



AgEcon SEARCH
RESEARCH IN AGRICULTURAL & APPLIED ECONOMICS

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search

<http://ageconsearch.umn.edu>

aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

Forward-Looking USDA Price Forecasts

Michael K. Adjemian¹, Valentina G. Bruno², and Michel A. Robe²

Abstract

USDA generates monthly season-average price forecasts for key agricultural commodities. Uncertainty about each forecast is indicated by its publication as a price interval. USDA's forecasting methodology is non-public, but its uncertainty levels are anecdotally based on historical patterns of price uncertainty and informed by expert opinion. No confidence level is attached to USDA's intervals, so it is difficult to gauge their accuracy. But in practice, realized season-average prices regularly fall outside of USDA-forecasted intervals, particularly those made prior to harvest and late in the marketing year. We demonstrate that forward-looking density forecasts for the season-average corn price can be constructed based on the market's expectation of volatility implied by commodity options premia, combined with historical forecast errors between futures market prices and cash prices paid to farmers. Because implied volatility is forward-looking, confidence intervals based on these densities reflect anticipatory market sentiment not present in historical data. In out-of-sample trials, our 95% confidence intervals contained the final season-average price for over 92% of the 358 forecasts made between 1995/96 and 2014/15. Compared to a model based on historical data alone, the forward-looking model is less susceptible to forecast errors. Our approach can enhance the informational value of USDA season-average price forecasts.

Keywords: USDA, forecasting, derivatives markets, implied volatility, situation and outlook, WASDE, grains

Selected Paper prepared for presentation at the 2016 Agricultural and Applied Economics Association Annual Meeting, Boston, MA, July 31-August 2nd, 2016

This material is based upon work supported by Cooperative Agreement #58-30000-5-0038, between the USDA Economic Research Service and American University. While this paper was written, Robe was also a part-time consulting senior economist to the U.S. Commodities Futures Trading Commission (CFTC); no CFTC resources or data were used for this project. The views expressed in this article are those of the authors and may not be attributed to the Economic Research Service, the U.S. Department of Agriculture, the CFTC, or any other staff at those institutions. We thank Thomas Capehart and Steve MacDonald for their comments on earlier versions of this manuscript, and Olga Isengildina-Massa for her gracious assistance in drawing together necessary data. This work is preliminary and should not be cited without permission.

¹Economic Research Service, United States Department of Agriculture, Washington, DC

²Kogod School of Business, American University, Washington, D.C.

USDA publishes monthly supply and demand forecasts for major agricultural commodities in the World Agricultural Supply and Demand Estimates (WASDE) report. Most of the forecasts, including crop production values, are listed as a simple point estimate. But season-average prices (SAPs)—which represent the expected average price paid to farmers over the course of the marketing year—are usually provided as a range. For any marketing year, USDA provides eighteen season-average forecasts for corn, from the month of May preceding the harvest up to the month of October of the following calendar year;¹ the final price-received figure is published that November. No statistical confidence level is attached to these ranges: the probability that the price realized by farmers will lie within the specified interval is not published (Isengildina-Massa et al., 2011). As a result, there is significant dispersion of beliefs about the reliability of the price interval—even among the USDA analysts responsible for their production (Isengildina, Irwin, and Good, 2004).

Without a known *ex-ante* confidence level, it is very difficult to judge forecast accuracy. But prior research has shown that USDA-forecasted intervals for corn and soybean prices have low “hit rates” (i.e., times when realized prices actually fell in the forecasted ranges) (see Isengildina, Irwin, and Good, 2004). Figure 1 shows the USDA “miss-rates” for all forecasts made from 1995/96-2014/15, segregated by the nineteen month forecasting cycle.² In this 20-year period, the price paid to farmers fell outside USDA’s forecasted intervals 31% of the time.³ Early-cycle forecasts were particularly error-ridden, missing between 40-60% of the time. As well,

¹ The US government shutdown of October 2013 lowered the number of forecasts to seventeen for both the 2012/13 and 2013/14 marketing years.

² The “miss rate” = 1 – “hit rate”.

³ This is calculated by averaging the miss rate for the first eighteen forecasts.

forecasts 16 and 17—just a couple months before the final value is known—also miss at or over 50% of the time, due to apparently premature interval narrowing.

The process that USDA uses to generate the season-average price interval is non-public. According to Vogel and Bange (1999), it 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”. Anecdotal reports from individuals involved in the lock-up environment where price forecasts are finalized indicate that historical data, such as realized volatility and past patterns of uncertainty resolution, inform the published price interval. Still, because similar ranges are published at volatile and tranquil times (Isengildina-Massa et al., 2011), price forecasts that appear in WASDE may not reflect the true uncertainty surrounding crop conditions.⁴ Supplying a price density forecast—or at least proper confidence values—along with these intervals would reduce confusion about the meaning of USDA price forecasts among consumers of the USDA’s reports and should improve their usefulness to stakeholders for decisions about storage, marketing, merchandising, and risk management.

Prior research has demonstrated that empirical confidence intervals can be constructed by calculating the distribution of historical errors between the WASDE SAP and the final average price received by farmers, at each point in the forecasting cycle (e.g., Isengildina-Massa et al., 2011). While offering a clear advantage in terms of lending informativeness to forecasted intervals, such methods still risk error because they are based on the implicit assumption that

⁴ Over the seventeen years from May 1989 – May 2006, USDA’s first interval prediction for the average farmgate price paid for corn raised in the upcoming harvest was always 40 cents.

uncertainty is constant through time (for the same point in the cycle). Forecasting models built solely on historical data cannot reflect shifting forward-looking market sentiments.

We show that more accurate out-of-sample forecasted SAP densities can be constructed by combining (i) the market's expectation of futures contract price volatility that are implied by commodity options premia with (ii) historical forecast errors between futures and National Agricultural Statistics Service (NASS) reported average cash received prices. Resulting price density forecasts respond dynamically to changes in option-implied volatilities; they narrow or widen with updates to market expectations. Out-of-sample tests confirm that this feature improves their ability to predict the final SAP compared to a model built on historical data, alone.

Market-implied volatility expectations ("implied volatility", or IV) can be recovered from the price of options traded on commodity futures contracts using option pricing models (e.g., Black and Scholes, 1973). Option-implied volatility is a measure of market uncertainty about the price of a futures contract over its remaining life. USDA's Risk Management Agency already uses implied volatilities to develop premium rates for crop revenue insurance (Goodwin et al., 2014), relying on their predictive power to inform about the expected future distribution of market prices. We adopt a similar intuition to simulate SAP forecast densities for corn at each monthly USDA forecast from 1995/96-2014/15, using Monte Carlo analysis.

Background

Uncertainty at horizons longer than a few hours or days is an important component of risk management choices (Christoffersen and Diebold, 2000), so forecasts that include higher moments than just the price expectation provide superior information compared to simple point

estimates (Armstrong, 2001). In 1977, USDA began offering monthly interval predictions for the average price that farmers of major US crops could expect to receive over the course of a marketing year. Absent published confidence intervals to guide forecast consumers, several researchers have attempted to at least evaluate the accuracy of these forecasts. Most of those studies focus on the accuracy of the interval midpoint as a point forecast (Kastens, Schroeder, and Plain, 1998; Egelkraut et al., 2003; Hoffman et al., 2015). Furthermore, three studies consider the accuracy of the original price intervals, preserving the information they contain about anticipated uncertainty (Sanders and Manfredo, 2003; Isengildina, Irwin, and Good, 2004; Isengildina and Sharp, 2012).

Because of USDA's low historical forecast "hit" rates, the black-box nature of the procedures its analysts use to generate forecasts, and the lack of confidence levels associated with the intervals, researchers have suggested ways to assign them uncertainty. Two recent articles explore the construction of "empirical confidence intervals", or uncertainty bands based on historical forecast errors, around WASDE price estimates (Isengildina-Massa, Irwin, and Good, 2010; Isengildina et al., 2011). Introduced by Williams and Goodman (1971), this approach allows the construction of confidence levels around point forecasts assuming that the distribution of forecast errors is time-invariant. Another approach is to forecast the entire price distribution, or probability density. Trujillo-Barrera, Garcia, and Mallory (2012) adapt the methods of Taylor (2005), Liu et al. (2007), and Høg and Tsiaras (2011) to generate price density forecasts for lean hogs futures prices using both backward and forward-looking methods. The latter start from volatilities implied by options prices and transform them from "risk-neutral" to "real-world" based on empirical evidence that Keynes-style (1930) risk premia prevail in the lean hog market

(see, e.g., Egelkraut and Garcia, 2006). Because there is scant evidence of such risk premia in major grain markets that enjoy far more liquidity (Hartzmark, 1991; Frank and Garcia, 2009; Fische and Smith, 2011), we need no such transformation in the case of the corn market – which is the focus of our study.

Data

WASDE corn SAP forecasts from 1980/81-present are maintained online by Cornell's Mann Library, and can be accessed freely. Cash prices received by farmers are published in the Agricultural Prices (AP) report by the National Agricultural Statistics Service (NASS); it is released with a two-month lag relative to the WASDE release schedule. For example, the March 30th 2016 AP report was the first to note that U.S. farmers received an average price of \$3.57/bu in February, so we assume that the first WASDE forecast that could have accounted for that information was made on the April 12th, 2016. We obtain data on corn futures and options prices and trading activity from Bloomberg data service, including estimates of annualized implied volatilities for active at-the-money options from January 1995-present.⁵ Conversions between annualized σ_a and horizon-specific σ_h implied volatilities (up to the receipt of a cash price) were done according to $\sigma_h = \sigma_a \sqrt{T}$, where T is the share of a trading year represented by h . Cash prices are assumed to be realized by farmers at the end of each calendar month.

⁵ See Cui (2012) for details on the Bloomberg methodology for extracting forward-looking volatility estimates from at-the-money option prices.

For the trading day before each of the 358 USDA forecasts in the period of interest, 1995/96-2014/15, we identify the last recorded price and IV for each of the six futures contracts that deliver over the marketing year that's SAP is to be forecasted, and the first contract of the next harvest (e.g., for the August SAP forecast we draw information from contracts expiring in September, December, and the following March, May, July, and September).⁶ We construct forward prices for inter-contract months assuming a constant daily price of storage between sequential deliveries. We apply a similar procedure to generate a price for any missing futures contract prices. The implied volatilities are associated with each forward price using either the IV for that month (if it contains a futures delivery) or the IV for the next-to-deliver futures contract (for non-contract months). In cases where no next-to-deliver IV is available, the IV for the nearest available last-to-deliver futures contract is used.

Methodology

Forecasting Model Components

The SAP forecast can be expressed as a function of the expected monthly m cash prices received by farmers P_m and marketing weights w_m .⁷ Over the course of a 12-month marketing year, the time t expected season-average price, or SAP , is

$$(1) \quad E_t[SAP] = \sum_{m=1}^{12} E_t[P_m w_m], \text{ for } \sum_{m=1}^{12} E_t[w_m] = 1$$

⁶ Throughout the analysis, we were careful to use only information that would have been available to analysts inside USDA "lockup", the isolated setting where SAP predictions are generated.

⁷ A marketing weight is the proportion of the harvested crop sold by farmers in a given month.

As recognized by Hoffman et al. (2015), absent a risk premium the futures market price $F_{t,m}$ represents an efficient forecast for each expected P_m that falls in a month with a futures contract delivery, adjusted by a basis b_m that represents characteristic differences between the futures delivery market and the average price prevailing at the local cash markets in which farmers participate, according to some function f .⁸ Furthermore, for inter-contract months, forward prices $\hat{F}_{t,m}$ can be interpolated from surrounding futures delivery months using a no-arbitrage condition, so that expression (1) can be re-stated as

$$(2) \quad E_t[SAP] = \sum_{m=1}^{12} E_t[f(F_{t,m}, b_m)w_m]I_m + E_t[f(\hat{F}_{t,m}, b_m)w_m](I_m - 1),$$

for $\sum_{m=1}^{12} E_t[w_m] = 1$ and where $I_m = 1$ for months with a futures contract delivery, and 0 otherwise.

Therefore, uncertainty about the average price that farmers will receive over the course of a marketing year can be decomposed into three sources: uncertainty about futures market prices, uncertainty about how futures prices relate to the prices that farmers will get paid, and finally uncertainty about the time (rate) at which the harvest will be marketed. Fortunately, uncertainty about the value of a futures contract over its remaining life is available directly from options prices. Because one determinant of an option's price is the market expectation of future

⁸ Even if a risk premium exists and biases the futures price relative to the expected price in the delivery market, the method we use to account for the basis between futures and cash prices received will account for its influence, historically.

volatility, the option pricing equation (see, e.g., Black and Scholes, 1973) can be rearranged to solve for IV.⁹

The Forward-looking Model

The basic intuition of our forward-looking model is that at each point j (for $j = 1 \dots 18$) in the forecasting cycle it (i) uses futures and options market data to generate a density (via Monte Carlo simulation) for the expected forward price in the delivery market for each month m in the marketing year being forecasted, (ii) modifies each density using the historical relationship at that j between expected forward prices for each m and the eventual cash price received in that m , (iii) applies a set of naive marketing weights to collapse all forecasted densities into a forecasted SAP density, and then (iv) re-centers the forecasted SAP distribution onto the midpoint of USDA's prediction, to approximate USDA's expected marketing weights.

Using the latest information before the date of each forecast, we identify the prevailing forward prices for each month over the marketing year of interest and associate them with the latest IV value. For forecasts that occur after the beginning of the harvest (in September), cash prices are assumed to be equal to the last recorded forward price at one lag, and known with certainty at two lags, once they are published in the AP report. For example, to construct the $j = 7$ November SAP forecast, we combine the cash price received by farmers in September (known with certainty from the AP report), the expected cash price received by farmers in October (based on the information used to make the previous month's SAP forecast), and then form the term

⁹ A corn option contract represents the right, but not the obligation, to assume a (long or short, depending on whether the option is a call or put) position in a specified corn futures contract at an agreed upon strike price. The value of that right is a function of how uncertain the future price is, i.e., of the forward-looking price volatility.

structure of forward prices and IVs for November through the following August by drawing from available futures and options data (for the yet-to-deliver December, March, May, July, and August contracts). In this example, the prices for September and October are not associated with an IV because they are not associated with active derivatives contract. In contrast, the $j = 1$ May forecast is constructed entirely using derivatives that are still trading, so all the forward prices are assigned IV values > 0 .

As the marketing year goes along, uncertainty about the average price paid to farmers is resolved, as more information about cash prices is learned. Following Goodwin et al. (2014), we generate forecasted price densities for each m using $N = 100,000$ Monte Carlo draws according to the appropriate IV and time horizon, assuming that futures prices are distributed lognormally.¹⁰ Specifically, for each time t forecast, we generate an $N \times 12$ matrix \mathbf{P}_t , representing the uncertainty about forward prices for each month over the marketing year. For those months in the marketing year prior to the forecast month, for example September in the November forecast mentioned above, the standard deviation of its column in \mathbf{P}_t is zero since it is assumed to be known with certainty.

Next, we modify each m 's density forecast according to the distribution of historical forecast errors between the forward price predicted for that month and the eventual cash price that was realized. To accomplish this step, we use the population of all historical forecast errors made at that point j (for $j = 1 \dots 18$) in the forecasting cycle, represented by the $k \times 12$ matrix

¹⁰ Scherrick, Garcia, and Tirupattur use a Burr-III distribution to recover probabilistic information from soybean futures, while Trujillo-Barrera, Garcia, and Mallory (2012) use a GB2 generalized beta distribution to parameterize uncertainty about lean hog prices. Testing the sensitivity of our results to varying representations of forward-looking commodity volatility is a step for future analysis.

$\mathbf{B}_{t,j}$.¹¹ The value k represents the number of historical years (before the forecasted one) for which errors can be computed; because the final SAP is not known until fifteen months after the harvest, the latest marketing year allowed for our purposes is two years before the current forecast. We use the 270 WASDE forecasts over the fifteen marketing years from 1980/81-1994/95 as training data. As a result, for the May 1995/96 forecast of the upcoming SAP, $\mathbf{B}_{t,j}$ is of dimension 14×12 , since it omits the immediately preceding 1994/95 year's errors; for the similar position May 2014/15 forecast, the $\mathbf{B}_{t,j}$ is 34×12 . Each value in the matrix represents the ratio of the eventual cash price received in that month and the forecasted forward price. As might be expected, the further along one goes in the forecasting cycle (i.e., as j approaches 18), the lower the magnitude of difference between forward and realized cash prices, and the smaller are the values in each row of $\mathbf{B}_{t,j}$. For matrix conformability, we stack $\mathbf{B}_{t,j}$ repeatedly until its number of rows $\geq N$, scramble it randomly, and choose the top N rows to create $\widehat{\mathbf{B}}_{t,j}$.¹²

We adjust the forward price densities by multiplying \mathbf{P}_t by $\widehat{\mathbf{B}}_{t,j}$, element by element. Each row of the resulting matrix contains forward price predictions for the months over the marketing year, modified by the historical uncertainty about the relationship between forward and cash prices for that month, at that point in the forecasting cycle. Next, we post-multiply that matrix by \mathbf{MW}_t' , the vector of marketing weights. We use a five-year moving average of marketing weights to calculate our results. The resulting $N \times 1$ vector \mathbf{C}_t represents the forward-looking forecasted SAP density. Realizing that USDA analysts in lockup have more information about

¹¹ Our forecast error data covers 1980/81 – 2014/15.

¹² Preserving each row of \mathbf{B} in this way maintains the pattern of forecast errors for any given historical year, for the proper j .

predicted prices than prior-day derivatives markets,¹³ and more information about that's years' crop disappearance than the simple moving average—especially as the marketing year proceeds—we re-center the vector \mathbf{C}_t by subtracting its median and adding the midpoint of the USDA forecast. Now, \mathbf{C}_t provides the SAP density around a price predicted by USDA analysts.

The Backward-Looking Model

In order to compare the forward-looking model to one that uses historical data alone, we apply a similar procedure to the one we use to calculate $\mathbf{B}_{t,j}$ to generate the $k \times 1$ empirical distribution $\mathbf{E}_{t,j}$. But, rather than comparing the eventual cash price received for each month to predicted forward prices at that j for every historical marketing year (marking the column dimension of the former), each element of $\mathbf{E}_{t,j}$ represents the ratio of the eventual SAP to the midpoint of that year's USDA forecasted interval at point j . Empirical confidence intervals are generated by sorting $\mathbf{E}_{t,j}$, multiplying each element by the current USDA interval midpoint, and then selecting the preferred confidence level. This approach resembles the “histogram method” employed by Isengildina-Massa et al. (2011); to distinguish it from the forward-looking (FL) model we develop, we term it the “backward-looking” (BL) model. Because identifying a consistent confidence level with this method is difficult (as the amount of historical data grows), we therefore compare the hit rates between entire population of predictions indicated by the empirical and forward-looking methods.

¹³ A large literature demonstrates that agricultural futures markets react to USDA announcements (see e.g., Adjemian, 2012).

Results and Discussion

Benefits of Forward-Looking Forecasts

Table 1 compares miss rates between USDA-forecasted SAP intervals to an empirical interval generated using backward-looking historical data, and our forward-looking forecasts (for a range of confidence levels), using out-of-sample data for all USDA forecasts made from May 1995/96 – October 2014/15. That is, for each forecast, the FL model generates a predicted price density using only data that would have been available to USDA analysts at the time they entered lockup conditions. The associated 95% confidence interval, for instance, is identified by slicing off the top and bottom 2.5% of predicted SAPs.

Results in table 1 demonstrate that—besides the advantage of offering a statistical interpretation to the forecast consumer—both the FL and BL models are on average more successful at predicting the final SAP than USDA forecasts.¹⁴ Table 1 also shows that the FL model produces more accurate population-level intervals than the BL model. Indeed, the BL model suffers a 9.5% miss rate, even at the 100% confidence level: that is, BL intervals (constructed using the universe of historical forecast errors between the USDA interval midpoint and the final SAP) were unsuccessful at predicting the proper SAP almost 10% of the time, in the period 1995/96-2014/15. Over the same period, in contrast, the FL model was able to predict the correct SAP 99.16% of the time in out-of-sample trials.

Results for specific marketing years can be illustrative. Figure 3 compares the USDA, 100% BL and 100% FL forecasted intervals for 1999/2000, a year when USDA published intervals

¹⁴ Except for the forward-looking forecasts made at the 67% level... an appropriate foreshadowing of the discussion about how confidence levels can be assigned to USDA forecasts, using the FL model.

achieved better than their average historical accuracy (14/18 = 78% hits). In the figure, the USDA intervals miss in forecasts #11-14, the BL forecast misses from #12-14, and the FL model never misses—yielding the results that one would expect in a 100% CI. Figure 4 shows the same results for 2007/2008, a marketing year that saw significant price volatility. That year, fully eleven USDA projected intervals missed the actual SAP, and the 100% BL model missed four times—several quite substantially. The 100% FL model, on the other hand, did not miss at all. Interestingly, 95% CI based on the FL model resembles the 100% BL intervals fairly closely, but did not miss as badly in the early part of the forecasting cycle. It is quite possible that better BL intervals could be generated using more sophisticated methods, as described by Isengildina-Massa et al. (2011); however, the nature of backward-looking models is that they cannot anticipate market sentiment transmitted by options markets.

Assigning a Range of Confidence Intervals

By forecasting the price density at each month, the FL model allows for the construction of statistically valid intervals over a range of confidence levels. As shown in Table 1, the 95%, 90%, and 67% CIs based on the FL densities hit at a rate of 92%, 87%, and 69%, respectively, in out-of-sample trials. Graphically, selected FL SAP densities for the 2007/08 marketing year are shown in Figure 5. Early-cycle forecasted densities are quite wide and skewed; they exhibit a long tail in the direction of higher prices. As the marketing year progresses, projected densities grow more bell shaped and narrow; later densities coalesce around the midpoint of the USDA forecast. Corresponding to figure 4, each density contains the eventual SAP received by farmers: 420 cents/bu.

Figure 6 compares the seasonality of forecast performance, for varying levels of statistical confidence. Like USDA forecasts, the FL model errors are clustered around the early and late portions of the cycle. Both the 95% and 90% FL intervals always outperform the USDA in terms of miss rate, except for forecast 18, when the performance of all models is tied. Figure 6 also shows that the miss rates for USDA intervals is far more volatile than the miss rates of the FL model, whatever the preferred level of confidence. This helps illustrate one of the weaknesses about the methodology that USDA currently uses to generate these intervals: their confidence levels are not consistent over the marketing year, so the information they transmit is very difficult to interpret. Figure 7 shows that all models suffer more misses in periods of high price volatility, such as the late 2000's. However, the flexibility of the FL model to anticipated market volatility improves its performance relative to USDA methods.

Another important aspect of the FL model is that its predicted densities can be used to assign confidence levels to the intervals that USDA predicts. If an interval continues to be the preferred candidate to relay uncertainty about the SAP (instead of densities), the FL model can at least afford WASDE consumers the understanding of the level of confidence they may place in USDA's published SAP estimates. Figure 8 displays the average, minimum, and maximum proportion of the FL model densities captured by the SAP intervals that USDA forecasted over the period of interest.¹⁵ According to these densities, the confidence that should be placed in USDA intervals varies with the forecasting cycle: low at the outset (35% in June before the harvest, on average), higher as information about the harvest is learned (83% avg. by January),

¹⁵ We allow for an additional half cent at the top of the FL density, and another half cent at the bottom of the density to account for the fact that USDA does not make SAP predictions in fractional cents/bu.

and then lower as the interval is narrowed, prematurely. By the following September (forecast 17), USDA's point estimate of the SAP captures only 31% of the corresponding FL density's values, failing to adequately capture uncertainty about farm prices. That's not a surprising finding, since USDA's $j=17$ SAP forecast suffers from a miss rate over 50%.

The proportion of *ex-ante* SAP variation explained by either forward-looking uncertainty about futures prices or the futures-cash basis (i.e., "basis uncertainty") represented by historical forecast errors can also be identified from the FL model. Figure 9 shows the sources of uncertainty in the FL model's 95% confidence interval, by forecast number. The values in the chart are computed by comparing the size of the 95% confidence interval based on forward prices alone (from IV) to the interval produced by the FL model; basis uncertainty represents the residual after accounting for forward prices.¹⁶ Clearly, IV alone is not sufficient to explain uncertainty about SAP; indeed, basis uncertainty relayed by historical forecast errors is a more prominent source of *ex-ante* SAP variation early in the forecasting cycle (accounting for 60% of the CI in the July preceding harvest), but grows relatively less important over time (falling to 30% by the following April). Until, that is, forward prices are no longer "forward"; they are known with certainty by the completion of the forecasted marketing year. The only remaining source of uncertainty beginning with forecast 17, then, is due to the basis relationship.

¹⁶ Recall that uncertainty about marketing weights is addressed by re-centering the FL density on the midpoint of the USDA forecast.

Conclusion

We demonstrate that forward-looking density forecasts for the season-average corn price can be constructed based on the market's expectation of volatility implied by commodity options premia, combined with historical forecast errors between futures market prices and cash prices paid to farmers. Because implied volatility is forward-looking, confidence intervals based on these densities reflect anticipatory market information and sentiment not present in historical data. In out-of-sample trials, 95% confidence intervals based on our forward-looking model contained the final season-average price for over 92% of the 358 forecasts made between 1995/96 and 2014/15. USDA forecasts made over the same period contained the final SAP a mere 69% of the time, and do not reveal the confidence with which they should be interpreted. Compared to a model based on historical data alone, our forward-looking model is less susceptible to forecast errors.

The forward-looking model also identifies implied confidence intervals associated with previously published USDA forecasts. We find that these implied confidence levels vary substantially depending on the point at which they are made in the forecasting cycle. Our work enhances understanding about the reliability of USDA SAP forecasts. If adopted as part of the forecasting process, the forward-looking model should provide a portrait of uncertainty about the prices farmers can expect to receive over the course of a marketing year, and has the potential to improve resource allocation decisions made by farmers, grain merchandisers, livestock producers, and other market participants. Using the results of Adjemian, Bruno, Robe, and Wallen (2016), USDA forecasters can even use their expert judgment to adjust the IVs that form the basis of the forward-looking model, and exercise some control over model parameters.

Intervals based on the model can be assigned for any level of uncertainty preferred by these forecasters (Isengildina and Mattos, 2015). Currently, extensions of the model are being considered for other commodities and estimates presented in the WASDE report.

References

- Adjemian, M.K. 2012. "Quantifying the waste announcement effect." *American Journal of Agricultural Economics* 94(1):238-256.
- Adjemian, M.K., V. Bruno, M. Robe, and J. Wallen. 2016. "What drives volatility expectations in agricultural markets?" Paper presented at NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. St. Louis, MO.
- Armstrong, J.S. 2001. *Principles of forecasting*. Boston, MA: Kluwer Academic Publishers.
- Black, F., and M. Scholes. 1973. "The pricing of options and corporate liabilities." *Journal of Political Economy* 81(3):637-654.
- Christoffersen, P.F., and F.X. Diebold. 2000. "How relevant is volatility forecasting for financial risk management." *The Review of Economics and Statistics* 82(1):12-22.
- Cui, C. 2012. "Commodity implied volatility surface." Bloomberg OVDV commodity volatility surface white paper. Bloomberg L.P.
- Egelkraut, T.M., and P. Garcia. 2006. "Intermediate volatility forecasts using implied forward volatility: The performance of selected agricultural commodity options." *Journal of Agricultural and Resource Economics* 31(3):508-528.
- Egelkraut, T.M., P. Garcia, S.H. Irwin, and D.L. Good. 2003. "An evaluation of crop forecast accuracy for corn and soybeans: Usda and private information agencies." *Journal of Agricultural and Applied Economics* 35(1):79-95.
- Fishe, R.P.H., and A.D. Smith. 2011. "Identifying informed traders in futures markets." *Journal of Financial Markets* 15(3):329-359.
- Frank, J., and P. Garcia. 2009. "Time-varying risk premium: Further evidence in agricultural futures markets." *Applied Economics* 41:715-725.
- Goodwin, B.K., A. Harri, R.M. Rejesus, K.H. Coble, and T.O. Knight. 2014. "Actuarial review for the price volatility factor methodology." Sumaria Systems.
- Hartzmark, M.L. 1991. "Luck versus forecast ability: Determinant of trader performance in futures markets." *Journal of Business* 64(1):49-74.
- Hoffman, L.A., X.L. Etienne, S.H. Irwin, E.V. Colino, and J.I. Toasa. 2015. "Forecast performance of waste price projections for u.S. Corn." *Agricultural Economics* 46:157-171.
- Høg, E., and L. Tsiaras. 2011. "Density forecasts of crude-oil prices using option-implied and arch-type models." *Journal of Futures Markets* 31(8):727-754.
- Isengildina-Massa, O., S. Irwin, D.L. Good, and L. Massa. 2011. "Empirical confidence intervals for usda commodity price forecasts." *Applied Economics* 43:3789-3803.
- Isengildina-Massa, O., S.H. Irwin, and D.L. Good. 2010. "Quantile regression estimates of confidence intervals for waste price forecasts." *Journal of Agricultural and Resource Economics* 35(3):545-567.
- Isengildina, O., S.H. Irwin, and D.L. Good. 2004. "Evaluation of usda interval forecasts of corn and soybean prices." *American Journal of Agricultural Economics* 84:990-1004.
- Isengildina, O., S.H. Irwin, D.L. Good, and L. Massa. 2011. "Empirical confidence intervals for usda commodity price forecasts." *Applied Economics* 43:3789-3803.
- Isengildina, O., and F. Mattos. 2015. "Accuracy-informativeness tradeoff for interval forecast comparison." Paper presented at NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. St. Louis, MO.

- Isengildina, O., and J.L. Sharp. 2012. "Evaluation of usda interval forecasts revisited." *Agribusiness* 28(3):310-323.
- Kastens, T.L., T.C. Schroeder, and R. Plain. 1998. "Evaluation of extension and usda price and production forecasts." *Journal of Agricultural and Resource Economics*.
- Keynes, J.M. 1930. *A treatise on money*. New York: Harcourt, Brace.
- Liu, X., M. Shackleton, S.J. Taylor, and X. Xu. 2007. "Closed-form transformations from risk-neutral to real-world distributions." *Journal of Banking & Finance* 31(5):1501-1520.
- Sanders, D.R., and M.R. Manfredo. 2003. "Usda livestock price forecasts: A comprehensive evaluation." *Journal of Agricultural and Resource Economics* 28(2):316-334.
- Taylor, S.J. 2005. *Asset price dynamics, volatility, and prediction*. Princeton, NJ: Princeton University Press.
- Trujillo-Barrera, A., P. Garcia, and M. Mallory. 2012. "Density forecasts of lean hog futures prices." Paper presented at NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. St. Louis, MO.
- Vogel, F.A., and G.A. Bange. 1999. *Understanding usda crop forecasts*. Washington DC: U.S. Department of Agriculture, National Agricultural Statistics Service and Office of the Chief Economist, World Agricultural Outlook Board.
- Williams, W.H., and M.L. Goodman. 1971. "A simple method for the construction of empirical confidence limits for economic forecasts." *Journal of the American Statistical Association* 66:752-754.

Table 1. Comparison between out-of-sample forecasting performance, 1995/96 – 2014/2015

Forecasting Model	Obs.	Miss %
<i>USDA</i>	358	30.73%
<i>Backward Looking 100%</i>	358	9.50%
<i>Forward Looking 100%</i>	358	0.84%
<i>Forward Looking 95%</i>	358	7.82%
<i>Forward Looking 90%</i>	358	12.85%
<i>Forward Looking 67%</i>	358	31.01%

Figure 1. Proportion of USDA forecast misses by forecast number, 1995/1996-2014/2015

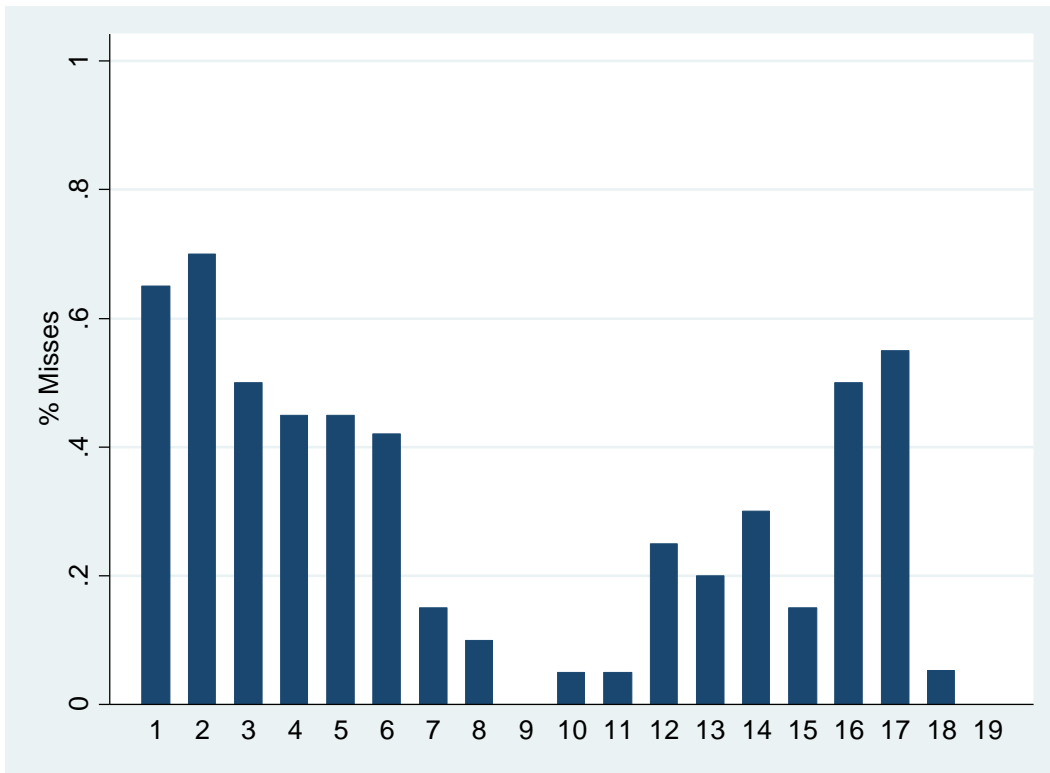


Figure 2. USDA forecast misses by marketing year

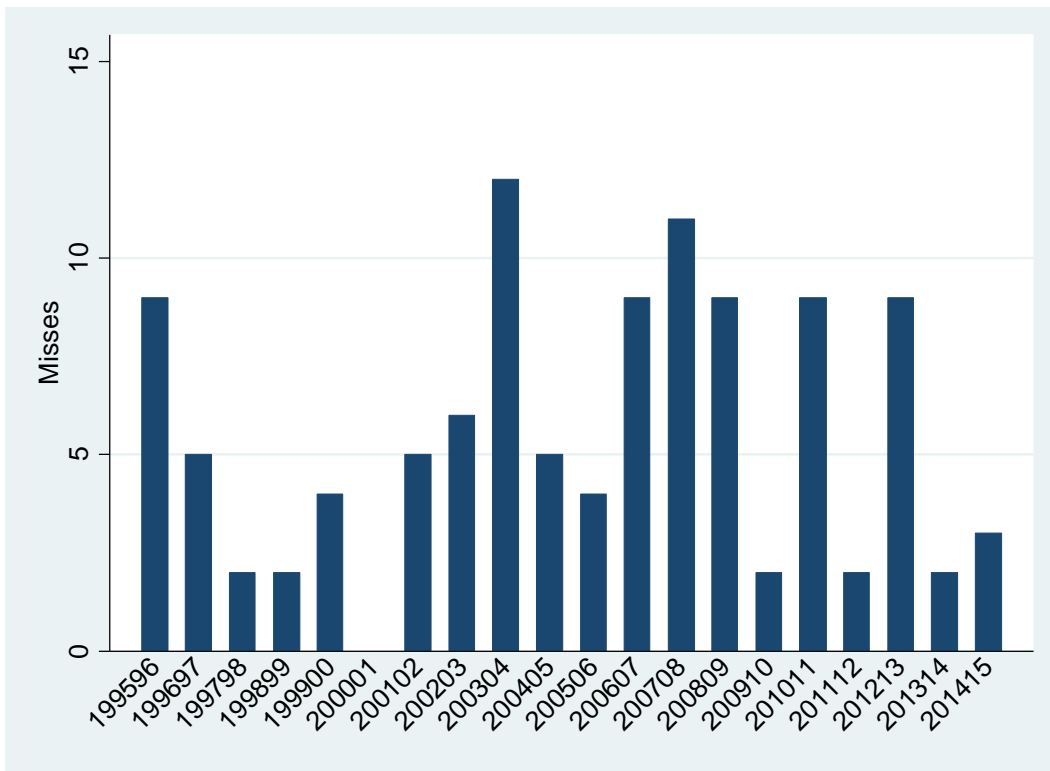


Figure 3. Forecasted SAP intervals, 1999/00

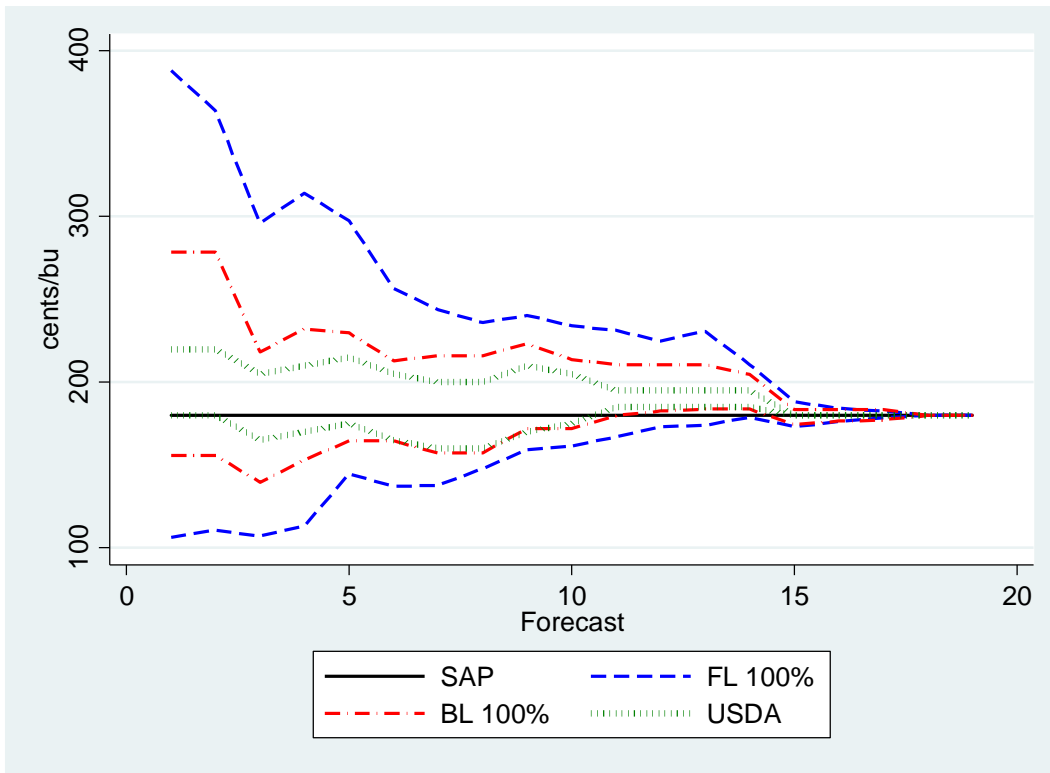


Figure 4. Forecasted SAP intervals, 2007/08

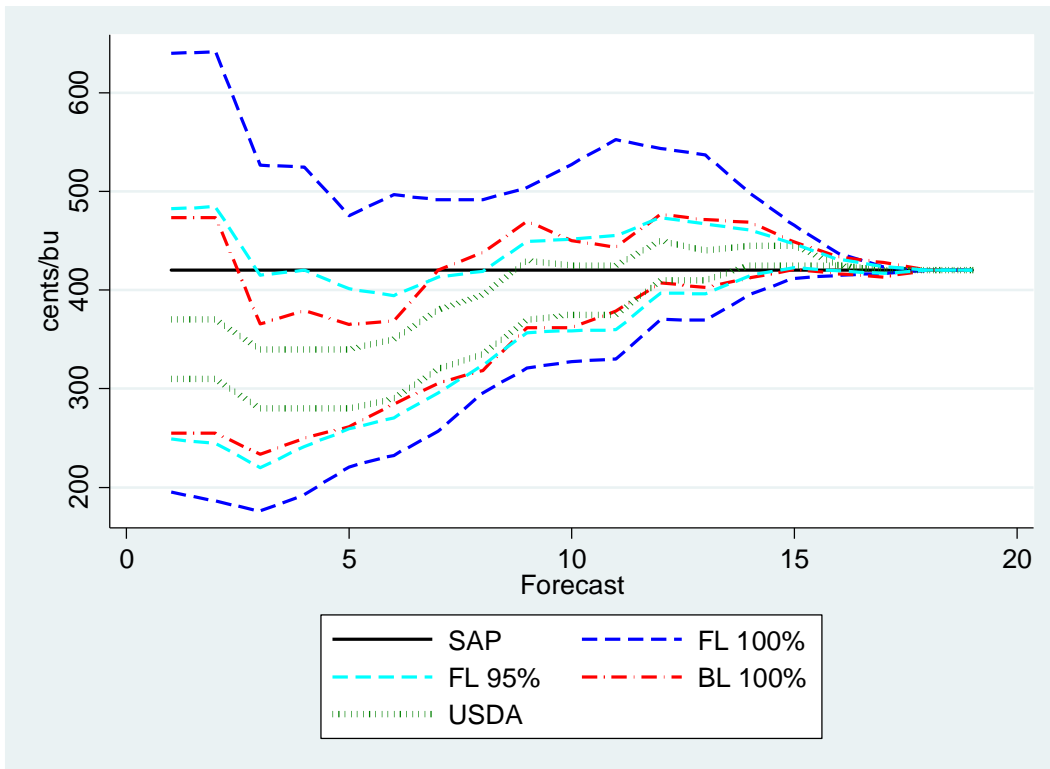
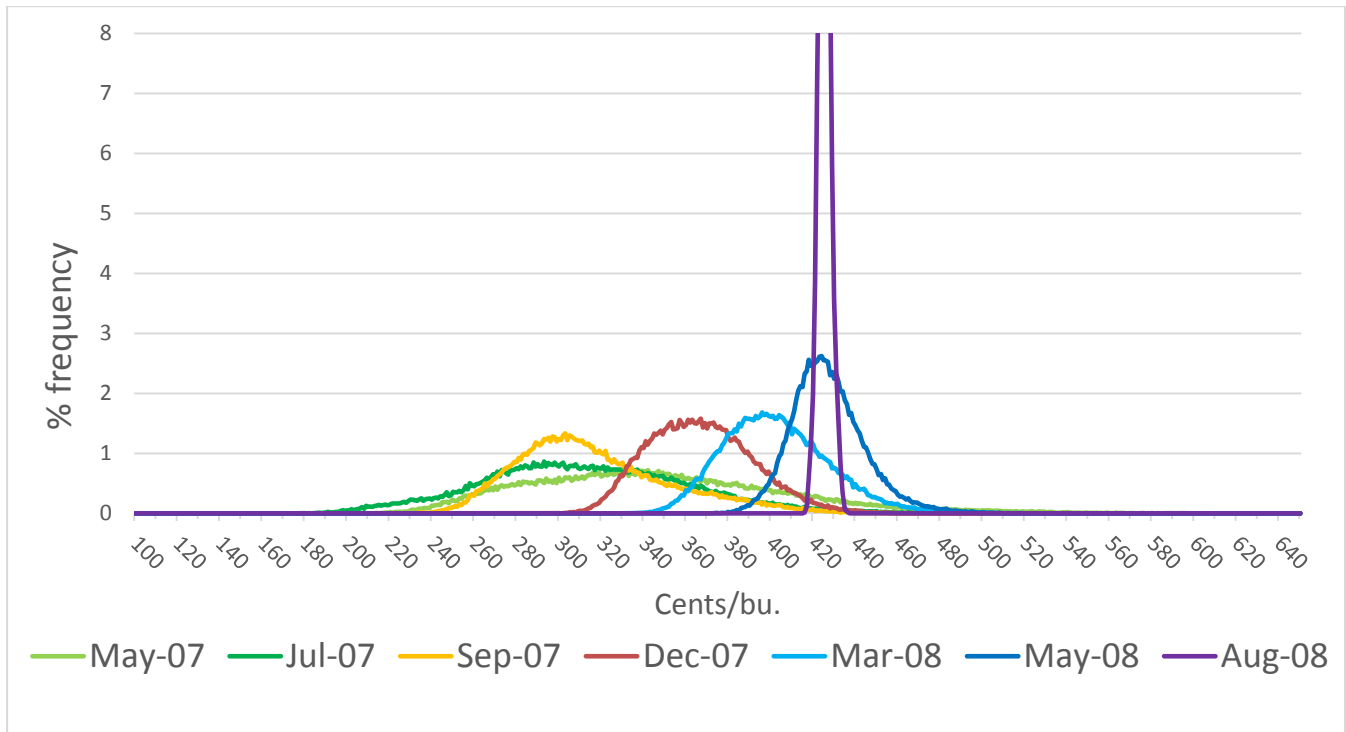


Figure 5. Selected forward-looking SAP density forecasts, 2007/08



Note: N=100,000 Monte Carlo random draws were used to generate each of these distributions. To display the other densities clearly, the peak of the August density is not shown; it reaches 13.8% at 426 cents/bu. The eventual corn SAP for 2007/2008 was 420 cents/bu.

Figure 6. Seasonality of forecast performance

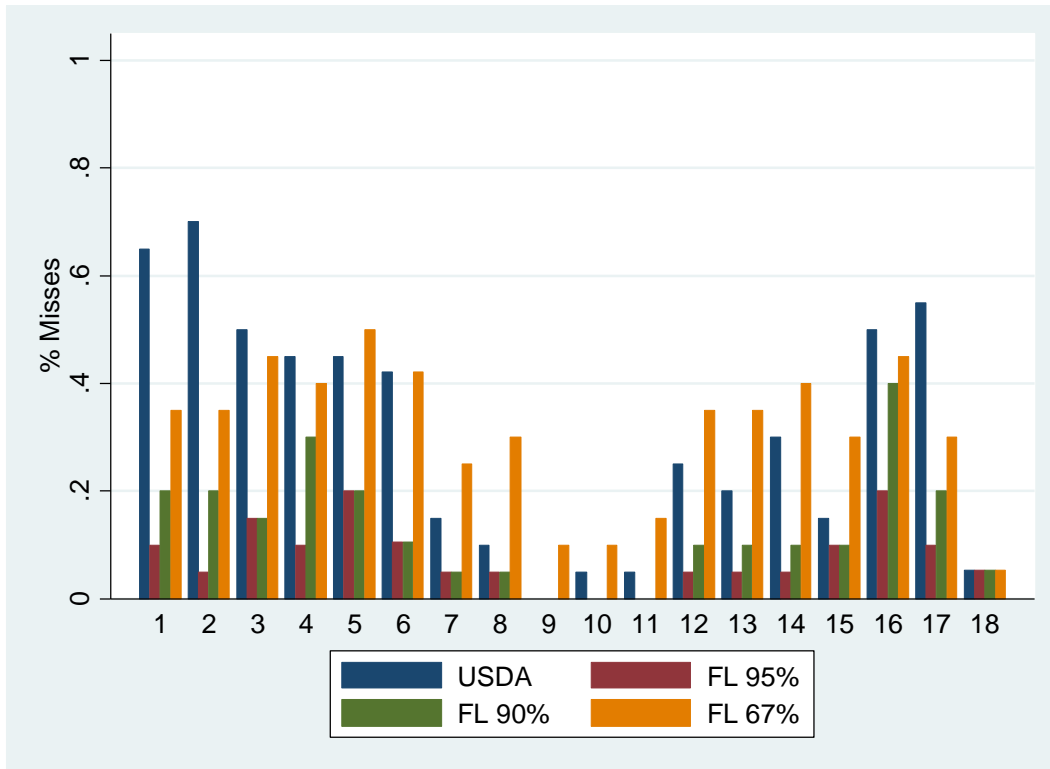


Figure 7. Forecast performance by marketing year

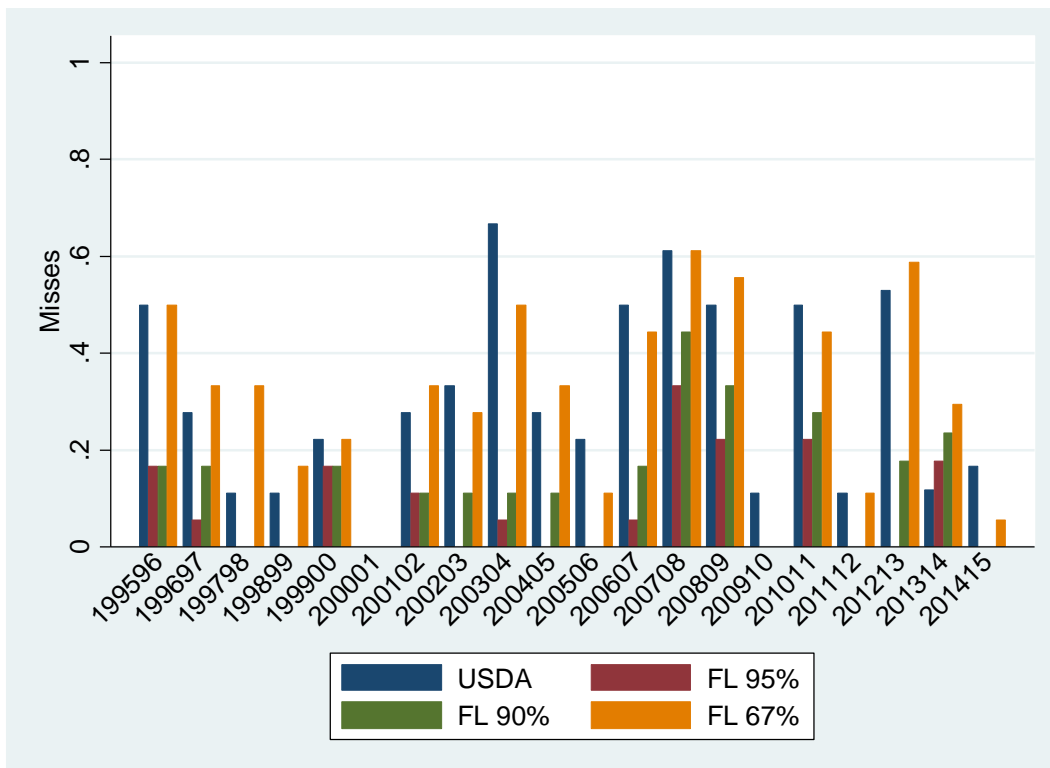


Figure 8. Average, minimum, and maximum confidence level of USDA forecasts, by number, based on FL model price densities, 1995/96-2014/15

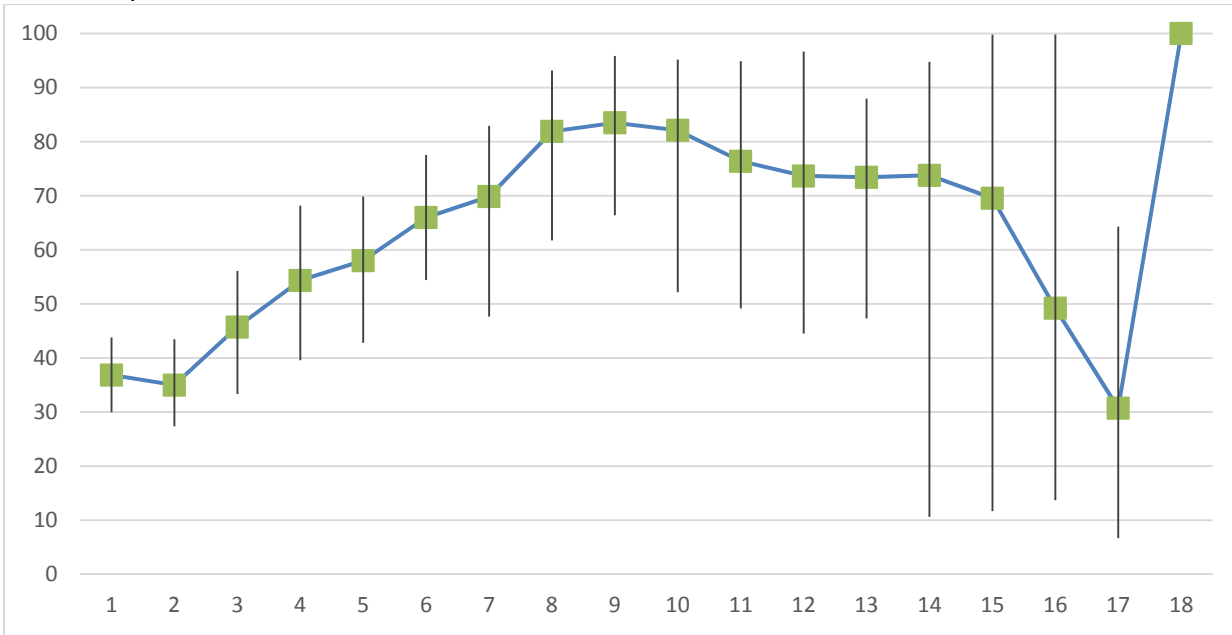


Figure 9. Proportion of 95% FL confidence interval represented by different sources of uncertainty, on average

