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Practical Alternatives for Forecasting Corn and Soybean Basis in the Eastern Corn Belt throughout the Crop-Marketing Year

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This paper re-evaluates practical methods of forecasting corn and soybean basis in the eastern Corn Belt. The accuracy of forecast methods differs over the course of the crop-marketing year. At harvest, historical moving average forecasts perform best. Post-harvest forecasts may be improved at short forecast horizons (<8–12 weeks ahead) by combining historical moving averages and recent basis levels. Results suggest that using 3-to-5-year moving average forecasts for corn basis and a 2- or 5-year moving average for soybean basis from harvest through April. The accuracy of these corn and soybean basis forecasts decreases markedly during the summer months.

Key words: basis forecasting, crop basis, current information, forecast error regression model, moving averages, naïve forecast

Introduction

Commodity price risk is one of the biggest risks agricultural producers face (Lubben, 2014; Thompson, Bir, and Widmar, 2019). Schroeder et al. (1998) conclude that futures markets are an efficient and low-cost source of national agricultural commodity price forecasts, but to effectively manage risks faced by their operations, farm decision makers need local cash price forecasts. Kastens, Jones, and Schroeder (1998) concluded that combining current futures prices with basis forecasts, where basis is defined as cash price less futures price, is an effective approach to generate local cash price forecasts.

Producers and agribusinesses can buy and sell commodities year-round. However, commodity price risk may not be the same across the entire crop-marketing year. Therefore, producers and other cash market participants need accurate basis forecasts throughout the year to evaluate pricing opportunities and to estimate expected sale or purchase prices when placing hedges (Chicago Board of Trade, 1990; Tomek, 1997). One category of basis forecasting models that accounts for these temporal variations is econometric basis forecasting models. These models often rely on time-series econometrics and/or consider explanatory variables such as futures price spreads, storage cost and availability, and transportation costs (e.g., Hauser, Garcia, and Tumblin, 1990; Sanders and Manfredo, 2006; Welch, Mkrtchyan, and Power, 2009; Sanders, 2013; Bekkerman, Brester, and Taylor, 2016). However, producers' use of these models is problematic given that they often require data that are not widely available or, in some cases, forecasts of right-side variables to generate basis forecasts.

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A second approach to basis forecasting is moving averages based on historical data, sometimes combined with recent basis levels. These forecasts are relatively easy to generate and provide reasonably accurate basis forecasts, in many cases outperforming more sophisticated econometric models (Dhuyvetter and Kastens, 1998; Sanders and Manfredo, 2006; Sanders, 2013). For these reasons, farm decision makers, grain merchandisers, extension economists, and professionals teaching commodity marketing and risk management courses often rely on the easier-to-implement moving average approach to forecasting basis.[1] However, existing research evaluating moving average forecast methods has been limited to evaluating the accuracy of these forecasts during two narrowly defined periods: harvest and storage (Taylor, Dhuyvetter, and Kastens, 2006; Hatchett, Brorsen, and Anderson, 2010; Lee and Brorsen, 2017). While this approach acknowledges within-year differences, it fails to fully explain the dynamics of the accuracy of basis forecasting methods throughout the crop-marketing year. Dhuyvetter and Kastens (1998) estimate month fixed effects in their forecast error regression model, which allows for a brief discussion of forecast accuracy by month. However, by not interacting forecast method and month fixed effects, they fail to account for the fact that different forecasts may respond differently throughout the marketing year. Hence, the objective of this study is to examine for the first time the accuracy of various moving average basis forecasts over the course of the crop-marketing year.

In doing so, we also re-evaluate previous recommendations regarding the optimal length of moving averages to use when forecasting corn and soybean basis in the eastern Corn Belt. Previous research has shown that optimal length for moving average basis forecasting models (e.g., 3- or 5-year moving average) varies by region and commodity (Dhuyvetter and Kastens, 1998; Taylor, Dhuyvetter, and Kastens, 2006; Hatchett, Brorsen, and Anderson, 2010; Lee and Brorsen, 2017). In addition, the time period evaluated can influence forecast recommendations. For example, increased volatility of crop basis in recent years has necessarily reduced the accuracy of basis forecasts based on historical data (Lee and Brorsen, 2017). While this increase in volatility has been attributed to a number of factors, the increase in corn-based ethanol production is generally considered the largest contributor to this shift in basis patterns (Irwin and Good, 2009). Since the Renewable Fuel Standard (RFS) was created under the Energy Policy Act of 2005 and expanded by the Energy Independence and Security Act of 2007 (U.S. Environmental Protection Agency, 2018), the construction of ethanol biorefineries across the Midwest has greatly influenced both national and local supply and demand fundamentals.[2]

A number of studies have linked commodity price levels and price volatility with ethanol production (e.g., McNew and Griffith, 2005; Bekkerman and Pelletier, 2009; Fausti, Qasmi, and Mc Daniel, 2017). However, to date, little work has been done to re-evaluate optimal length moving average basis forecast recommendations in the post-ethanol era. It is important to note that we are not attempting to describe the impact of ethanol production on basis forecast accuracy in this paper. Instead, the objective here is to provide recommendations for pragmatic moving average forecast methods, which are often used by practitioners.

Recent research has posited that the optimal-length moving average forecast is tied to the occurrence of structural breaks, such as ethanol (Hatchett, Brorsen, and Anderson, 2010; Lee and Brorsen, 2017). During eras of stable market conditions, longer moving average forecasts would be expected to provide more accurate basis forecasts; when a structural break has occurred, the previous year's basis is recommended (Hatchett, Brorsen, and Anderson, 2010; Lee and Brorsen, 2017).

[1] The popularity of moving average basis forecasts is illustrated by their availability on extension websites (e.g., Kansas State University, 2019; farmdoc, 2019; Purdue University Center for Commercial Agriculture, 2019). Web resources have significant potential to make more sophisticated basis forecasts accessible to a larger audience. For example, the Montana State University Wheat Basis and Price Forecasting Tool (2019) provides wheat basis forecasts based on more sophisticated econometric models (Bekkerman, Brester, and Taylor, 2016). The disadvantage is that some users may hesitate to accept forecasts produced by a "black box" as opposed to the simplicity of a moving average forecast.

[2] For perspective, nine ethanol biorefineries in the eastern Corn Belt (Illinois, Indiana, Michigan, and Ohio), the focus of this study, produced 936 million gallons in 2004 (Renewable Fuels Association, 2004). By 2017, 40 biorefineries in the same region produced 3.8 billion gallons (Renewable Fuels Association, 2017).

Lee and Brorsen attempted to model the impact of permanent shocks on identifying optimal length moving average forecasts. Their results indicated that most shocks are permanent; as a result, 1-year moving averages were generally preferred in their analysis. However, the authors acknowledged that some large permanent shocks occurred over the period studied (1975–2013). Therefore, they pointed out that as commodity markets stabilize in the post-ethanol era, a return to longer moving average forecasts will likely again prove valuable.

While their study provided a formal model for explaining why searching for an optimal-length moving average depends on the period studied, it did not provide those implementing these forecast methods with the ability to foresee these shocks or even identify that a permanent shock has taken place, nor did it evaluate the accuracy of these forecasts for the entire crop-marketing year. Thus, there is still a need for rigorous analysis of these forecast methods from time to time to provide current recommendations on the optimal length of moving averages to use when forecasting corn and soybean basis throughout the crop-marketing year. This is especially true in light of Lee and Brorsen's (2017) finding that most shocks are permanent. That is, by definition a temporary shock would not change the forecast recommendations and could be easily handled by ignoring years expected to represent exceptional, but not persistent, basis patterns. Permanent shocks, on the other hand, indicate that the market is operating under a fundamentally new regime that (i) takes time to stabilize and (ii) requires re-evaluation of forecasting methods as the market restabilizes.

Our research also extends previous work by evaluating whether basis forecast accuracy can be improved by incorporating current information that is readily available to farmers in the form of current basis deviations from historical averages. Previous research found that current market information increased the accuracy of post-harvest basis forecasts in Kansas (Taylor, Dhuyvetter, and Kastens, 2006), but this approach has not been evaluated for corn and soybeans in the important production region of the eastern Corn Belt.[3,4]

We use a rich dataset consisting of cash prices from 129 corn and soybean buyers across four eastern Corn Belt states (Illinois, Indiana, Michigan, and Ohio) to evaluate the accuracy of moving average basis forecasts over the course of the crop-marketing year. In addition, we re-evaluate previous recommendations of the optimal-length moving average basis forecasts. The results presented here represent generalized recommendations across the entire four state region and can be implemented using data provided by the Purdue University Center for Commercial Agriculture (2019) Crop Basis Tool. While one could use similar methods to identify location-specific recommendations, our objective here is to provide general recommendations that encompass the entire region. Because the data are limited to the eastern Corn Belt, the basis forecast recommendations made here may not be appropriate in other locations. Data from 2004–2017 are included, providing the most comprehensive analysis of post-ethanol basis data to date. We find that, compared to some recent studies, which recommend 1-year moving average basis forecasts for corn and soybeans, longer moving averages (3–5 years) may provide more accurate basis forecasts in the post-ethanol era, particularly for corn. Further, we find that the accuracy of moving average basis forecasts differs throughout the crop-marketing year. This important contribution has implications for those forecasting basis but has been largely overlooked in previous studies.

Data

We purchased cash prices for corn and soybeans from the first week of 2004 to the last week of 2017 from DTN (2018), which maintains a historical cash price database for thousands of U.S.

[3] Basis is an inherently local concept driven by local supply and local demand. Therefore, as Taylor, Dhuyvetter, and Kastens (2006)pointed out, empirical results from an analysis of data strictly from Kansas locations may not apply to other locations, such as the eastern Corn Belt.

[4] The importance of the eastern Corn Belt as a production region is evident from its share of U.S. corn and soybean production. Over 2013–2017, the eastern Corn Belt region (Illinois, Indiana, Michigan, and Ohio) produced, on average, 28% of U.S. corn and 30% of U.S. soybeans (U.S. Department of Agriculture, 2018).

grain buyers. In this study, we focus specifically on four eastern Corn Belt states: Illinois, Indiana, Michigan, and Ohio. Aggregating across individual locations in these four states, our primary analysis seeks to provide generalized recommendations that encompass the entire eastern Corn Belt region. This is similar to previous studies that have sought to provide generalized recommendations across a geographic region that is assumed to have a similar market structure rather than attempting to make location-specific recommendations (e.g., Taylor, Dhuyvetter, and Kastens, 2006). However, it is important to point out that aggregating across locations from several states may raise concerns about the contribution of any given state to the overall results. Thus, we evaluate the robustness of the generalized results by comparing them with the results for each individual state.

We also collected corresponding nearby futures prices from DTN, where nearby is defined as the nearest contract to delivery without going into the delivery month. We used Wednesday prices to create a weekly price series.[5] If Wednesday happened to fall on a holiday, we used Thursday prices. Data were structured to have 4 weeks per month (48 weeks per year). If a month had five Wednesdays, we averaged the fourth- and fifth-weeks' prices and reported the result as the fourth week. After omitting buyers who started reporting prices after 2004 and those who were missing two or more consecutive weekly cash prices, 129 unique locations remained, 90 of which reported prices for both corn and soybeans, while 23 and 16 reported just corn or just soybean prices, respectively. We extrapolated missing data by averaging the reported values the week before and the week after the missing values. Missing values were rare (less than 0.01% of the sample) since the selected sample of locations was chosen for completeness of historical data.

It is important to note that the period represented is characterized by significant structural change as a result of biofuel policy and the resulting construction of ethanol plants throughout the study region. In addition to structural change, the eastern Corn Belt experienced severe drought during the 2012 growing season that resulted in what has been characterized as "once-in-a-generation crop calamity" (Rippey, 2015). Short supplies resulting from significantly lower yields greatly impacted basis patterns (Figure 1). However, this has been characterized as a likely temporary shock (Lee and Brorsen, 2017). For this reason, we subject the analysis to a variety of robustness checks to evaluate the sensitivity of the results to the inclusion or exclusion of years deemed "exceptional."

Procedures

We created nearby basis values by taking the cash price less the nearby futures market price. We then used three general forecast methods (11 specific forecasts) to create basis forecasts for corn and soybeans for each week of the year. The first five forecasts are based on historical moving averages:

$$\widehat{Basis}_{j,k,t}(N) = \frac{1}{N}\sum_{i=1}^{N} Basis_{j,k,t-i}, \tag{1}$$

where $\widehat{Basis}_{j,k,t}(N)$ represents the nearby basis forecast for location j in week of the year k and year t.[6] N represents the number of years included in the historical average ($N = 1,\ldots,5$). Initially, we chose 5 years as the longest moving average forecast to be evaluated based on previous research in the study region (Hatchett, Brorsen, and Anderson, 2010; Lee and Brorsen, 2017) and to provide a reasonable number of out-of-sample forecasts years for evaluation. However, following Dhuyvetter and Kastens (1998) and Taylor, Dhuyvetter, and Kastens (2006), we also ran the analysis with up to 7-year moving average forecasts to determine the robustness of the results to this assumption.

[5] We selected Wednesday prices based on convention, following previous studies that evaluated moving average basis forecasts (Dhuyvetter and Kastens, 1998; Taylor, Dhuyvetter, and Kastens, 2006; Hatchett, Brorsen, and Anderson, 2010; Lee and Brorsen, 2017). We also explored weekly averages, and results were qualitatively similar (results available from authors).

[6] Notice that the basis forecast $\widehat{Basis}_{j,k,t}(N)$ in equation (1) depends on the year subscript t. Hence, these, and all of the forecasts in this paper, are fixed rolling-window forecasts.

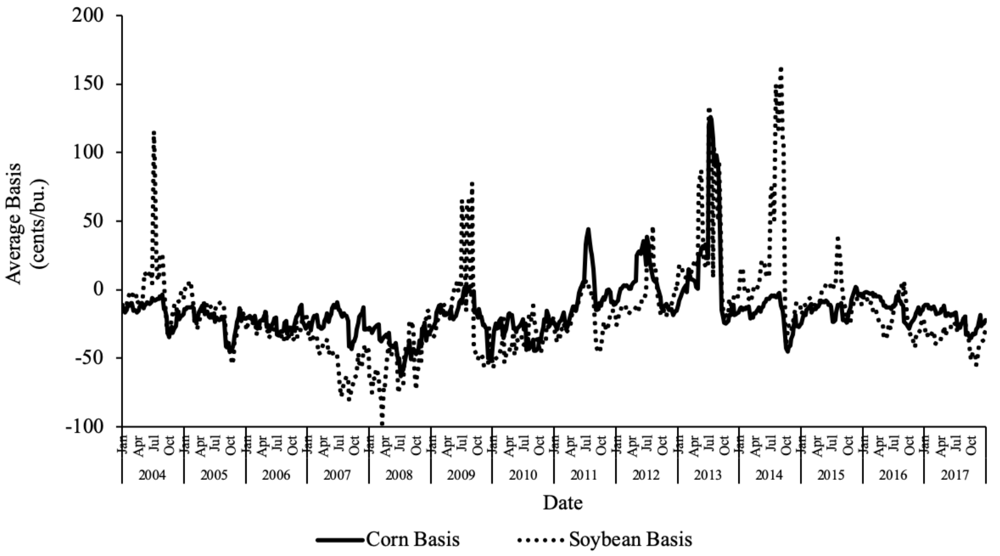

Figure 1. Weekly Corn and Soybean Basis for 2004–2017, Averaged across All Locations

The next five forecasts are a modification of the moving averages in equation (1), with the incorporation of current market information, defined as the deviation of current basis values from historical basis values h weeks prior to the forecast:

$$(2) \qquad \widehat{Basis}_{j,k,h,t}(N) = \frac{1}{N}\sum_{i=1}^{N} Basis_{j,k,t-i} + \left(Basis_{j,k-h,t} - \frac{1}{N}\sum_{i=1}^{N} Basis_{j,k-h,t-i} \right),$$

where $\widehat{Basis}_{j,k,h,t}(N)$ is the nearby basis forecast for location j in week of the year k for forecast horizon h (i.e., weeks prior to k) and year t. N again represents the number of years included in the historical average. Notice that the forecast horizon h only impacts the second portion of equation (2), which represents the adjustment for current market information.[7] However, the first component of equations (1) and (2) does not depend on h, given that the historical average portion of the forecast for a particular week is the same regardless of when the forecast is made within a given crop year.

The final forecast evaluated is what Dhuyvetter and Kastens (1998) call a naïve forecast. That is, we used nearby basis h weeks prior to the forecast as the nearby basis forecast:

$$(3) \qquad \widehat{Basis}_{j,k,h,t} = Cash_{j,k-h,t} - Futures_{j,k-h,t}.$$

Following previous research, we evaluated forecast accuracy using mean absolute error (MAE), where the absolute value of each forecast error is averaged over all locations, weeks, forecast horizons, and years (Dhuyvetter and Kastens, 1998; Hatchett, Brorsen, and Anderson, 2010). However, condensing the information embodied in a forecast error series into a single test statistic restricts evaluation to pairwise comparisons (Dhuyvetter and Kastens, 1998). To alleviate this problem and generalize the results, previous research specified a forecast error regression model (Dhuyvetter and Kastens, 1998; Hatchett, Brorsen, and Anderson, 2010), where forecast errors from competing forecast methods across time and space are stacked and forecast errors are regressed on explanatory variables such as forecast method and month of forecast. This allows for partial effects of interest to be isolated and tested using analysis of variance (ANOVA).

[7] Our current information forecasts follow Dhuyvetter and Kastens (1998) in that we assume historical basis is "fully adjusted" for the current basis deviation. Taylor, Dhuyvetter, and Kastens (2006) relaxed this assumption, allowing for a "partial adjustment" factor that they solve to minimize the in-sample mean absolute error associated with a particular forecast method and forecast horizon.

It is well established that these types of models are wrought with potential econometric misspecifications given the complex nature of the variance–covariance matrix of the error terms in time series cross-sectional data—in particular spatial-autocorrelation, cross-correlations, and heteroskedasticity (Hatchett, Brorsen, and Anderson, 2010). While previous research acknowledged these problems, attempts to correct for these issues generally fell short, resulting in the possibility of biased and inconsistent standard errors leading to problems with statistical inference. Dhuyvetter and Kastens (1998) identified groupwise heteroskedasticity among forecast methods and time horizon variables in their research. Interaction terms of forecast methods and time horizons squared were included in their model to correct for heteroskedasticity, but dependence of the error terms among competing forecasts was not addressed. Hatchett, Brorsen, and Anderson (2010) used a variation of the Dhuyvetter and Kastens (1998) approach to correct for heteroskedasticity and investigated a year by location interaction random effect to correct for unequal error variance. However, data limitations prevented convergence for this model specification, resulting in an approach analogous to that of Irwin, Good, and Martines-Filho (2006): aggregate across locations and commodities and include a year random effect. While this is an improvement over Dhuyvetter and Kastens's (1998) approach, the possibility of incorrectly assuming independence and the resulting problems with statistical inference still exist.

In this paper, we attempt (for the first time in the eastern Corn Belt) to re-evaluate previous recommendations for optimal basis forecast methods post-ethanol while also producing a forecast error regression model specification that better accounts for potential econometric misspecifications. Forecast errors from the first 5 years of each data series are not used, so that an equal number of out-of-sample forecasts are evaluated for each forecast method. Since the data start in 2004, the first out-of-sample forecast year evaluated is 2009. The regression analysis includes 3,878,928 out-of-sample forecasts (11 forecast methods, 6 of which have 6 time horizons [4, 8, 12, 16, 20, and 24 weeks] $\times$ 219 crop locations [113 corn locations and 106 soybean locations] $\times$ 9 years $\times$ 48 weeks per year). The null hypothesis that a pooled model for both corn and soybeans is preferred was rejected ($F = 342.99,\ p < 0.01$) using a Chow (1960) test. As a result, individual mixed models for each crop (corn and soybeans) were estimated as

$$
\begin{aligned}
AE_{i,\,j,\,k,\,h,\,m,\,t} = {} & \beta_0 + \sum_{i=1}^{10} \beta_{1,\,t} Forecast_i + \sum_{i=5}^{10}\sum_{h=1}^{6} \beta_{2,\,i,\,h} Forecast_i \times Horizon_h \\
& + \sum_{i=5}^{10}\sum_{h=1}^{6} \beta_{3,\,i,\,h} Forecast_i \times Horizon_h^2 + \sum_{m=1}^{11} \beta_{4,\,m} Month_m \\
& + \sum_{i=5}^{10}\sum_{m=1}^{11} \beta_{5,\,i,\,m} Forecast_i \times Month_m + u_{jt} + \varepsilon_{i,\,j,\,k,\,h,\,m,\,t},
\end{aligned} \tag{4}
$$

where $AE_{i,\,j,\,k,\,h,\,m,\,t}$ is the absolute error for the ith forecast in location j in week of the year k and month m for forecast horizon h (i.e., weeks prior to k) and year t. $Forecast_i$ is a fixed effect equal to 1 if the absolute error is associated with forecast i and 0 otherwise (5-year moving average is dropped as the reference category). $Horizon_h$ is the forecast horizon, 4, 8, 12, 16, 20, or 24 weeks prior to the forecast date. Notice that the forecast–horizon interaction is only estimated for forecasts that incorporate current information or the naïve forecast methods ($i = 5, \ldots, 11$). That is, moving average forecasts without current information do not have an interaction with horizon, given that these forecasts only use historical information and therefore are the same regardless of when the forecast is made during the crop year. $Month_m$ is a month fixed effect that equals 1 if the absolute error is for a forecast in month m and 0 otherwise. Previous research evaluating moving average forecasts has tended to focus on forecasting during two narrowly defined periods: harvest and storage (March/April) (Taylor, Dhuyvetter, and Kastens, 2006; Hatchett, Brorsen, and Anderson, 2010). While this approach acknowledges within-year differences, it fails to fully explain the dynamics of the accuracy of basis forecasting methods throughout the crop-marketing year. Dhuyvetter and

Kastens (1998) estimated month fixed effects in their model, which allowed for a brief discussion of forecast accuracy by month. However, by not interacting forecast method and month fixed effects, they failed to account for the fact that different forecasts may respond differently throughout the marketing year. Hence, this is the first study to allow for complete flexibility by measuring forecast accuracy of various basis forecasts throughout the crop-marketing year. Finally, $u_{jt} \sim N\left(0, \sigma_u^2\right)$ is a year by location interaction random effect and $\varepsilon_{i,\,j,\,k,\,h,\,m,\,t} \sim N\left(0,\, \sigma_\varepsilon^2\right)$ is the random error term.

In estimating the models, as expected, we identified several violations of the linear model assumptions. A D'Agostinio–Pearson K^2 omnibus test of residuals rejects the null hypothesis of normality. This appears to be the result of high skewness and kurtosis values given the nature of the dependent variable (i.e., absolute value). Although the absence of normality is not considered a serious statistical problem in this case (Irwin, Good, and Martines-Filho, 2006), we estimated the linear mixed model using the minimum variance quadratic unbiased estimation (MIVQUE0) method, which does not require normality assumptions for the residual error term or the random effects (Rao, 1971). Similarly, a conditional variance test identified evidence of static heteroskedasticity. The year by location interaction random effect was included to partially control for the systematic correlation of error terms within specific years and locations. In addition, we estimated robust standard errors ("sandwich estimators") to obtain asymptotically consistent standard errors (White, 1980).

Models were estimated in SAS PROC MIXED (SAS Institute, Inc., 2013). Tests of simple effects (i.e., paired *t*-tests) were conducted using the ESTIMATE statement in PROC MIXED. More complex hypothesis tests were evaluated using the CONTRAST statement. The modified Diebold–Mariano (DM) test was used to test for statistical differences in the accuracy of competing forecasts (Diebold and Mariano, 1995; Harvey, Leybourne, and Newbold, 1997).

Results and Discussion

Corn, Aggregated across All Months

Table 1 presents mean absolute errors for corn averaged across all locations, years, and months for each of the 11 forecast methods. Results are presented both with and without the 2012–2013 crop-marketing year included in the forecasts, given the exceptional impact of extreme drought on corn basis patterns during that year (Figure 1). Slopes of the linear and quadratic forecast by horizon interaction terms are presented for the relevant forecasts and breakeven number of weeks for these forecasts are calculated relative to the moving average forecast with the lowest MAE.

While the aggregate MAEs reported in Table 1 are useful for generalizing the results, especially the evaluation of forecast horizon on the value of current information, a significant forecast by month interaction ($F = 242.60,\ p < 0.01$) indicates that a more thorough analysis of month by forecast MAEs is necessary.

Corn, Month-by-Month

Table 2 reports the forecast methods with the lowest MAE for each month for three forecast horizons (4, 12, and 20 weeks).[8] Results are again presented both with and without the 2012–2013 crop-marketing year included in the development and evaluation of the forecasts. For example, if we ignore the 2012–2013 crop year due to exceptional basis from the short crop, someone interested in forecasting nearby corn basis at harvest (October–November) would want to use a 5-year moving average regardless of the forecast horizon. However, it is important not to overemphasize the practical value of a particular forecast for any given month or forecast horizon. That is, in any given

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[8] Results for 8-, 16-, and 24-week forecast horizons are available from the authors. Results are quantitatively different but follow a consistent pattern, as expected.

Table 1. Mean Absolute Forecast Errors (cents/bu), Forecast × Horizon Interactions, and Breakeven Forecast Horizons (in weeks) for 11 Forecast Methods for Corn

	All Years				Without 2012–2013 Crop Year			
Forecast	**Mean Absolute Forecast Error, Forecast Horizon = 4 weeks[a] (cents/bu)**	**Forecast × Horizon Interaction**	**Forecast × Horizon^2 Interaction**	**Breakeven Forecast Horizon with 5-Year Moving Avg. (weeks)**	**Mean Absolute Forecast Error, Forecast Horizon = 4 weeks[a] (cents/bu)**	**Forecast × Horizon Interaction**	**Forecast × Horizon^2 Interaction**	**Breakeven Forecast Horizon with 5-Year Moving Avg. (weeks)**
1-year moving avg.	23.67***				20.52***			
2-year moving avg.	21.95***				17.77***			
3-year moving avg.	22.05***				16.56***			
4-year moving avg.	21.99***				16.82***			
5-year moving avg.	21.48***				16.28***			
1-year moving avg. plus current information[b]	17.17***	1.84***	−0.04***	7.03	15.28***	1.21***	−0.02***	4.99
2-year moving avg. plus current information	14.98***	1.51***	−0.03***	10.15	13.15***	0.99***	−0.02***	8.11
3-year moving avg. plus current information	14.48***	1.64***	−0.04***	10.09	12.72***	1.06***	−0.02***	8.58
4-year moving avg. plus current information	14.16***	1.69***	−0.04***	10.36	12.06***	1.03***	−0.02***	9.55
5-year moving avg. plus current information	13.54***	1.63***	−0.04***	11.29	11.72***	1.01***	−0.02***	10.34
Naïve[c]	11.96***	1.40***	−0.03***	16.15	11.14***	0.97***	−0.02***	11.86
Forecast main effect, forecast horizon = 4 weeks[d]	$F = 507.94$***				$F = 353.20$***			
Month main effect	$F = 230.86$***				$F = 134.78$***			
Forecast × month interaction, forecast horizon = 4 weeks[d]	$F = 242.60$***				$F = 193.33$***			

Notes: Triple asterisks (***) indicate significance at the 1% level.
[a] Forecast horizon is the weeks prior to the forecast date that the forecast is made.
[b] Moving average forecasts that incorporate current information adjust the historical moving average by the deviation of current basis values from historical basis values h weeks prior to the forecast.
[c] A naïve forecast assumes that current basis is future basis for a given forecast horizon. That is, basis h weeks prior to the forecast is the forecast.
[d] Mean absolute forecast errors, forecast main effect, and forecast by month interaction are reported at a 4-week forecast horizon. These tests were also conducted for forecast horizons = 8, 12, 16, 20, and 24 weeks; the results were statistically significant at each horizon. Results are available from the authors.

Table 2. Optimal Forecast Method and Corresponding Mean Absolute Forecast Error (cents/bu) by Month and Forecast Horizon for Corn with up to a 5-Year Moving Average Forecast

Month	All Years: Optimal Forecast Method[a]	All Years: Mean Absolute Forecast Error (cents/bu)	Without 2012–2013 Crop Year: Optimal Forecast Method[a]	Without 2012–2013 Crop Year: Mean Absolute Forecast Error (cents/bu)
Forecast horizon = 4 weeks				
September	MA5CI	13.96	MA5CI	12.68
October	MA4	15.90	MA5	12.73
November	MA5	15.30	MA5	12.25
December	Naïve	15.05	Naïve	12.87
January	Naïve	12.13	MA3	11.56
February	MA5CI	7.82	MA5CI	9.43
March	MA5CI	5.09	MA5CI	7.80
April	MA5CI	2.41	MA5CI	5.69
May	MA1CI	6.74	Naïve	8.09
June	MA1CI	6.75	Naïve	9.42
July	Naïve	21.20	Naïve	14.37
August	Naïve	14.16	Naïve	10.69
Forecast horizon = 12 weeks				
September	MA5	22.13	MA5CI	18.16
October	MA4	15.90	MA5	12.73
November	MA5	15.30	MA5	12.25
December	MA5	16.32	MA4	12.90
January	MA4	13.69	MA3	11.56
February	MA5	13.11	MA3	11.36
March	Naïve	12.85	MA3	12.26
April	MA5CI	10.92	MA5	11.08
May	Naïve	14.31	Naïve	13.29
June	Naïve	15.14	Naïve	14.62
July	Naïve	28.48	Naïve	19.58
August	Naïve	21.44	Naïve	15.89
Forecast horizon = 20 weeks				
September	MA5	22.13	MA5	20.00
October	MA4	15.90	MA5	12.73
November	MA5	15.30	MA5	12.25
December	MA5	16.32	MA4	12.90
January	MA4	13.69	MA3	11.56
February	MA5	13.11	MA3	11.36
March	MA5	15.14	MA3	12.26
April	MA5	12.30	MA5	11.08
May	Naïve	17.68	Naïve	15.94
June	Naïve	18.51	Naïve	17.27
July	Naïve	31.86	Naïve	22.22
August	Naïve	24.82	Naïve	18.54

Notes: MA1–MA5 are 1-to-5-year moving average forecasts. MA1CI–MA5CI are 1-to-5-year moving average forecasts plus current information. Moving average forecasts that incorporate current information adjust the historical moving average by the deviation of current basis values from historical basis values h weeks prior to the forecast. Naïve forecasts assume that current basis is future basis for a given forecast horizon. That is, basis h weeks prior to the forecast is the forecast.

[a] The most accurate optimal forecast method, of the forecasts evaluated, is identified for each month and forecast horizon and are presented with the corresponding mean absolute forecast error. For example, if we ignore the 2012–2013 crop year due to exceptional basis from the short crop, someone interested in forecasting nearby corn basis at harvest (October–November) would want to use a 5-year moving average regardless of the forecast horizon.

year, these recommendations may or may not provide the most accurate basis forecast. Instead, it is more important to generalize these results into actionable recommendations for how various forecast methods perform at different points throughout the crop-marketing year.

The results seem to offer three distinct forecasting periods, starting with harvest basis forecasts. When the 2012–2013 crop-marketing year is included, results indicate that basis tends to anchor to historical averages around harvest: 4- and 5-year moving averages produced the lowest MAEs in October and November, respectively, for each of the forecast horizons evaluated (4–24 weeks). The modified DM test indicates that the accuracy of 4- and 5-year moving average forecasts is not significantly different in those months ($DM = 0.92,\ p = 0.36$). This result is generally unchanged when the 2012–2013 crop-marketing year is excluded, with the 5-year moving average producing the lowest MAE in October and November for each forecast horizon.

Forecasts made for post-harvest months (December–August) generally depend on the forecast horizon. At shorter forecast horizons, naïve forecasts and forecasts that incorporate current information generally have lower MAEs than historical moving averages. Unsurprisingly, as forecast horizon increases, the value of current information deteriorates. This is particularly true for months closer to harvest. For, example, when the 2012–2013 crop-marketing year is included, 4- or 5-year moving averages outperform current information/naïve forecasts from October through February at a 12-week forecast horizon and are not statistically different at the 1% level ($DM = 2.22,\ p = 0.03$). At a 20-week forecast horizon, 4- and 5-year moving averages outperform current information/naïve forecasts from October through April and are not statistically different ($DM = 0.23,\ p = 0.82$).

When the 2012–2013 crop-marketing year is excluded, a similar trend emerges, except that 3-, 4-, and 5-year moving averages produce the lowest MAEs in various months from October through April. Pairwise comparisons indicate that differences in the accuracy of 3-, 4-, and 5-year moving average forecasts are small, less than 0.2 cents/bu. The 3-year moving average ultimately produced the lowest MAE over this period, although it was not significantly different from the 5-year moving average at the 5% level ($DM = 1.72,\ p = 0.09$). This shift toward shorter-length moving averages (3-year) producing lower MAEs in some months when the 2012–2013 crop year is excluded is intuitive. That is, when the exceptional basis values observed in 2012–2013 are included in the analysis, longer moving averages may be preferred, given their ability to pull in additional years that will drag the forecast back toward historical values. However, when these extreme observations are dropped from the derivation of moving average forecasts, shorter-length moving averages may become preferred if recent history is a better predictor of current basis patterns.

Forecasts late in the crop-marketing year (May–August) indicate that a naïve forecast is generally the best forecast method regardless of forecast horizon. Initially, the fact that naïve forecasts provide the lowest MAEs at the longest forecast horizons evaluated (up to 24 weeks) may seem surprising. However, when interpreting this result, it is important to note the levels of MAE differ throughout the year. For example, at a forecast horizon of 20 weeks, MAEs from October to April are 12–16 cents/bu regardless of forecast method (Table 2; Figure 2). However, after April, MAEs increase sharply, with the 5-year moving average reaching an MAE of nearly 50 cents/bu in July. Hence, forecasting basis during the summer months is notably less accurate, especially at longer forecast horizons, than earlier in the crop-marketing year regardless of the forecast method. This is an important point that previous research has largely overlooked.

Although our analysis does not lend itself to identifying the cause of this shift in forecast accuracy empirically, it is useful to provide some discussion on this point. Mainly, the identified reduction in forecast accuracy after April coincides with the point in the year when uncertainty regarding crop inventories has reached its peak. In the months following harvest, inventories of grain are known and generally plentiful, resulting in relatively predictable basis values. However, as we move into late spring and early summer, interest begins to shift to new crop production. At this point in the season, there is uncertainty about crop acreage as well as about early crop conditions for new crop production, which leads to uncertainty in valuing the remaining old crop inventories. Thus, basis becomes much more difficult to forecast during this time of year. For example, signals of

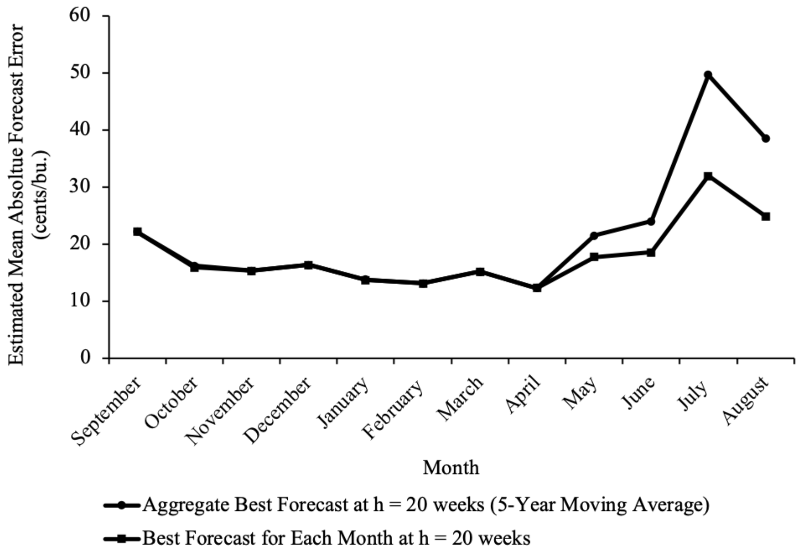

Figure 2. Estimated Mean Absolute Forecast Errors by Month for the Aggregate Best Forecast for the Entire Year (5-Year Moving Average) and the Best Forecast for Each Month at a 20-Week Forecast Horizon for Corn, Averaged across All Locations and All Years

a potentially short crop in the coming fall would increase the value of remaining old crop inventories, causing basis to increase above average levels. Conversely, signals of a large new crop would diminish the value of old crop inventories, flattening or weakening basis during this period.

Corn, Discussion and Comparison with Previous Recommendations and Accuracy

Differences in geographies, time periods, and forecasts evaluated limit the conclusions that can be drawn from comparisons to previous research. Nonetheless, it is still instructive to compare our results with previous basis forecasting recommendations and accuracy. Hatchett, Brorsen, and Anderson (2010) and Lee and Brorsen (2017) are the closest studies geographically (Illinois) to the present research. Hatchett, Brorsen, and Anderson concluded that a 1-year moving average forecast provided the lowest MAE forecast for corn basis at harvest, although no significant forecast main effect was identified in the forecast error regression model. That is, the accuracy of 1-to-5-year moving average forecasts was not significantly different for harvest-time basis forecasts. Lee and Brorsen identified a 5-year moving average as the most accurate harvest basis forecast for corn.

However, lacking in these two studies is the evaluation of alternative forecasts (current information/naïve) relative to moving average forecasts. For this reason, it is also useful to compare our results with Taylor, Dhuyvetter, and Kastens (2006), even though their study focused on forecasting basis in Kansas. Their results also suggest that a 1-year moving average produced the lowest MAE forecast for corn at harvest. However, similar to Hatchett, Brorsen, and Anderson (2010), they did not find the 1-year moving average to be significantly different from 5-, 6-, or 7-year moving average forecasts in a series of paired *t*-tests. Therefore, our finding that corn basis tends to anchor to historical moving averages at harvest is consistent with previous research. This is largely because alternative forecasts that incorporate current market information into basis forecasts are not particularly useful at harvest given that this information generally reflects two different crop years: current information as old crop and historical basis as new crop (Taylor, Dhuyvetter, and Kastens, 2006). As for the optimal-length moving average, previous results have been mixed, but our analysis suggests that longer moving averages (4- or 5 years) provide the most accurate corn basis forecast at harvest.

When forecasting corn basis later in the crop-marketing year, Hatchett, Brorsen, and Anderson (2010) and Lee and Brorsen (2017) both found a 1-year moving average to provide the most accurate forecast in April. On the other hand, Taylor, Dhuyvetter, and Kastens (2006) found that naïvebasis forecasts provided the most accurate forecast for corn basis in March across forecast horizons of 4–20 weeks. Therefore, our finding that current information/naïve forecasts improve the accuracy of basis forecasts post-harvest (December–August), especially at shorter forecast horizons, is consistent with Taylor, Dhuyvetter, and Kastens. However, contrary to Taylor, Dhuyvetter, and Kastens, our results indicate that the accuracy of these forecasts is usurped by historical moving averages as forecast horizon increases. Hence, our results seem to offer a more nuanced view of optimal basis forecasts post-harvest, depending on both the forecast horizon and time of year for the forecast.

As for the accuracy of these forecasts, it seems as though it has become generally more difficult to forecast basis, as indicated by higher MAEs. Hatchett, Brorsen, and Anderson (2010), Lee and Brorsen (2017), and Taylor, Dhuyvetter, and Kastens (2006)reported MAEs for corn basis forecasts of 9–12 cents/bu at harvest and 1–10 cents/bu for storage basis (March/April). In our study, MAEs were near 16 cents/bu at harvest and 3–15 cents/bu for storage basis (depending on forecast horizon). In general, this is not surprising given the volatility of commodity prices during the study period (2004–2017). It is also important to point out when excluding the 2012–2013 crop-marketing year, MAEs in our study are only slightly higher than those reported in previous research: around 13 cents/bu at harvest and 6–12 cents/bu for storage basis depending on the forecast horizon.

Corn, Robustness Checks

As with any research effort, the baseline results presented above are conditional on a number of underlying model assumptions. Here we briefly discuss two of these assumptions and evaluate the robustness of our results to them. First, we relax the selection of a 5-year moving average as the longest moving average forecast considered to a 7-year moving average. Results indicate that when the 2012–2013 crop-marketing year is included, the 7-year moving average produced the lowest MAE from October to February, depending on forecast horizon (see Online Supplement Table S1). However, when the 2012–2013 crop year is excluded from the development and evaluation of the forecasts, the optimal-length moving forecast from October to April varies from a 3-year to a 7-year moving average depending on month and forecast horizon. Identical to the original analysis, a 3-year moving average produced the lowest aggregate MAE during this period (October–April) and is statistically different than the 7-year moving average forecast (DM $= 4.16$, $p < 0.01$). Hence, although they were preferred in some months, the general narrative of the results was qualitatively unchanged by including the longer moving averages in the analysis. It is also important to recognize that differences in the results for analyses with different longest length moving average forecasts (e.g., 5-year vs. 7-year) are confounded by differences in the out-of-sample time period available for analysis.

Second, we run the model for each of the four states represented (Illinois, Indiana, Michigan, and Ohio) to investigate the robustness of the generalized results for the eastern Corn Belt region to individual states (see Online Supplement Tables S2–S5). As expected, while the most accurate forecast for any given month and forecast horizon were not exactly the same across the four states, the general recommendations drawn from these results remained unchanged. While this exercise of evaluating the results for each individual state serves as a useful robustness check, these state-level results should be used and interpreted with caution, mainly because inferring increased accuracy of a more "localized" forecast recommendation based on state boundaries is unfounded given that state boundaries are irrelevant to the flow of grain.

Soybean, Aggregated across All Months

Table 3 presents mean absolute errors for soybeans averaged across all locations, years, and months for each of the 11 forecast methods. Results are presented both with and without the 2012–2013 and 2013–2014 crop-marketing years included in the forecasts, given the exceptional impact of extreme drought on basis patterns during these two years (Figure 1).[9] Again, while the aggregate MAEs reported in Table 3 offer useful information about the impact of forecast horizon on the value of current information, a significant forecast by month interaction ($F = 177.60,\ p < 0.01$) indicates that more thorough analysis of month by forecast means is necessary for soybeans as well.

Soybean, Month-by-Month

Table 4 reports soybean forecast methods with the lowest MAE for each month. Results are again presented both with and without the 2012–2013 and 2013–2014 crop-marketing years included in the development and evaluation of the forecasts. While the information in Table 4 can be used to identify the most accurate forecast method for any given month and forecast horizon, it is again useful to generalize these results into actionable recommendations for soybean basis forecasting throughout the crop-marketing year.

Similar to corn, three distinct forecasting periods emerge. Results indicate that soybean basis tends to anchor to historical averages around harvest (Table 4). When the 2012–2013 and 2013–2014 crop-marketing years are included in the development and evaluation of the forecasts, results indicate that 1- and 2-year moving averages produced the lowest MAEs in October and November, respectively, for each of the forecast horizons evaluated. Although the 2-year moving average was found to be significantly more accurate during this harvest period ($\mathrm{DM} = 4.69,\ p < 0.01$), practical differences in MAEs were small, less than 0.2 cents/bu Excluding the 2012–2013 and 2013–2014 crop-marketing years produced a similar result. However, the 1-year average is statistically more accurate that the 2-year moving average ($\mathrm{DM} = 5.75,\ p < 0.01$), although the practical implications of this are again weak given a difference in MAEs of around 0.2 cents/bu. In either case, shorter-length moving averages (1- or 2 years) are clearly preferred for harvest-time soybean basis forecasts.

Forecasts made for post-harvest months (December–August) generally depend on the forecast horizon. At shorter forecast horizons, naïve forecasts generally have lower MAEs than historical moving averages. However, as the forecast horizon increases, naïve forecasts become less accurate. This is again exacerbated for months closer to harvest. For example, when the 2012–2013 and 2013–2014 crop-marketing years are included, 1- or 2-year moving averages outperform naïve forecasts from harvest (October) through February at forecast horizons of 12 weeks or more. However, the 2-year moving average was again found to be significantly more accurate during this time period ($\mathrm{DM} = 7.02,\ p < 0.01$).

When the 2012–2013 and 2013–2014 crop-marketing years are excluded, a similar trend emerges, except 1-, 2-, and 5-year moving averages produce the lowest MAEs in various months from October to April. Pairwise comparisons indicate that the 2- and 5-year moving average forecasts are not statistically different at the 1% level ($\mathrm{DM} = 2.32, p = 0.02$) and both produce a more accurate forecast than the 1-year moving average. This shift toward potentially longer moving averages (5-year) producing lower MAE in some months when the 2012–2013 and 2013–2014 crop-marketing years are excluded differs from the results for corn. However, this can again be explained by the underlying structure of the moving average forecasts and the prolonged impact of the 2012 drought on soybean basis patterns. That is, when exceptional basis values observed in 2012–2013 and 2013–2014 crop-marketing years are included in the analysis, shorter moving averages provide more accurate forecasts given their ability to avoid including those years in the calculation of moving

[9] Models were also estimated without just 2012–2013 and without just 2013–2014. Results were robust to each of these specifications, so we present only the results without the 2012–2013 and 2013–2014 crop-marketing years for conciseness.

Table 3. Mean Absolute Forecast Errors (cents/bu), Forecast × Horizon Interactions, and Breakeven Forecast Horizons (in weeks) for 11 Forecast Methods for Soybeans

	All Years				Without 2012–2013 and 2013–2014 Crop Years			
Forecast	Mean Absolute Forecast Error, Forecast Horizon = 4 weeks[a] (cents/bu)	Forecast × Horizon Interaction	Forecast × Horizon^2 Interaction	Breakeven Forecast Horizon with 2-Year Moving Avg. (weeks)	Mean Absolute Forecast Error, Forecast Horizon = 4 weeks[a] (cents/bu)	Forecast × Horizon Interaction	Forecast × Horizon^2 Interaction	Breakeven Forecast Horizon with 5-Year Moving Avg. (weeks)
1-year moving avg.	29.47***				29.02***			
2-year moving avg.	28.72***				26.19***			
3-year moving avg.	29.45***				25.48***			
4-year moving avg.	29.49***				24.78***			
5-year moving avg.	28.74***				24.36***			
1-year moving avg. plus current information[b]	25.96***	1.81***	−0.04***	5.94	26.55***	1.67***	−0.04***	2.47
2-year moving avg. plus current information	23.53***	1.59***	−0.03***	8.38	22.69***	1.38***	−0.03***	5.54
3-year moving avg. plus current information	22.74***	1.64***	−0.04***	9.05	21.42***	1.17***	−0.03***	7.36
4-year moving avg. plus current information	21.43***	1.56***	−0.03***	11.03	20.12***	1.14***	−0.02***	9.19
5-year moving avg. plus current information	20.22***	1.49***	−0.03***	13.27	19.37***	1.16***	−0.03***	10.25
Naïve[c]	18.83***	1.95***	−0.05***	12.23	17.75***	1.55***	−0.04***	10.59
Forecast main effect, forecast horizon = 4 weeks[d]	$F = 396.11$***				$F = 179.18$***			
Month main effect	$F = 399.86$***				$F = 157.81$***			
Forecast × month interaction, forecast horizon = 4 weeks[d]	$F = 177.60$***				$F = 130.18$***			

Notes: Triple asterisks (***) indicate significance at the 1% level.
[a] Forecast horizon is the weeks prior to the forecast date that the forecast is made.
[b] Moving average forecasts that incorporate current information adjust the historical moving average by the deviation of current basis values from historical basis values h weeks prior to the forecast.
[c] A naïve forecast assumes that current basis is future basis for a given forecast horizon. That is, basis h weeks prior to the forecast is the forecast.
[d] Mean absolute forecast errors, forecast main effect, and forecast by month interaction are reported at a 4-week forecast horizon. These tests were also conducted for forecast horizons = 8, 12, 16, 20, and 24 weeks; the results were statistically significant at each horizon. Results are available from the authors.

Table 4. Optimal Forecast Method and Corresponding Mean Absolute Forecast Error (cents/bu) by Month and Forecast Horizon for Soybeans with up to a 5-Year Moving Average Forecast

	All Years		Without 2012–2013 and 2013–2014 Crop Years	
Month	Optimal Forecast Method[a]	Mean Absolute Forecast Error (cents/bu)	Optimal Forecast Method[a]	Mean Absolute Forecast Error (cents/bu)
Forecast horizon = 4 weeks				
September	Naïve	28.59	Naïve	30.25
October	MA1	13.75	MA1	12.63
November	MA2	16.60	MA2	16.66
December	MA2	14.15	MA2	13.64
January	Naïve	20.88	Naïve	21.17
February	Naïve	14.77	Naïve	17.06
March	Naïve	8.30	Naïve	12.76
April	Naïve	4.17	Naïve	8.23
May	Naïve	12.06	Naïve	10.97
June	Naïve	7.20	Naïve	11.80
July	Naïve	24.76	Naïve	20.34
August	MA5CI	31.67	MA5CI	22.41
Forecast horizon = 12 weeks				
September	Naïve	38.28	Naïve	37.84
October	MA1	13.75	MA1	12.63
November	MA2	16.60	MA2	16.66
December	MA2	14.15	MA2	13.64
January	MA2	21.55	MA2	21.47
February	MA2	18.87	MA5	21.40
March	Naïve	17.99	Naïve	20.36
April	Naïve	13.87	Naïve	15.83
May	Naïve	21.76	Naïve	18.57
June	Naïve	16.89	Naïve	19.40
July	Naïve	34.45	Naïve	27.93
August	MA5CI	39.34	MA5CI	28.45
Forecast horizon = 20 weeks				
September	MA5	41.31	MA5	39.10
October	MA1	13.75	MA1	12.63
November	MA2	16.60	MA2	16.66
December	MA2	14.15	MA2	13.64
January	MA2	21.55	MA2	21.47
February	MA2	18.87	MA5	21.40
March	Naïve	21.81	MA5	22.22
April	Naïve	17.69	MA5	18.63
May	Naïve	25.58	Naïve	21.40
June	Naïve	20.71	Naïve	22.22
July	Naïve	38.12	Naïve	30.76
August	MA5CI	42.75	MA5CI	31.27

Notes: MA1–MA5 are 1-to-5-year moving average forecasts. MA1CI–MA5CI are 1-to-5-year moving average forecasts plus current information. Moving average forecasts that incorporate current information adjust the historical moving average by the deviation of current basis values from historical basis values *h* weeks prior to the forecast. Naïve forecasts assume that current basis is future basis for a given forecast horizon. That is, basis *h* weeks prior to the forecast is the forecast.

[a] The most accurate optimal forecast method, of the forecasts evaluated, is identified for each month and forecast horizon and are presented with the corresponding mean absolute forecast error. For example, if we ignore the 2012–2013 and 2013–2014 crop years due to exceptional basis from the short crop, someone interested in forecasting nearby soybean basis at harvest (October–November) would want to use a 1- or 2-year moving average regardless of the forecast horizon.

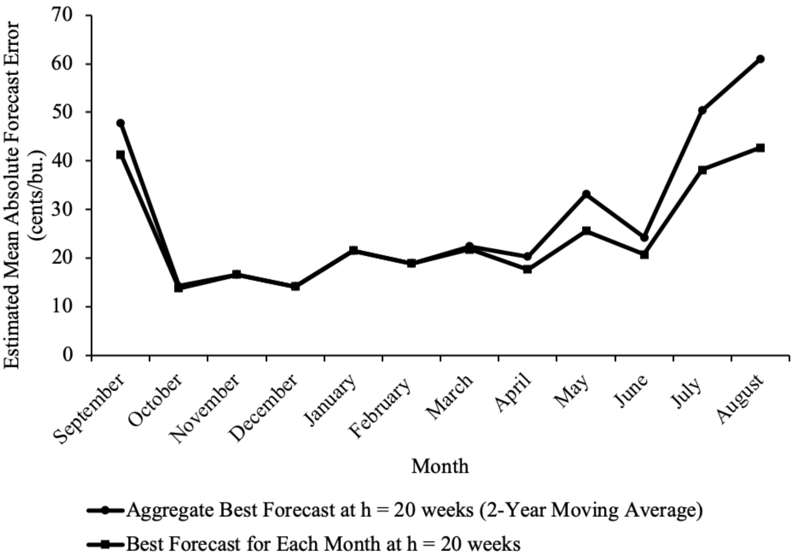

Figure 3. Estimated Mean Absolute Forecast Errors by Month for the Aggregate Best Forecast for the Entire Year (2-Year Moving Average) and the Best Forecast for Each Month at a 20-Week Forecast Horizon for Soybeans, Averaged across All Locations and All Years

average forecasts following 2012. This is consistent with the results of Hatchett, Brorsen, and Anderson (2010) and Lee and Brorsen (2017). However, when those drought-impacted years are dropped from the estimation, longer moving averages may be preferred if data in prior years are helpful for explaining current basis patterns.

Forecasts late in the crop-marketing year (May–August) indicate that a naïve forecast is generally the best forecast method regardless of forecast horizon. While again surprising, especially at the longest forecast horizons, this result is consistent with the results for corn above. That is, MAEs for forecasts late in the crop-marketing year increase significantly regardless of the forecast method (Figure 3).

Soybean, Discussion and Comparison with Previous Recommendations and Accuracy

Comparing these results with previous soybean basis forecast recommendations and accuracy is also instructive. Hatchett, Brorsen, and Anderson (2010) and Lee and Brorsen (2017) concluded that a 2-year moving average and 1-year moving average forecast, respectively, provided the lowest MAE forecast for soybean basis at harvest in Illinois. Including naïveand current information forecasts in their analysis, Taylor, Dhuyvetter, and Kastens (2006) found that a 1-year moving average also produced the lowest MAE soybean basis forecast in Kansas at harvest. Therefore, our finding that soybean basis tends to anchor to historical moving averages at harvest is consistent with previous research. This is again largely because alternative forecasts that incorporate current market information into basis forecasts are not particularly useful at harvest given that this information generally reflects two different crop years (Taylor, Dhuyvetter, and Kastens, 2006). In addition, our results also seem to confirm previous findings that shorter-length moving averages (1- or 2-year moving averages in our analysis) may be preferred to longer moving averages for forecasting soybean basis at harvest.

Hatchett, Brorsen, and Anderson (2010) and Lee and Brorsen (2017) both found a 1-year moving average to provide the lowest MAE forecast for soybean basis later in the crop-marketing year. On the other hand, Taylor, Dhuyvetter, and Kastens (2006)found that naïvebasis forecasts provided the most accurate forecast for soybean basis in March across forecast horizons of 4–20 weeks. This is largely consistent with our findings, except that—contrary to Taylor, Dhuyvetter, and Kastens—our results indicate that the accuracy of naïve forecasts is usurped by historical moving averages at relatively short forecast horizons for soybeans, about 8 weeks for post-harvest forecasts.

Consistent with corn basis forecasts, it has also become generally more difficult to forecast soybean basis, as indicated by higher MAEs. Hatchett, Brorsen, and Anderson (2010), Lee and Brorsen (2017), and Taylor, Dhuyvetter, and Kastens (2006)reported MAEs for soybean basis forecasts of 10–11 cents/bu at harvest and 5–9 cents/bu for storage basis (March/April). In our study, MAEs were around 14 cents/bu at harvest and 8–22 cents/bu for storage basis (depending on forecast horizon). In general, this is not surprising, given commodity price volatility in recent years. Contrary to corn, excluding exceptional years (2012–2013 and 2013–2014) did not greatly increase the accuracy of soybean basis forecasts.

Soybean, Robustness Checks

Similar to corn, we subjected the soybean results to robustness checks for the specification of the longest length moving average and results for individual states. When the longest moving average considered was extended to 7 years, shorter moving averages were still preferred for most of the year (see Online Supplement Table S6). Specifically, a 1-year moving average was preferred from harvest (October) to April, depending on forecast horizon and was statistically different from the 7-year moving average forecast over that period ($\text{DM} = 8.15,\ p < 0.01$). It is important to acknowledge that the 1-year moving average here is different than the 2-year moving average identified in the original analysis. This difference is the result of the shorter out-of-sample time period available for analysis (2011–2017) due to the longer moving average forecasts.

Second, we ran the model for each of the four states represented (Illinois, Indiana, Michigan, and Ohio). The most accurate forecast for any given month and forecast horizon was not exactly the same across the four states, but the general recommendations drawn from these results remained unchanged (see Online Supplement Tables S7–S10). Again, caution is warranted: These more "localized" forecast recommendations should not be interpreted as necessarily more accurate than the generalized recommendations for the eastern Corn Belt region since grain flow is not restricted by state boundaries.

Conclusions

Commodity markets in the eastern Corn Belt have undergone significant structural change in recent years. As a result, recent studies have indicated that shorter-length moving average forecasts, typically 1-year moving averages, should be preferred for forecasting corn and soybean basis. However, it has also been shown that these recommendations depend on the time period evaluated. Therefore, the lack of sufficient data post-ethanol may limit the usefulness of previous recommendations if basis patterns have stabilized in recent years. This study re-evaluates commonly used optimal-length moving average basis forecasts for corn and soybeans in the eastern Corn Belt.

We find that, relative to the most recent recommendations, longer moving averages (3–5 years) may currently provide more accurate basis forecasts, in particular for corn. That is, as expected, longer moving averages are again proving to provide accurate corn and soybean basis forecasts as basis patterns stabilize. As we move further into the biofuel era of commodity marketing, one would expect this trend to continue. However, if additional structural change takes place, shorter moving averages would once again be preferred (Hatchett, Brorsen, and Anderson, 2010; Lee and Brorsen, 2017). We also show that temporary shocks, such as the 2012 drought, impact the accuracy of moving average forecasts. We find that excluding years deemed exceptional and unlikely to repeat from the development of moving average corn and soybean basis forecasts can increase the accuracy of these forecasts.

Results generally indicate using 3-to-5-year moving average forecasts for corn from October to April and 2- or 5-year moving averages for soybeans from October to April. Contrary to previous research (Taylor, Dhuyvetter, and Kastens, 2006; Hatchett, Brorsen, and Anderson, 2010), we identified statistically significant differences in the accuracy of competing forecasts in many cases. Nonetheless, these differences were often small, less than 1 cent/bu, and thus not likely to be economically important. Hence, similar to Hatchett, Brorsen, and Anderson, we generally conclude that the selected length of moving averages may not matter all that much.

Instead, the primary contribution of this analysis is that the accuracy of moving average basis forecasts differs throughout the crop-marketing year. This important contribution has implications for those forecasting basis yet has been largely overlooked in previous studies. Our results indicate that simple historical moving averages tend to perform best at and around harvest (October–November). Post-harvest (December–April) forecasts may be improved at short forecast horizons (<8–12 weeks) by combining historical moving averages and recent basis levels. The accuracy of forecasts late in the crop-marketing year (May–August) declines regardless of forecast method.

As a result, our results offer a more nuanced view of basis forecasting than some previous research. Generalized rules of thumb regarding the use of naïveor moving average basis forecasts may need to be modified with respect to both commodity and the time of year of the forecast. This is critical information for practitioners, among whom these forecasts are used widely to create accurate forecasts of basis which play an important role in a number of marketing and management decisions. In particular, risk managers need to be aware of the notable deterioration of moving average basis forecast accuracy late in the crop-marketing year. Extreme caution should be practiced when forecasting corn and soybean basis beyond April, which implies that farmers interested in earning storage returns for corn and soybeans should be cognizant of the risk associated with basis forecasts for the latter stages of the crop storage season.

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Online Supplement: Practical Alternatives for Forecasting Corn and Soybean Basis in the Eastern Corn Belt throughout the Crop-Marketing Year

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MA1–MA5 are 1- to 5-year moving average forecasts. MA1CI–MA5CI are 1- to 5-year moving average forecasts plus current information. Moving average forecasts that incorporate current information adjust the historical moving average by the deviation of current basis values from historical basis values h weeks prior to the forecast. Naïve forecasts assume that current basis is future basis for a given forecast horizon. That is, basis h weeks prior to the forecast is the forecast.

Table S1. Optimal Forecast Method and Corresponding Mean Absolute Forecast Error (cents/bu.) by Month and Forecast Horizon for Corn with up to a 7-Year Moving Average Forecast

	All Years		Without 2012–2013 Crop Year	
Month	**Optimal Forecast Method**	**Mean Absolute Forecast Error (cents/bu)**	**Optimal Forecast Method**	**Mean Absolute Forecast Error (cents/bu)**
Forecast Horizon = 4 weeks				
September	MA7CI	14.36	MA7CI	13.18
October	MA7	16.54	MA5	13.01
November	Naïve	16.16	Naïve	12.55
December	Naïve	13.66	Naïve	10.59
January	Naïve	11.33	Naïve	11.22
February	MA6CI	5.87	MA7CI	8.10
March	MA4CI	3.43	MA5CI	6.98
April	MA5CI	0.99	MA5CI	5.28
May	MA1CI	7.01	Naïve	9.29
June	MA1CI	6.12	Naïve	10.67
July	Naïve	24.45	Naïve	16.04
August	Naïve	15.28	Naïve	10.98
Forecast Horizon = 12 weeks				
September	MA7	21.21	MA7CI	18.06
October	MA7	16.54	MA5	13.01
November	MA7	16.76	MA7	13.00
December	MA7	16.19	MA4	12.03
January	MA7	14.52	MA3	12.32
February	MA7	13.11	MA3	11.38
March	MA7CI	12.03	MA7CI	12.07
April	MA7CI	9.77	MA7CI	10.30
May	Naïve	15.50	Naïve	14.50
June	MA1CI	15.67	Naïve	15.88
July	Naïve	32.33	Naïve	21.25
August	Naïve	23.16	Naïve	16.19
Forecast Horizon = 20 weeks				
September	MA7	21.21	MA7	18.90
October	MA7	16.54	MA5	13.01
November	MA7	16.76	MA7	13.00
December	MA7	16.19	MA4	12.03
January	MA7	14.52	MA3	12.32
February	MA7	13.11	MA3	11.38
March	Naïve	15.62	MA3	12.54
April	MA7	12.52	MA3	11.75
May	Naïve	19.08	Naïve	17.14
June	MA1	18.80	Naïve	18.52
July	Naïve	35.92	Naïve	23.90
August	Naïve	26.74	Naïve	18.84

Notes: See notes on the title page.

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Table S2. Optimal Forecast Method and Corresponding Mean Absolute Forecast Error (cents/bu.) by Month and Forecast Horizon for Corn with up to a 5-Year Moving Average Forecast in Illinois

	All Years		Without 2012–2013 Crop Year	
Month	**Optimal Forecast Method**	**Mean Absolute Forecast Error (cents/bu)**	**Optimal Forecast Method**	**Mean Absolute Forecast Error (cents/bu)**
Forecast Horizon = 4 weeks				
September	MA5CI	13.10	MA5CI	11.78
October	MA3	15.07	MA5	12.02
November	Naïve	14.61	MA5	11.08
December	Naïve	14.52	Naïve	12.08
January	Naïve	11.32	MA3	10.42
February	MA5CI	7.14	MA5CI	8.82
March	MA5CI	5.02	MA5CI	7.22
April	MA4CI	2.54	MA5CI	5.51
May	MA1CI	7.52	Naïve	7.95
June	MA1CI	6.09	Naïve	8.60
July	Naïve	21.48	Naïve	14.11
August	Naïve	13.37	Naïve	10.36
Forecast Horizon = 12 weeks				
September	MA5	20.51	MA5CI	16.96
October	MA3	15.07	MA5	12.02
November	MA5	14.81	MA5	11.08
December	MA5	16.27	MA3	12.23
January	MA3	13.40	MA3	10.42
February	MA5	12.34	MA3	10.02
March	Naïve	12.79	MA3	10.30
April	MA5CI	11.20	MA5	9.81
May	Naïve	14.67	Naïve	12.68
June	Naïve	14.65	Naïve	13.32
July	Naïve	28.61	Naïve	18.84
August	Naïve	20.51	Naïve	15.08
Forecast Horizon = 20 weeks				
September	MA5	20.51	MA3	18.97
October	MA3	15.07	MA5	12.02
November	MA5	14.81	MA5	11.08
December	MA5	16.27	MA3	12.23
January	MA3	13.40	MA3	10.42
February	MA5	12.34	MA3	10.02
March	MA5	13.49	MA3	10.30
April	MA5	11.74	MA5	9.81
May	Naïve	18.04	Naïve	15.06
June	Naïve	18.02	Naïve	15.70
July	Naïve	31.98	Naïve	21.22
August	Naïve	23.88	Naïve	17.47

Notes: See notes on the title page.

Table S3. Optimal Forecast Method and Corresponding Mean Absolute Forecast Error (cents/bu.) by Month and Forecast Horizon for Corn with up to a 5-Year Moving Average Forecast in Indiana

	All Years		Without 2012–2013 Crop Year	
Month	Optimal Forecast Method	Mean Absolute Forecast Error (cents/bu)	Optimal Forecast Method	Mean Absolute Forecast Error (cents/bu)
Forecast Horizon = 4 weeks				
September	MA5CI	15.61	MA5CI	13.19
October	MA4	17.22	MA5CI	13.27
November	MA4	17.01	MA4	14.93
December	Naïve	16.66	Naïve	14.79
January	Naïve	13.97	MA4	13.07
February	MA5CI	9.48	MA5CI	10.45
March	MA5CI	5.54	Naïve	8.26
April	MA5CI	2.54	MA5CI	6.12
May	MA1CI	6.34	Naïve	8.47
June	MA1CI	8.55	Naïve	10.95
July	Naïve	22.19	Naïve	15.81
August	Naïve	15.73	Naïve	11.00
Forecast Horizon = 12 weeks				
September	Naïve	23.12	MA5CI	18.86
October	MA4	17.22	MA3	14.16
November	MA4	17.01	MA4	14.93
December	MA5	17.53	MA4	14.83
January	MA4	14.23	MA4	13.07
February	MA4	14.34	MA3	13.19
March	Naïve	12.77	Naïve	13.94
April	MA5CI	10.47	MA5CI	11.79
May	Naïve	13.90	Naïve	14.16
June	MA2CI	16.02	Naïve	16.64
July	Naïve	29.43	Naïve	21.50
August	Naïve	22.96	Naïve	16.69
Forecast Horizon = 20 weeks				
September	MA5	23.29	MA5	19.46
October	MA4	17.22	MA3	14.16
November	MA4	17.01	MA4	14.93
December	MA5	17.53	MA4	14.83
January	MA4	14.23	MA4	13.07
February	MA4	14.34	MA3	13.19
March	Naïve	16.14	MA3	14.78
April	MA4	13.13	MA3	12.05
May	Naïve	17.27	MA5	17.06
June	Naïve	19.56	Naïve	19.65
July	Naïve	32.79	Naïve	24.51
August	Naïve	26.33	Naïve	19.70

Notes: See notes on the title page.

Table S4. Optimal Forecast Method and Corresponding Mean Absolute Forecast Error (cents/bu.) by Month and Forecast Horizon (in weeks) for Corn with up to a 5-Year Moving Average Forecast in Michigan

	All Years		Without 2012–2013 Crop Year	
Month	Optimal Forecast Method	Mean Absolute Forecast Error (cents/bu)	Optimal Forecast Method	Mean Absolute Forecast Error (cents/bu)
Forecast Horizon = 4 weeks				
September	Naïve	14.03	Naïve	14.41
October	MA4	15.39	MA5CI	12.33
November	MA4	12.23	MA5	10.90
December	MA5	10.65	MA4	8.97
January	MA5	10.17	MA5	9.41
February	MA5CI	6.63	MA5CI	8.30
March	MA4CI	3.31	MA5CI	7.04
April	MA5CI	1.09	MA4CI	4.81
May	Naïve	6.15	Naïve	8.32
June	MA1CI	6.21	Naïve	9.06
July	Naïve	20.12	Naïve	12.88
August	Naïve	15.00	Naïve	11.18
Forecast Horizon = 12 weeks				
September	Naïve	22.10	Naïve	20.77
October	MA4	15.39	MA5	12.36
November	MA4	12.23	MA5	10.90
December	MA5	10.65	MA4	8.97
January	MA5	10.17	MA5	9.41
February	MA4	11.21	MA5	10.77
March	MA5CI	12.09	MA5CI	13.03
April	MA5CI	9.75	MA5CI	11.09
May	Naïve	14.22	Naïve	14.68
June	Naïve	14.84	Naïve	15.42
July	Naïve	28.19	Naïve	19.24
August	Naïve	23.07	Naïve	17.55
Forecast Horizon = 20 weeks				
September	MA5	25.18	Naïve	23.53
October	MA4	15.39	MA5	12.36
November	MA4	12.23	MA5	10.90
December	MA5	10.65	MA4	8.97
January	MA5	10.17	MA5	9.41
February	MA4	11.21	MA5	10.77
March	MA4	14.54	MA3	13.14
April	MA3	10.91	MA3	11.95
May	Naïve	17.34	MA5	16.52
June	MA1	17.86	MA5	17.95
July	Naïve	31.31	Naïve	22.01
August	Naïve	26.19	Naïve	20.31

Notes: See notes on the title page.

Table S5. Optimal Forecast Method and Corresponding Mean Absolute Forecast Error (cents/bu.) by Month and Forecast Horizon for Corn with up to a 5-Year Moving Average Forecast in Ohio

	All Years		Without 2012–2013 Crop Year	
Month	**Optimal Forecast Method**	**Mean Absolute Forecast Error (cents/bu)**	**Optimal Forecast Method**	**Mean Absolute Forecast Error (cents/bu)**
Forecast Horizon = 4 weeks				
September	MA5CI	15.02	MA5CI	14.89
October	MA5CI	16.96	MA5CI	13.42
November	MA4	15.70	MA4	13.28
December	Naïve	15.48	Naïve	13.85
January	Naïve	13.23	Naïve	14.22
February	MA5CI	8.84	MA5CI	10.81
March	MA5CI	5.23	Naïve	8.94
April	MA5CI	2.04	MA4CI	5.90
May	MA1CI	4.34	Naïve	8.09
June	MA1CI	7.43	Naïve	10.84
July	Naïve	19.34	Naïve	14.08
August	Naïve	15.22	Naïve	11.42
Forecast Horizon = 12 weeks				
September	Naïve	23.00	MA5CI	21.14
October	MA4	17.29	MA5	13.76
November	MA4	15.70	MA4	13.28
December	MA5	16.44	MA4	13.85
January	MA5	14.71	MA4	14.37
February	MA5	14.90	MA3	14.39
March	Naïve	13.28	Naïve	15.16
April	MA5CI	10.61	MA5CI	12.23
May	Naïve	13.42	Naïve	14.32
June	Naïve	15.89	Naïve	17.07
July	Naïve	27.06	Naïve	20.31
August	Naïve	22.94	Naïve	17.64
Forecast Horizon = 20 weeks				
September	MA5	26.20	MA5	23.43
October	MA4	17.29	MA5	13.76
November	MA4	15.70	MA4	13.28
December	MA5	16.44	MA4	13.85
January	MA5	14.71	MA4	14.37
February	MA5	14.90	MA3	14.39
March	Naïve	16.75	MA3	16.60
April	MA4	13.20	MA3	13.97
May	Naïve	16.89	Naïve	17.52
June	Naïve	19.37	Naïve	20.27
July	Naïve	30.53	Naïve	23.51
August	Naïve	26.41	Naïve	20.84

Notes: See notes on the title page.

Table S6. Optimal Forecast Method and Corresponding Mean Absolute Forecast Error (cents/bu.) by Month and Forecast Horizon for Soybeans with up to a 7-Year Moving Average Forecast

	All Years		Without 2012–2013 and 2013–2014 Crop Years	
Month	Optimal Forecast Method	Mean Absolute Forecast Error (cents/bu)	Optimal Forecast Method	Mean Absolute Forecast Error (cents/bu)
Forecast Horizon = 4 weeks				
September	Naïve	29.18	Naïve	32.11
October	MA1	13.31	MA1	11.95
November	MA1	14.90	MA1	13.90
December	MA1	10.77	MA1	8.79
January	Naïve	20.00	Naïve	20.94
February	MA7CI	14.44	Naïve	18.40
March	Naïve	7.92	Naïve	14.90
April	Naïve	4.46	Naïve	11.14
May	Naïve	13.65	Naïve	13.64
June	Naïve	7.09	Naïve	14.37
July	MA2CI	24.64	Naïve	20.06
August	MA6CI	32.00	MA5CI	21.39
Forecast Horizon = 12 weeks				
September	MA7CI	37.43	Naïve	38.33
October	MA1	13.31	MA1	11.95
November	MA1	14.90	MA1	13.90
December	MA1	10.77	MA1	8.79
January	MA1	20.31	MA1	21.47
February	MA1	15.84	MA1	19.96
March	Naïve	17.22	MA1	19.09
April	MA7CI	13.58	Naïve	17.35
May	Naïve	22.96	Naïve	19.86
June	MA7CI	16.00	MA2CI	19.06
July	MA2CI	31.64	MA3CI	24.53
August	MA6CI	39.09	MA4CI	25.25
Forecast Horizon = 20 weeks				
September	MA7CI	40.49	Naïve	39.69
October	MA1	13.31	MA1	11.95
November	MA1	14.90	MA1	13.90
December	MA1	10.77	MA1	8.79
January	MA1	20.31	MA1	21.47
February	MA1	15.84	MA1	19.96
March	MA1	17.61	MA1	19.09
April	MA7CI	16.64	MA7	18.24
May	Naïve	26.02	Naïve	21.22
June	MA7CI	19.06	MA2CI	20.76
July	MA2CI	35.39	MA3CI	25.76
August	MA6CI	42.12	MA4CI	26.63

Notes: See notes on the title page.

Table S7. Optimal Forecast Method and Corresponding Mean Absolute Forecast Error (cents/bu.) by Month and Forecast Horizon for Soybeans with up to a 5-Year Moving Average Forecast in Illinois

	All Years		Without 2012–2013 and 2013–2014 Crop Years	
Month	Optimal Forecast Method	Mean Absolute Forecast Error (cents/bu)	Optimal Forecast Method	Mean Absolute Forecast Error (cents/bu)
Forecast Horizon = 4 weeks				
September	Naïve	26.48	Naïve	26.80
October	MA1	14.03	MA1	13.06
November	MA1	16.58	MA1	17.14
December	MA1	14.32	MA1	13.93
January	Naïve	19.94	Naïve	19.37
February	Naïve	14.24	Naïve	15.50
March	Naïve	8.17	Naïve	11.50
April	Naïve	4.37	Naïve	7.43
May	Naïve	12.13	Naïve	10.16
June	Naïve	6.85	Naïve	10.53
July	Naïve	25.29	Naïve	19.86
August	MA5CI	30.87	MA5CI	20.73
Forecast Horizon = 12 weeks				
September	Naïve	35.33	Naïve	33.88
October	MA1	14.03	MA1	13.06
November	MA1	16.58	MA1	17.14
December	MA1	14.32	MA1	13.93
January	MA2	21.22	MA2	20.21
February	MA3	17.94	MA5	20.04
March	Naïve	17.01	Naïve	18.58
April	Naïve	13.22	Naïve	14.51
May	Naïve	20.98	Naïve	17.24
June	Naïve	15.69	Naïve	17.61
July	Naïve	34.13	Naïve	26.95
August	MA5CI	38.25	MA5CI	26.69
Forecast Horizon = 20 weeks				
September	MA5	38.59	MA5	35.47
October	MA1	14.03	MA1	13.06
November	MA1	16.58	MA1	17.14
December	MA1	14.32	MA1	13.93
January	MA2	21.22	MA2	20.21
February	MA3	17.94	MA5	20.04
March	Naïve	20.41	MA5	20.61
April	Naïve	16.62	Naïve	17.03
May	Naïve	24.38	Naïve	19.76
June	Naïve	19.09	Naïve	20.13
July	Naïve	37.53	Naïve	29.46
August	MA5CI	41.62	MA5CI	29.61

Notes: See notes on the title page.

Table S8. Optimal Forecast Method and Corresponding Mean Absolute Forecast Error (cents/bu.) by Month and Forecast Horizon for Soybeans with up to a 5-Year Moving Average Forecast in Indiana

	All Years		Without 2012–2013 and 2013–2014 Crop Years	
Month	**Optimal Forecast Method**	**Mean Absolute Forecast Error (cents/bu)**	**Optimal Forecast Method**	**Mean Absolute Forecast Error (cents/bu)**
Forecast Horizon = 4 weeks				
September	Naïve	31.52	Naïve	33.70
October	MA3	13.23	MA5	11.79
November	MA3	17.79	MA5	15.31
December	MA2	14.69	MA2	13.83
January	Naïve	22.83	MA2	23.40
February	Naïve	15.99	Naïve	18.95
March	Naïve	8.55	Naïve	13.73
April	Naïve	4.49	Naïve	8.81
May	Naïve	12.32	Naïve	11.72
June	Naïve	8.13	Naïve	12.99
July	Naïve	23.53	Naïve	20.25
August	Naïve	30.10	Naïve	22.38
Forecast Horizon = 12 weeks				
September	MA5	41.25	MA5	39.81
October	MA3	13.23	MA5	11.79
November	MA3	17.79	MA5	15.31
December	MA2	14.69	MA2	13.83
January	MA2	23.06	MA2	23.40
February	MA2	21.07	MA5	23.57
March	Naïve	19.90	Naïve	22.55
April	MA5CI	14.99	Naïve	17.63
May	MA5CI	22.19	Naïve	20.54
June	MA5CI	19.47	Naïve	21.81
July	Naïve	34.88	Naïve	29.07
August	MA5CI	40.11	MA4CI	30.32
Forecast Horizon = 20 weeks				
September	MA5	41.25	MA5	39.81
October	MA3	13.23	MA5	11.79
November	MA3	17.79	MA5	15.31
December	MA2	14.69	MA2	13.83
January	MA2	23.06	MA2	23.40
February	MA2	21.07	MA5	23.57
March	MA3	23.89	MA5	24.22
April	MA5CI	18.71	MA5	19.57
May	MA5CI	25.91	MA5	23.48
June	MA5CI	23.19	MA5CI	25.33
July	Naïve	39.65	Naïve	32.73
August	MA5CI	43.84	MA4CI	33.49

Notes: See notes on the title page.

Table S9. Optimal Forecast Method and Corresponding Mean Absolute Forecast Error (cents/bu.) by Month and Forecast Horizon for Soybeans with up to a 5-Year Moving Average Forecast in Michigan

	All Years		Without 2012–2013 and 2013–2014 Crop Years	
Month	**Optimal Forecast Method**	**Mean Absolute Forecast Error (cents/bu)**	**Optimal Forecast Method**	**Mean Absolute Forecast Error (cents/bu)**
Forecast Horizon = 4 weeks				
September	Naïve	25.82	Naïve	32.31
October	MA4	12.66	MA4	9.90
November	MA5	13.12	MA5	8.06
December	MA4	9.85	MA5	4.78
January	MA5	15.93	MA3	17.38
February	MA5	11.70	MA4	14.43
March	Naïve	4.27	Naïve	11.67
April	MA3CI	1.88	MA4CI	6.44
May	Naïve	8.69	Naïve	10.03
June	Naïve	7.12	Naïve	12.39
July	Naïve	23.14	Naïve	19.09
August	Naïve	37.12	Naïve	22.39
Forecast Horizon = 12 weeks				
September	Naïve	38.80	Naïve	40.92
October	MA4	12.66	MA4	9.90
November	MA5	13.12	MA5	8.06
December	MA4	9.85	MA5	4.78
January	MA5	15.93	MA3	17.38
February	MA5	11.70	MA4	14.43
March	MA5	14.66	MA5	16.76
April	MA3CI	10.12	MA5	12.97
May	MA5CI	20.21	MA5	17.03
June	Naïve	20.10	Naïve	20.99
July	Naïve	36.12	Naïve	27.69
August	Naïve	50.09	Naïve	30.99
Forecast Horizon = 20 weeks				
September	MA5	45.07	MA5	41.61
October	MA4	12.66	MA4	9.90
November	MA5	13.12	MA5	8.06
December	MA4	9.85	MA5	4.78
January	MA5	15.93	MA3	17.38
February	MA5	11.70	MA4	14.43
March	MA5	14.66	MA5	16.76
April	MA5	11.85	MA5	12.97
May	MA5CI	24.45	MA5	17.02
June	MA5CI	26.49	Naïve	25.94
July	Naïve	42.91	Naïve	32.64
August	Naïve	56.88	Naïve	35.95

Notes: See notes on the title page.

Table S10. Optimal Forecast Method and Corresponding Mean Absolute Forecast Error (cents/bu.) by Month and Forecast Horizon for Soybeans with up to a 5-Year Moving Average Forecast in Ohio

	All Years		Without 2012–2013 and 2013–2014 Crop Years	
Month	Optimal Forecast Method	Mean Absolute Forecast Error (cents/bu)	Optimal Forecast Method	Mean Absolute Forecast Error (cents/bu)
Forecast Horizon = 4 weeks				
September	Naïve	34.73	Naïve	41.03
October	MA3	11.20	MA5	10.47
November	MA2	15.23	MA5	13.04
December	MA2	12.37	MA2	11.34
January	MA2	21.82	MA5	24.84
February	Naïve	15.89	Naïve	21.59
March	Naïve	8.83	Naïve	17.05
April	Naïve	3.29	Naïve	10.90
May	Naïve	11.75	Naïve	13.61
June	Naïve	7.82	Naïve	15.83
July	Naïve	23.75	Naïve	22.34
August	MA5CI	33.80	MA5CI	27.21
Forecast Horizon = 12 weeks				
September	Naïve	46.26	Naïve	49.62
October	MA3	11.20	MA5	10.47
November	MA2	15.23	MA5	13.04
December	MA2	12.37	MA2	11.34
January	MA2	21.82	MA5	24.84
February	MA2	20.05	MA5	25.37
March	Naïve	20.36	Naïve	25.64
April	MA5CI	14.62	Naïve	19.49
May	MA5CI	22.40	Naïve	22.20
June	Naïve	19.35	Naïve	24.42
July	MA5CI	34.24	Naïve	30.93
August	MA5CI	42.11	MA5CI	33.36
Forecast Horizon = 20 weeks				
September	Naïve	50.79	Naïve	52.86
October	MA3	11.20	MA5	10.47
November	MA2	15.23	MA5	13.04
December	MA2	12.37	MA2	11.34
January	MA2	21.82	MA5	24.84
February	MA2	20.50	MA5	25.37
March	MA2	22.92	MA3	27.04
April	MA5CI	17.87	MA5	21.79
May	MA5CI	25.65	Naïve	25.44
June	MA5CI	22.85	MA5CI	27.26
July	MA5CI	37.49	MA5CI	33.75
August	MA5CI	45.36	MA5CI	35.64

Notes: See notes on the title page.