Incorporating Uncertainty into USDA Commodity Price Forecasts: A Review

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The U.S. Department of Agriculture (USDA) produces monthly marketing-season-average price (SAP) forecasts for major U.S. crops that are closely watched by farmers and commodity market participants. For decades, the USDA published SAP forecast ranges whose upper and lower bounds had no statistical significance. In 2019, the USDA switched to publishing monthly single-point SAP forecasts. This paper argues that conducting and publishing density forecasts, or providing intervals based on those densities, would be very valuable to consumers of the SAP forecasts. In a recent paper published in the American Journal of Agricultural Economics (2020), we use corn and soybean market data to demonstrate how a density forecasting format can improve the usefulness of USDA forecasts by simulating the historical performance of out-of-sample forecasts via different methods (in this review article, we cover the corn market alone). We use forward-looking, backward-looking, and composite approaches, and evaluate them based on commonly-accepted criteria. Backward-looking methods require little data yet provide significant improvements. For commodities with active derivatives markets, option-implied volatilities (IVs) can be used to generate forward-looking and composite models that reflect (and adjust dynamically to) market sentiment about uncertainty—a feature that is not possible using backward-looking data alone.

Each month, the USDA predicts the average price that farmers of major U.S. crops can expect to receive over the course of the commodity marketing year, referred to as the season-average price (SAP). These forecasts appear in the Department's monthly World Agricultural Supply and Demand Estimates (WASDE) report, and are closely watched by producers and government agencies, since their range affects expected farm payments and outlays (see, *e.g.*, Zulauf and Schnitkey, 2014).

For corn, the largest U.S. crop in terms of the number of bushels produced each year, USDA analysts make price predictions about the twelve-month marketing year (that covers September-August) over an 18-month forecasting cycle, beginning in May preceding the harvest, and continuing until October in the following calendar year. The final farmer-price-received value is published that following November. From April 1977 through April 2019, USDA published the SAP as an interval, with upper and lower price bounds that tended to tighten over the course of the forecasting cycle; late-cycle forecasts were regularly made as a point estimate. These forecasted bounds, however, were essentially meaningless: the USDA attached no statistical confidence to them—the probability that the price realized by farmers would lie within the extremes was not provided. As a result, the ranges were difficult to interpret for report consumers and market observers. To wit, Isengildina *et al.* (2004) showed that USDA intervals for corn and soybean prices had very low "hit rates", i.e., a low proportion of forecasts for which the realized prices fell within the projected bounds.

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The process that the USDA used to generate its SAP intervals was not public. According to Vogel and Bange (1999), it was "a complex one involving the interaction of expert judgment, commodity models, and in-depth research by Department analysts on key domestic and international issues." One might assume that published intervals were informed by historical data, such as realized volatility and past patterns of uncertainty resolution. However, given that the USDA published similar ranges at both volatile and tranquil times (Isengildina-Massa *et al.*, 2011), SAP forecasts that appeared in WASDE clearly did not accurately reflect market uncertainty about crop conditions.[1]

In 2019, the USDA chose to eliminate these SAP ranges altogether, in favor of publishing single price point forecasts in each month's WASDE for both commodities and livestock (USDA, 2019). The probability that a point forecast will be realized, however, is very low (and we explore that fact in detail below).

We argue that conducting and publishing density forecasts, or providing intervals based on those densities, would be very valuable to consumers of USDA forecasts, including government agencies attempting to plan program payments as well as other stakeholders who must make decisions about storage, marketing, and merchandising. In this article, we explain how probabilistic SAP densities can be constructed using backward- and/or forward-looking information, demonstrate how useful price intervals can be generated based on these densities, and document that these density methods outperform USDA's SAP forecasting approaches.

Each density method we consider has advantages. Because they require only the set of historical forecast errors, backward-looking densities can be generated for any commodity; their data requirements are low and they are easy to estimate. For commodities with liquid derivatives markets, we show that forward-looking information extracted from commodity option prices can improve forecast performance according to commonly-applied forecast evaluation criteria; intervals based on those densities would adjust to market sentiment, an important consideration in the current environment of policy uncertainty and trade tensions. Finally, we find that composite methods that blend backward- and forward-looking information can enhance SAP model performance. Since financial markets are efficient, this last result might seem surprising at first pass. Yet it reflects the intuition that prices for agricultural options on futures contracts reveal uncertainty about cash market prices in a single location at a single delivery date, whereas SAP are average commodity prices across the United States at the farm level, over the entirety of the marketing year: these differences explain why backward-looking data about average U.S. prices, as well as forward-looking data from the central options market, are both informationally useful.

Probabilistic Forecasting

Increasingly, private and public organizations involved in economic and price forecasting offer their predictions probabilistically. By indicating the forecaster's confidence level over a range of potential outcomes, probabilistic forecasts supply a much richer prediction profile to their consumers—as compared to a simple point estimate, whose chances of being realized are often very low.

Density forecasts of a given variable can be estimated using a few general approaches. Forward-looking methods are based on expectations about the future. Backward-looking methods are based on historical observations, or past forecast performance. Composite methods combine elements of both forward- and backward-looking techniques. Within each broad class, many different choices are available to the forecaster: the appropriate set of expectations from which to draw, the right timeframe of past observations to consider, whether or not to include exogenous variables, assumptions about the distributions followed by each of the variables that underpin the forecasting exercise, and so on.

Tay and Wallis (2000) trace the origin of density forecasts of macroeconomic variables back to the *Survey of Professional Forecasters*, developed by a partnership between the American Statistical Association and the National Bureau of Economic Research in the late 1960s, and later run by the Federal Reserve Bank of Philadelphia. By the 1990s, central banks around the world began to adopt the technique and to publish density forecasts of key macroeconomic aggregates in the form of "fan charts," whose widening color shades—resembling a handheld folding fan—indicate visually the level of certainty that forecasters place in each band of potential observations.[2]

On the one hand, researchers and governments have started using density forecasts to project price levels for some commodities, as well. For example, Trujillo-Barrera, Garcia, and Mallory (2016) 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. For several energy commodities, the U.S. Energy information Administration adds confidence bands—built via forward-looking techniques—to the price forecasts offered in its monthly *Short-Term Energy Outlook* report. Internally, in the same vein, the USDA's Risk Management Agency (RMA) uses option-implied volatilities to develop premium rates for crop revenue insurance

(Goodwin *et al*., 2014), relying on their predictive power to provide information about the expected future distribution of market prices at a single time of year. On the other hand, USDA monthly SAP forecasts have, for decades, been published without any probabilistic context.

Enhancing USDA Price Forecasts

In this section, we describe various probabilistic techniques that can be used to enhance USDA price forecasts. For more information about how we implemented these methods and what data we used, please see the original article—Adjemian *et al.* (2020).

Backward-Looking Approach

One way to gauge uncertainty about a given forecast is to measure the historical reliability of previous forecasts made using the same model. By assuming that new forecasts will maintain the same level of reliability as past projections at the same step in the series (i.e., by assuming that the distribution of future forecast errors will follow the distribution of errors observed up to that point), the analyst can generate a probability density to quantify predictive uncertainty. This is precisely the type of approach used for grains and oilseeds by Isengildina-Massa *et al.* (2010) and Isengildina-Massa *et al*. (2011): at each forecast step, historical errors are used to construct "empirical confidence intervals" around projected commodity prices based on the method introduced by Williams and Goodman (1971).

A straightforward backward-looking method is to organize a histogram of the frequencies of various historical miss rates and apply it to the current forecast. Yet a richer probability density function can be estimated by fitting a function, such as a kernel, that smoothes the observations in the histogram. Compared to a histogram, an error-based density provides more flexibility to the SAP forecast, supplying a positive probability to ranges of prices that fall in between values that line up precisely with the forecast errors that the Department has made in the past.

All backward-looking approaches are sensitive to the adequacy of the available history of forecast errors. Small samples reduce reliability, since they may not be large enough to provide an adequate basis for the construction of empirical densities (Taylor and Bunn, 1999). Moreover, no backward-looking method has the capacity to reflect expectations about market conditions that may be uncorrelated with past price behavior—they all assume that the error distribution is time invariant.

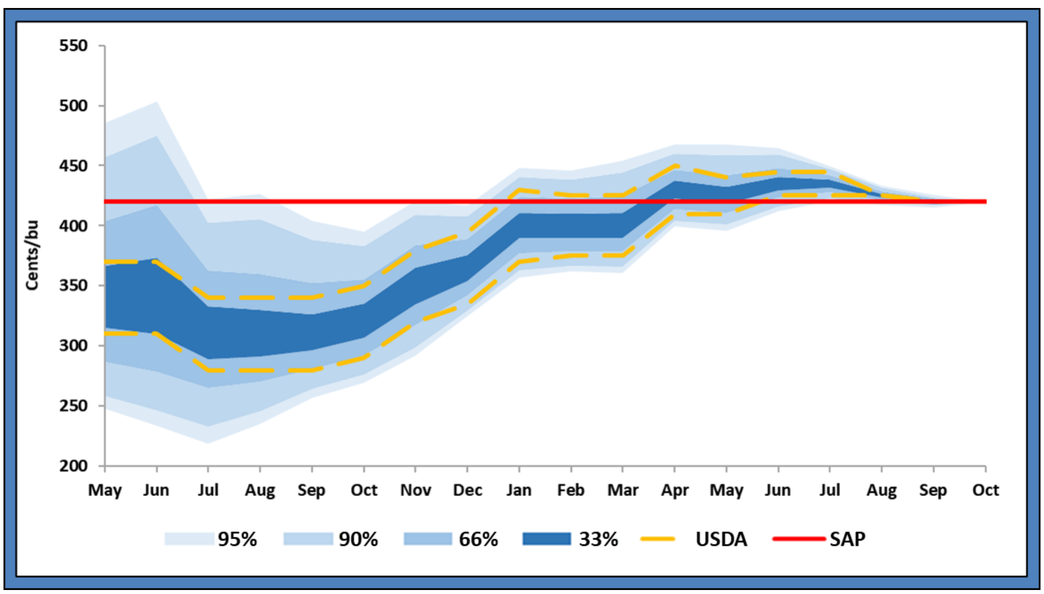
Forward-Looking Approach

Forecast densities can also be constructed using forward-looking information, for those commodity markets that supply it (or perhaps even for smaller markets that do not, as long as their features are relatable enough to larger markets that do; this is analogous to, for example, cross-hedging sorghum risk using the liquid corn market derivatives (CME Group, 2015)). Liquid and active futures and options values reveal the market's expectations about the first and second moments of a given commodity's expected price distribution.[3] Futures prices represent the market's risk-neutral expectation about future commodity prices,[4] while options premia—whose value is based in part on the expected variance of the underlying futures contract price—can be inverted to solve for market-implied volatilities using an option pricing model, as in Black (1976). The resulting forward-looking price density forecasts respond dynamically to changes in the option-implied volatilities: they narrow or widen with the updates to market uncertainty that are embedded in options prices.

This market-sensitive feature is not possible when using backward-looking methods, yet its impact can be substantial. In July 2007, for example, the implied volatility observed for corn contracts was among the highest observed over the previous ten years. As a result, the *ex-ante* forecast density we estimate using that level of uncertainty is fairly wide, as shown in Figure 1a. The benefit of incorporating option-implied volatility, at least for that specific month, is better grasped when considering that the final SAP realized in the 2007 marketing year was well outside the kernel-based backward-looking density shown in Figure 1b; in other words, the backward-looking method missed completely. In the same vein, the price spike later in Fall 2007 was not anticipated by USDA analysts (i.e., note how the dashed yellow range in Figure 1b is too low), and the spike's effect on price was so substantial that the resulting forecast error was far larger than any forecast error those analysts had made at the same point in the forecasting cycle in *any* of the previous 26 years. In contrast, the forward-looking density, while placing a low probability that corn prices might move that high, nevertheless assigned a positive probability to the eventual realized SAP value. In short: options prices reflect traders' concerns about future volatility that can help predict possible future SAP paths.

Figure 1
Forecast Densities of the Corn Season-Average Price over 2007/08

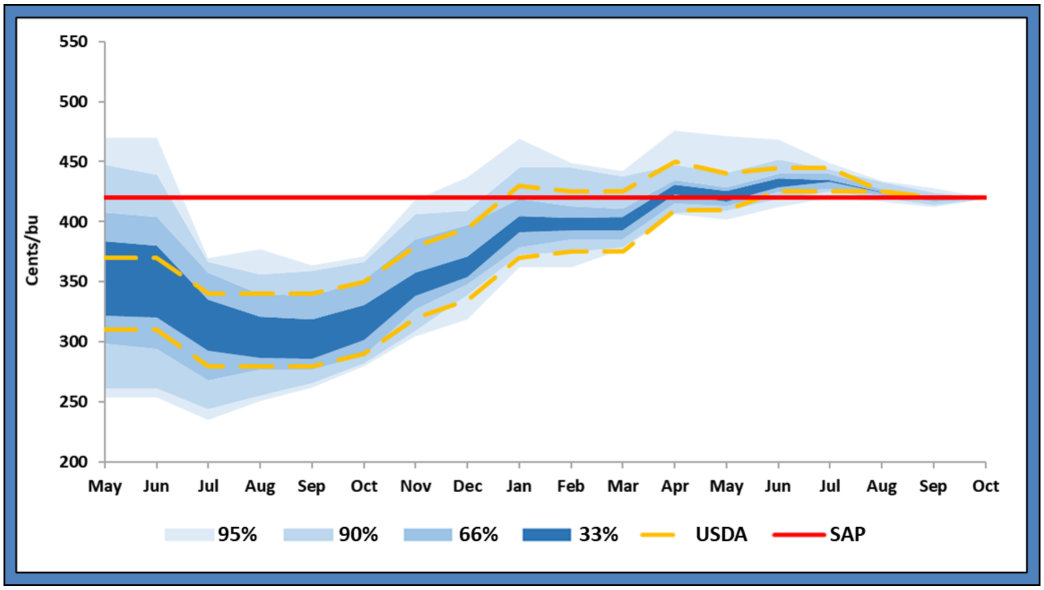
1a. Forward-Looking Forecast Intervals at Various Confidence Levels



Source: Author calculations based on USDA and Chicago Mercantile Exchange (CME) Group data.

Notes: Shaded regions represent *ex-ante* predictions of confidence intervals for the marketing year's season-average price (SAP), at each forecast step. "USDA" is the interval predicted by USDA in the WASDE report. This figure is reproduced with permission from Wiley.

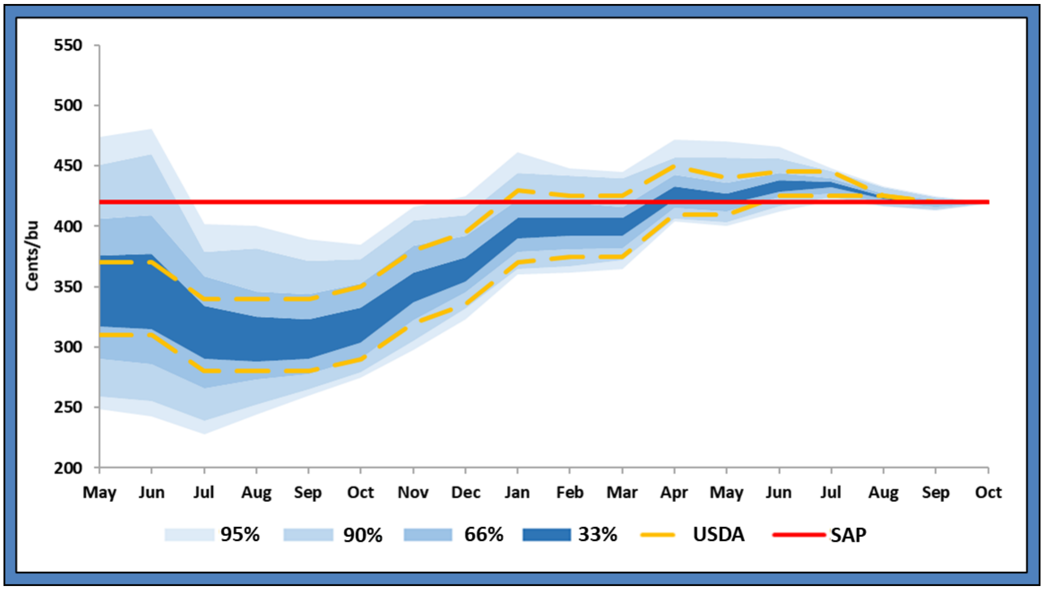
1b. Backward-Looking Forecast Intervals at Various Confidence Levels



Source: Author calculations based on USDA and CME Group data.

Notes: Shaded regions represent *ex-ante* predictions of confidence intervals for the marketing year's season-average price (SAP), at each forecast step. "USDA" is the interval predicted by USDA in the WASDE report. This figure is reproduced with permission from Wiley.

1c. Composite Forecast Intervals at Various Confidence Levels



Source: Author calculations based on USDA and CME Group data.

Notes: Shaded regions represent *ex-ante* predictions of confidence intervals for the marketing year's season-average price (SAP), at each forecast step. "USDA" is the interval predicted by USDA in the WASDE report. This figure is reproduced with permission from Wiley.

Composite Approach

Forecast densities generated *via* forward- and backward-looking approaches can be combined, so that features of both are incorporated into the process. This is a useful step if backward-looking information can add explanatory power to the forecast of average commodity prices across the United States *at the farm level*, an important concern given that the prices for options on futures contracts traded in Chicago represent uncertainty about cash-market prices in a single location at a single delivery date. That is, futures and options-on-futures prices do not address spatial basis risk, i.e., the possibility that futures and farm-level prices might not move perfectly together. We therefore create composite forecast densities by applying equal weights to both forecast methods at every step over the period of observation. In effect, our composite density is a simple average of both original densities. To gauge the benefits of including features of both original methods into a single density, we include that simple composite forecast in our evaluation.

Comparing the Backward-Looking, Forward-Looking, and Composite Approaches

Standard evaluation techniques for probabilistic forecasts focus on *sharpness* and *calibration* (Kling and Bessler, 1989; Gneiting *et al.*, 2007), which represent, respectively, the ability of the model to place a high-density value at the eventual realized price, and the similarity of the forecast densities to the true expected price density. Sharpness and calibration can be jointly measured using scoring rules (Gneiting and Raftery, 2007), while calibration is generally assessed via the probability integral transform (Diebold *et al.*, 1998; Berkowitz, 2001) or coverage tests for selected intervals (Christoffersen, 1998). Two popular examples of the former include the logarithmic score (calculated as the logarithm of the forecast density evaluated at the realized outcome) and the continuous ranked probability score (CRPS), which measures the divergence of the forecast distribution from a perfect forecast with a probability mass located at the realized observation (Gneiting and Raftery, 2007).

The SAP forecasting cycle is 18-steps long, further ahead in time than forecasts considered in many other contexts. Longer horizons correspond to higher levels of uncertainty: as a result, we cannot usefully employ log scoring methods (Good, 1952; Bernardo, 1979; Gneiting *et al.*, 2007), since they depend on the logarithm of the value of the forecasted cumulative distribution function at the realized price. In some cases, our forecast densities do not include the realized price, so the value of the respective cumulative distribution function is zero—and of course the logarithm of zero is undefined.

Rather than assigning an arbitrary log score (Boero *et al.*, 2011), therefore, we employ instead the CRPS—a quadratic scoring method that calculates the divergence of each forecasted density from an "ideal forecast" that places all probability mass at the realized price. An important advantage of the CRPS is that, unlike the log score, it awards forecasts that place more probability near (but not at) the realized value (Gneiting and Raftery, 2007). Densities with lower CRPS are preferred, and the units of the CRPS are the same units of the original forecast: in our case, the price of each agricultural commodity is expressed in cents per bushel.

From 1995/96 to 2015/16, the USDA made a total of 376 SAP forecasts for corn. To compare approaches, we estimate SAP price densities via forward-looking, backward-looking, and composite methods, using only information that would have been available to USDA forecasters at the time. To represent USDA's forecast policy, we include the traditional intervals as well as the point forecasts as candidate models. For the former, in the absence of any public information about USDA analysts' preferred functional form (Vogel and Bange, 1999), we assume a uniform probability distribution over the published interval; for the latter, we assume that the midpoint of an interval is USDA's price forecast. We judge sharpness and calibration of each approach according to the CRPS. Forecasts that produce lower CRPS values are preferred; following Colino *et al*. (2012) and Etienne *et al.* (2019), we compare the average scores produced by models at each forecast step using modified Diebold-Mariano tests (Harvey *et al*., 1997). To further evaluate the sample-wide calibration of forecast models, we explore their coverage at several selected confidence levels, i.e., whether the model-predicted level of uncertainty at forecast time matched the realized uncertainty over the period of observation; and, like Isengildina-Massa *et al*. (2011), we assess their statistical equivalence using unconditional coverage tests (Christoffersen, 1998).

Discussion of Model Performance

Table 1 compares the performance of all candidate corn models at each forecast step on the basis of CRPS. Outside of a handful of exceptions, probabilistic models produce lower CRPS values than either of USDA's methods. Indeed, for the clear majority of the cycle, the scores the USDA approaches produce are significantly worse. As expected, point forecasts, in particular, tend to produce very high average CRPS: they place all the probability mass on a SAP that is often distant from the realized value. Only in the late *post*-harvest period (i.e., after most of the crop has generally been marketed at known prices), does the relative precision of the point forecast method improve. USDA's interval method, which the Department used prior to switching to point forecasts in 2019, doesn't perform much better.

Table 1
Average CRPS for Out-of-Sample Corn Season-Average Price Forecasts over 1995/96 – 2015/16, by Model

	Forecast	N	Forward	Backward	Composite	USDA	Point
Pre-Harvest	May	21	39.5	40.7	39.9	47.3	55.0
	Jun	21	40.4	42.3	41.2	49.0	56.6
	Jul	21	33.2	34.2	33.6	38.5	46.0
	Aug	21	32.9	33.7	33.2	37.9	45.6
	Sep	21	29.8	29.7	29.6	33.4	42.0
	Oct	20	21.0	21.7	21.3	23.1	30.9
Post-Harvest	Nov	21	13.7	13.9	13.7	13.5	17.2
	Dec	21	9.8	10.3	10.0	9.7	12.7
	Jan	21	7.4	7.5	7.4	7.3	9.9
	Feb	21	6.1	6.4	6.2	6.2	8.5
	Mar	21	4.8	4.9	4.8	4.9	6.4
	Apr	21	4.3	4.2	4.2***	4.4	6.0
	May	21	3.6	3.5	3.5***	3.5	4.9
	Jun	21	3.8	3.8	3.7***	3.8	5.4
	Jul	21	1.8***	2.1	1.9	1.9	2.4
	Aug	21	1.3***	1.5	1.4	1.5	1.8
	Sep	21	0.7***	0.9	0.8	0.9	0.9
	Oct	20	0.2***	0.2	0.2	0.2***	0.2***

Source: Author calculations based on USDA and CME Group data.

Notes: A U.S. government shutdown in October 2013 curtailed publication of the WASDE report that month, so one new crop and one old crop forecast is missing from the 21-year forecast sample. “Interval” represents a density model that assigns uniform probability over USDA’s published intervals. Average CRPS scores at each forecast step are reported in cents/bushel. Lower CRPS values are preferred; the lowest score at each forecast step is shaded. Significance of modified Diebold-Mariano (MDM) tests between the lowest CRPS value and the model with the next lowest value at each step are indicated by asterisks: *** represents the 1% level, ** the 5% level, and * the 10% level. The null hypothesis of the MDM tests assumes equality of forecast performance. This table is reproduced with permission from Wiley.

In sharp contrast, CRPS results shine a favorable light on our models that include forward-looking information: forward-looking or equal-weight composite models produce the lowest average score at almost all forecast steps. In some cases, these scores are significantly lower than the next-best score, according to modified Diebold-Mariano tests. And forward-looking models tend to perform best at two times: *pre*-harvest, when option-implied volatility helps characterize the uncertainty about crop conditions and their implications for farmgate prices; and then again very late in the marketing cycle, well after the harvest came in.

Backward-looking forecast errors seem to hold the most predictive value in the *post*-harvest December-June period: that part of the year is when their inclusion in the form of a composite model produces lower average CRPS. Put differently, including the profile of past USDA forecast misses starts to improve on our futures-based approach to describing uncertainty expectations about farm-level corn prices just as about half of the crop has been marketed. This finding is consistent with the idea that, although futures and options markets can produce efficient forecasts for commodity prices in a single market at point in time, they do not fully represent uncertainty about the average price that farmers will get paid across the vast United States—historical USDA errors can help produce better density forecasts at certain steps. By the late-forecasting-cycle period, our forward-looking models again tend to produce the lowest average CRPS for both commodities. Although statistically significant, these improvements are fairly small in absolute terms; moreover, the utility of those forecasts is likely lower than those made before the harvest, and than those made before the bulk of the crop has been marketed.

Were USDA to publish intervals around its SAP forecast, the Department might choose among those depicted by the density forecasts in Figure 1. Table 2 reports hit rates achieved by each model (except the Point Estimate approach, which does not produce intervals) at each of those confidence levels, for the *pre*-harvest and *post*-harvest period, respectively, as well as the results of unconditional coverage tests that assume equivalence as the null hypothesis. Table 2 also reports the average size of those intervals in cents per bushel. Though it is not *always* the case, models that produce wider average intervals tend to achieve higher hit rates; better coverage is indicated by matching an interval's hit rate to its *ex-ante* confidence level.

Table 2
Corn Season-Average Price Forecast Hit Rates and Average Size (in cents/bushel) for Select Confidence Intervals Based on Out-of-Sample Density Forecasts over 1995/96 – 2015/16, by Model

Confidence Level	N		*Pre*-Harvest Period Forward	Backward	Composite	USDA	N	*Post*-Harvest Period Forward	Backward	Composite	USDA
95%	125	Hit Rate	92.8%	78.4%***	84.8%***	47.2%***	251	96.0%	95.6%	96.8%	82.5%***
		Avg. Size	203	175	187	56		43	54	49	27
90%	125	Hit Rate	82.4%***	78.4%***	80%***	40.8%***	251	94.4%**	92.4%	94%**	81.7%***
		Avg. Size	172	150	160	53		37	41	38	26
67%	125	Hit Rate	64.8%	61.6%	62.4%	32%***	251	80.5%***	70.1%	75.7%***	71.7%***
		Avg. Size	101	92	96	41		23	20	22	20
33%	125	Hit Rate	29.6%	30.4%	28.0%	12%***	251	56.6%***	48.2%***	52.2%***	56.2%***
		Avg. Size	46	48	47	22		11	9	10	11

Source: Author calculations based on USDA and CME Group data.

Notes: "Hit rate" represents the percentage of realized season-average prices that fall inside the *ex-ante* confidence intervals produced by each model, while "Avg. Size" is the mean range of the interval. Significance of unconditional coverage tests that compare observed hits to the specified confidence level (where the null hypothesis is that the hit rate and the target confidence level are equivalent) is indicated by asterisks: *** represents the 1% level, ** the 5% level, and * the 10% level. This table is reproduced with permission from Wiley.

Coverage tests reject every confidence interval produced by the USDA's model: over time, it produced very low hit rates (and relatively small intervals) at each confidence level. Other models in the table produce far fewer test rejections than the USDA's approach.

In the *pre*-harvest period, our corn forward-looking model has just one test rejection (at the 90% confidence level), and the backward-looking and composite models only have two. In the *post*-harvest period, our forward-looking and composite intervals have three test rejections: each produces too-high hit rates at every confidence level in the table besides 95%.

The backward-looking model has the fewest total coverage test rejections, but these are clustered early in the forecasting cycle—when those intervals should be the most valuable to consumers. In contrast, the forward-looking model's coverage misses (while slightly more numerous) are clustered in the *post*-harvest period, when they are likely to be less costly.

Conclusions

From 1977 through 2019, the USDA produced forecasts of the average price that farmers should expect to receive over the course of a marketing year for major domestic crops. Until April 2019, to indicate uncertainty about the forecast, the Department's analysts placed symmetric intervals around each forecasted price; these intervals narrowed over the course of the forecasting cycle and eventually collapsed onto the single point. The USDA, however, did not indicate the degree of statistical confidence attached to those intervals, so they were not very (if at all) meaningful. In May 2019, the Department altogether abandoned intervals in favor of a single point estimate.

In this *GCARD* article, we reference research we published in the *American Journal of Agricultural Economics* (Adjemian *et al*., 2020) to describe the benefits of probabilistic forecasting and evaluate three approaches to making out-of-sample density forecasts of the season-average price for corn. These densities would permit the USDA to construct empirically-based price intervals at a range of confidence levels. Because consumers of the SAP forecasts include market participants and government agencies responsible for planning their program outlays, bounding the uncertainty around farmgate commodity prices using any or all of these densities would offer far more information than a mere point estimate, providing a richer profile of price expectations. Every density model that we estimate (using backward- and/or forward-looking information) is better than the USDA SAP forecast methods across the bulk of the forecasting cycle, both in terms of locating a greater level of probability near the *ex-post* realized SAP, and in terms of coverage tests at selected confidence levels. And, since they are provided in a probabilistic format, every density model produces richer forecast profiles that can be better utilized by forecast consumers, compared to a simple point forecast or to a range estimate without confidence figures.

Each density approach has its own advantages and drawbacks. Because it is constructed using historical USDA forecast errors, the backward-looking model is easy to estimate. It also does not require that a related derivatives market exist or work well. And although it is generally not favored according to CRPS, the *post*-harvest confidence intervals that it produces are reasonably accurate. The forward-looking and composite models that we estimate require information from derivatives markets, and are constructed using the market's expectation of future price volatility implied by commodity options premia. Their densities and confidence intervals therefore adjust dynamically to changes in market sentiment, and intuitively they can reflect expected volatility better than historical models. Indeed, we show that widely-used calibration evaluations tend to favor these models which, on average, place a higher amount of probability closer to the realized SAP. Including forward-looking information, in other words, is valuable when it matters the most—and it is especially useful in volatile or uncertain times (like the situation depicted in Figure 1).

Endnotes

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1 For example, over the 17 years from May 1989 to May 2006, the USDA's first interval prediction for the average price paid to farmers for corn harvested in the ensuing Fall was always 40 cents.

2 Prominent examples of fan charts include those published quarterly by the Monetary Policy Committee (MPC) of the Bank of England, illustrating its expectations about output growth, inflation, and unemployment in the United Kingdom. In April 2017, the U.S. Federal Reserve Bank began issuing fan chart projections for all those variables in the United States, as well as for the target federal funds rate (FOMC, 2017).

3 A commodity 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 commodity futures contract at an agreed upon price. The value of that right is a function of how uncertain the future price is, i.e., of the forward-looking price volatility.

4 Some economists argue that a commodity futures price represent its expected future price plus a risk premium for speculators (see, *e.g.*, Keynes, 1930). This claim has received mixed empirical support in the literature, particularly as it relates to grains (Hartzmark, 1991; Frank and Garcia, 2009; Fishe and Smith, 2012). We do not consider risk adjustments to the determination of implied volatilities in this analysis, but intend to explore them in future work.

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