	0.09	83	0.09
4 (August)	75	0.18	92	1.24	92	1.24
5 (September)	67	1.17	67	1.17	75	0.18
6 (October)	58	2.92 *	75	0.18	75	0.18
Average	67		80		82	
After harvest						
7 (November)	67	4.83 **	92	0.04	83	0.50
8 (December)	75	2.22	83	0.50	75	2.22
9 (January)	75	2.22	83	0.50	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	83	0.50
15 (July)	25	28.58 ***	83	0.50	92	0.04
16 (August)	42	16.99 ***	67	4.83 **	75	2.22
17 (September)	42	16.99 ***	67	4.83 ***	67	4.83 ***
Average	56		84		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 11. 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 ***	42	8.46 ***	50	5.36 **
2 (June)	33	12.26 ***	50	5.36 **	42	8.46 ***
3 (July)	67	1.17	75	0.18	67	1.17
Average	44		56		53	
After harvest						
4 (August)	75	2.22	92	0.04	92	0.04
5 (September)	83	0.50	100	n/a	100	n/a
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	100	n/a
10 (February)	75	2.22	100	n/a	92	0.04
11 (March)	83	0.50	92	0.04	92	0.50
12 (April)	67	4.83 **	92	0.04	92	0.04
13 (May)	42	16.99 ***	92	0.04	92	0.04
14 (June)	42	16.99 ***	67	4.83 **	83	0.50
Average	71		92		92	

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.

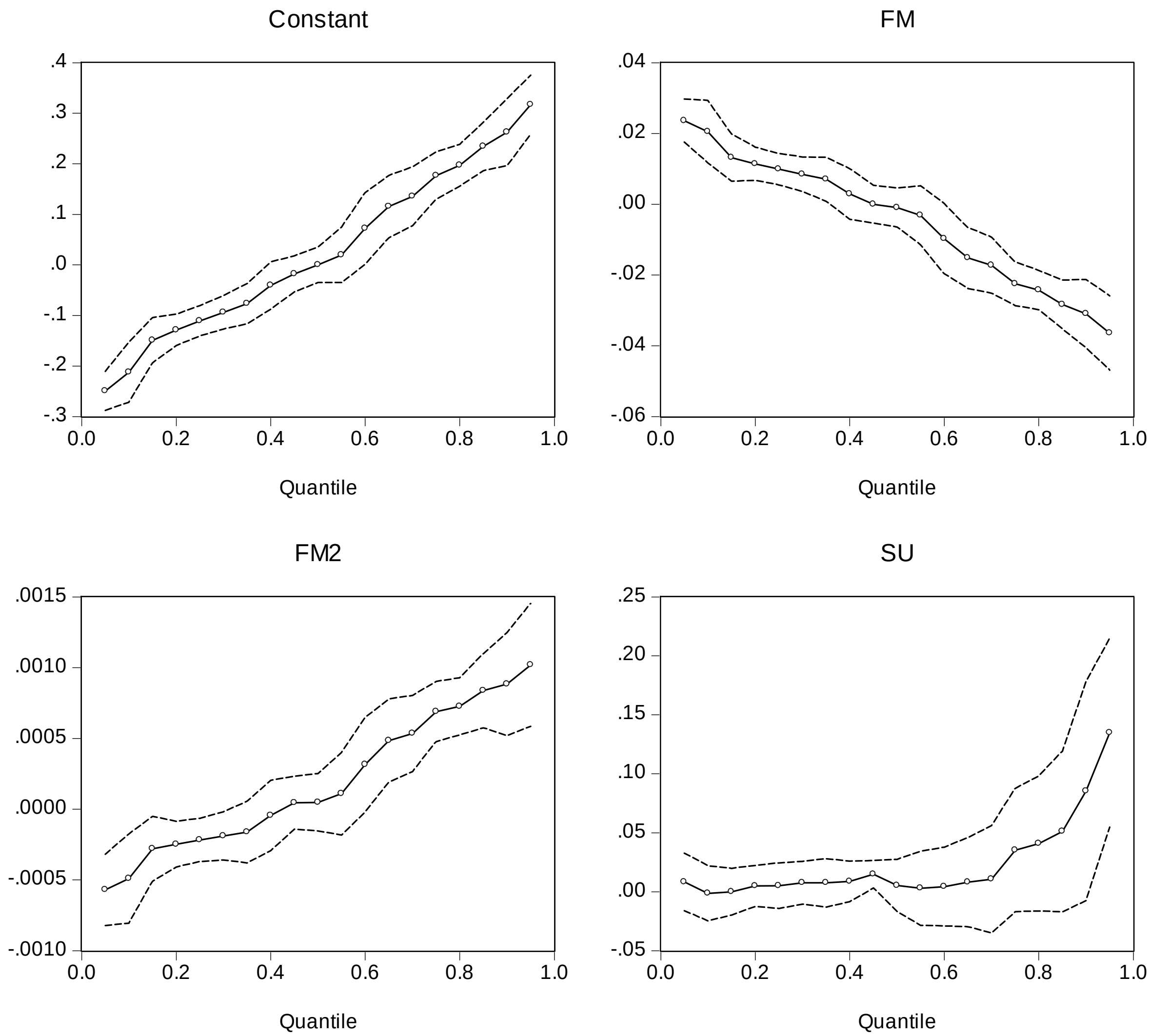

Figure 1. Quantile Regression Estimates with 95% Confidence Bounds for Corn Forecast Errors, 1980/81-2006/07 Marketing Years.

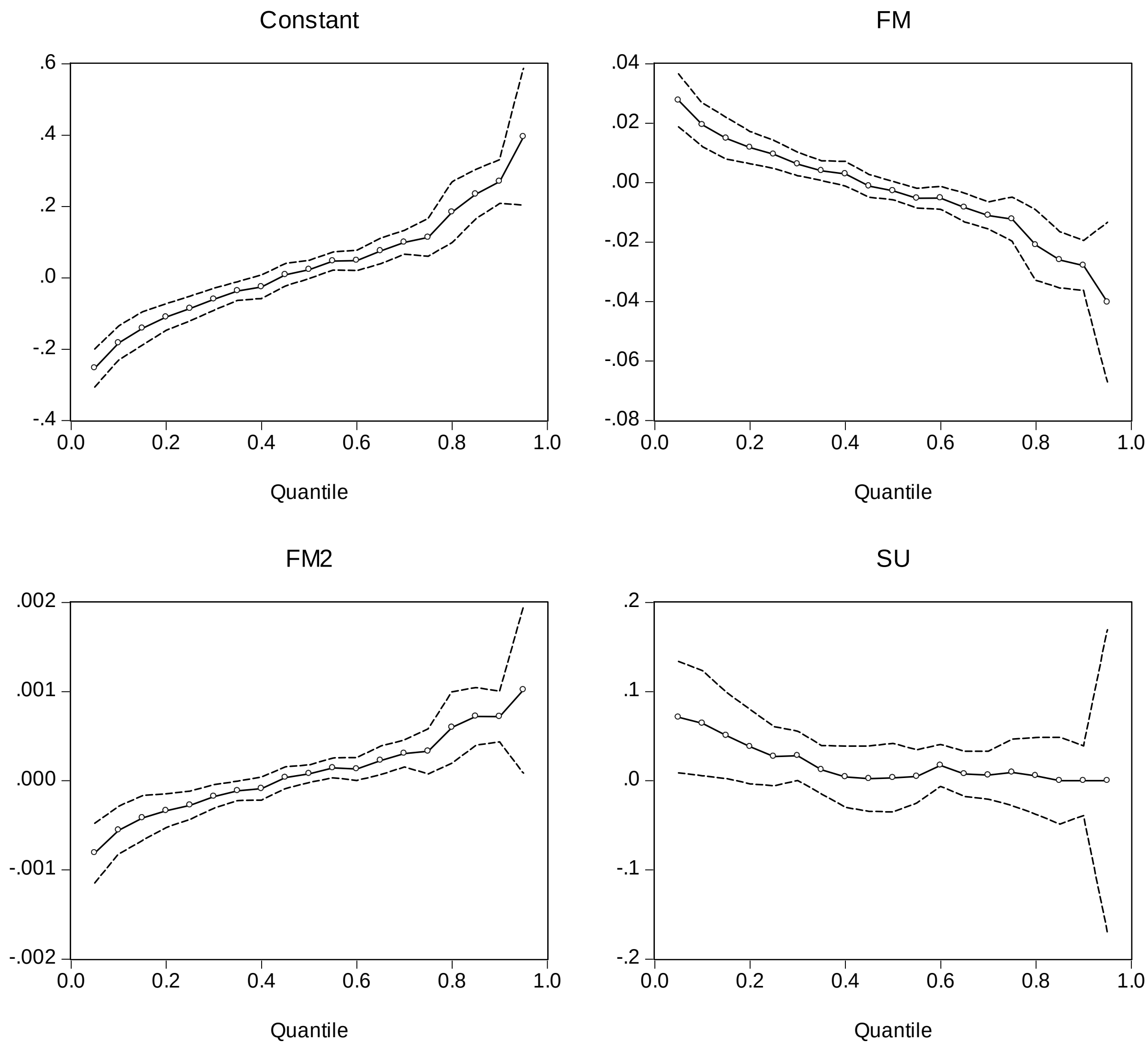

Figure 2. Quantile Regression Estimates with 95% Confidence Bounds for Soybean Forecast Errors, 1980/81-2006/07 Marketing Years.

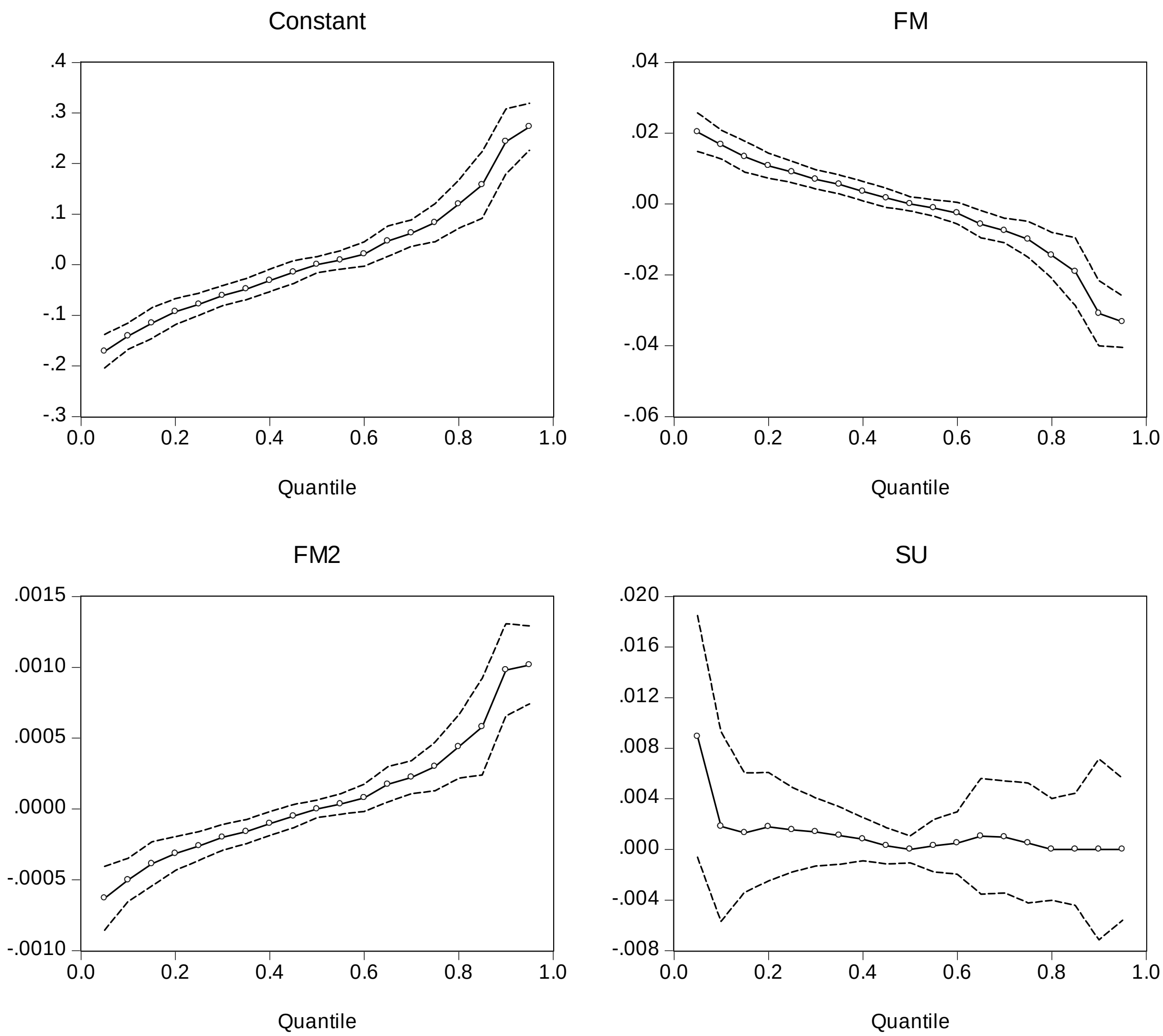

Figure 3. Quantile Regression Estimates with 95% Confidence Bounds for Wheat Forecast Errors, 1980/81-2006/07 Marketing Years.

Endnotes

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

[2] 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.

[3] 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.

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

[5] 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).