Journal of Agricultural and Resource Economics 37(2):228–246

Composite and Outlook Forecast Accuracy

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This paper investigates whether the accuracy of outlook hog price forecasts can be improved using composite forecasts in an out-of-sample context. Price forecasts from four widely-recognized outlook programs are combined with futures-based forecasts, ARMA, and unrestricted Vector Autoregressive (VAR) models. Quarterly data are available from 1975.I through 2007.IV for Illinois/Purdue and 1975.I-2010.IV for Iowa, Missouri, and USDA forecasts, which allow for a relatively long out-of-sample evaluation after permitting model specification and appropriate composite-weight training periods. Results show that futures and numerous composite procedures outperform outlook forecasts, but no-change forecasts are inferior to outlook forecasts. At intermediate horizons, OLS composite procedures perform well. The superiority of futures and composite forecasts decreases at longer horizons except for an equal-weighted approach. Importantly, with few exceptions, nothing outperforms the equal-weight approach significantly in any program or horizon. In addition, the equal-weight approach as well as other composite approaches can generally produce larger trading profits compared to outlook forecasts. Overall, findings favor the use of equal-weighted composites, consistent with previous empirical findings and recent theoretical papers.

Key words: forecast combination, futures, out-of-sample, outlook, time-series

Introduction

U.S. public outlook forecasts are viewed as a valuable source of information and traditionally have played an important role in agricultural decision making. As a consequence, agricultural economists have devoted considerable effort evaluating their forecast performances (e.g., Allen, 1994). Recent studies by Colino and Irwin (2010) and Colino, Irwin, and Garcia (2011) address the accuracy of livestock price forecasts and assess whether outlook forecasts can be improved by combining with other forecasts. Colino and Irwin (2010) evaluate the accuracy of four outlook programs relative to hog and cattle futures prices. Results indicate that futures prices outperform outlook forecasts in most root mean squared error (RMSE) comparisons with several statistically significant differences. However, in a forecast-encompassing framework, forecast combinations among outlook and futures are found to outperform futures alone.

Colino, Irwin, and Garcia (2011) investigate whether the predictability of outlook programs providing hog price forecasts can be improved. Examining numerous time-series forecasts and futures-based forecasts, they find that these alternative forecasts can substantially improve the performance of outlook forecasts. Evidence from an encompassing analysis indicates that simple combinations of outlook and any of the alternative forecasts are able to reduce the errors of outlook

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A number of individuals generously contributed outlook forecast data to this project: the late Gene Futrell, Darrel Good, Glenn Grimes, Chris Hurt, Dave Miller, John Lawrence, Ron Plain, and Laurian Unnevehr. We are indebted to each of them for their invaluable assistance. Funding support from the Aurene T. Norton Trust is gratefully acknowledged.
Review coordinated by Joseph Atwood.

alone by economically significant levels. Averaging of multiple forecast models is also shown to improve the accuracy of outlook forecasts.

Several earlier studies by Bessler and Brandt (1981) and Brandt and Bessler (1981, 1983) also directly examine the benefits of combining outlook livestock price forecasts with econometric, time series, and expert judgment forecasts. Using quarterly data and a one-period horizon for 1976 to 1979, they demonstrate that composite out-of-sample forecasts, formed by simple averaging or by choosing weights for the individual forecasts by minimizing historical errors, can improve mean-squared-error (MSE) accuracy of the Purdue outlook quarterly hog price forecasts (Brandt and Bessler, 1981) as well as Purdue outlook quarterly cattle and broiler prices forecasts (Bessler and Brandt, 1981). Extending the forecast period and simplifying the composite to include only an average of the econometric, time series, and expert opinion, they find evidence that the composite MSE for quarterly hog prices is statistically smaller than the naïve MSE, but the outlook expert opinion is not (Brandt and Bessler, 1983). However, simulated producer returns/risk outcomes based on the forecasts present a different story. The average composite provides higher mean returns and lower risk than the expert forecasts (as do all the individual forecasts), but the economic value of their additional information is questionable. (Bessler and Brandt, 1981) cautiously argue that the composite forecasts improve on the outlook forecasts, and in most cases on the best individual forecasts, and conclude that outlook commodity experts and quantitative econometric models should combine efforts to improve the quality of information provided to producers.

Despite the tenor of these findings, which highlight the benefits of combining price forecasts in livestock markets, several unanswered questions remain, including how they should be combined and whether they possess economic value. Theoretical research and applications of combinatorial forecast methods have expanded significantly in recent decades (Bates and Granger, 1969; Granger and Ramanathan, 1984; McIntosh and Bessler, 1988; Bessler and Chamberlain, 1988; Clark and McCracken, 2004, 2006; Stock and Watson, 2004; Capistrán and Timmermann, 2009). A systematic comparison of alternative techniques would provide insight into which procedures lead to more accurate forecasts. This is consistent with Clemen (1989) who emphasizes that "...combining forecasts has been shown to be practical, economical, and useful ... We no longer need to justify this methodology. We do need to find ways to make the implementation of the technique easy and efficient" (p. 567).

In a related vein, many recently developed combinatorial methods use encompassing regressions to identify composite weights (Fang, 2003). However, the same data or periods are often used both to develop the composite weights—as a product of encompassing regressions—and to assess the performance of the composite forecasts, which limits the usefulness of the analysis (e.g., Colino and Irwin, 2010). A more complete out-of-sample evaluation of composite forecasts requires splitting the time series data into three individual periods. The first period is used for estimating individual models, the second for investigating out-of-sample performance of individual models and identifying optimal composite weights, and the third is used as a final for out-of-sample comparison of forecast accuracy.

A final issue is related to the economic importance of the forecast information. A number of studies find that results of forecast evaluations based on economic criteria may not be consistent with results obtained from using statistical criteria (e.g., Brandt and Bessler, 1983; Garcia et al., 1988; Park, Garcia, and Leuthold, 1989). Here, we assess the economic benefits of using combinatorial forecast procedures by simulating trading activities in the futures markets and comparing them to those from expert opinion.

This paper examines various composite procedures in a realistic out-of-sample context in order to provide a thorough analysis of whether the accuracy of outlook hog price forecasts can be improved through composite forecasts. Price forecasts from four well-recognized outlook programs are combined with forecasts based on futures, ARMA, and unrestricted Vector Autoregressive (VAR) models. In addition, forecast performance from the naïve no-change model based on the previous period price is also evaluated. The outlook programs are the same as those evaluated by Colino and

Irwin (2010). The time-series models, though relatively simple, performed well in the composite analysis conducted by Colino, Irwin, and Garcia (2011). Quarterly data are available from 1975.I through 2010.IV for most of the analysis, allowing for a relatively long out-of-sample evaluation after accounting for model specification and appropriate composite-weight training periods.

Here, straightforward pooling techniques are considered. Several procedures have not yet been applied to agricultural markets, and their accuracy is compared to more standard composite procedures. Composite methods include equally-weighted average, equally-weighted average with a bias correction, weights based on constrained and unconstrained regressions, time-varying weights based on mean squared error, an odds matrix approach, and a shrinkage approach. These procedures represent the most used and nearly all of the composite categories identified by Timmermann (2006).

Individual Forecast Models

Five individual forecasts are examined: an outlook forecast, a futures-based forecast, forecasts from two time-series models, a VAR and an ARMA model, and the naïve no-change forecast based on the previous period price. These models provide a representation of the main forecast approaches available for agricultural markets. Outlook forecasts and forecasts based on futures prices are among the most relevant instruments for agricultural decision-makers when planning future actions. Quarterly finished hog price forecasts from four different outlook programs are available for comparison. The outlook price forecasts considered here are issued by the University of Illinois in combination with Purdue University, Iowa State University, the University of Missouri, and the Economic Research Service of the USDA. Information about timing of release, target cash prices, and sources for each outlook forecast series are provided in Colino and Irwin (2010). The sample period for the Illinois/Purdue forecast runs from 1975.I to 2007.IV, while the other three outlook programs run from 1975.I to 2010.IV. The difference in the sample period stems from the cessation of the Illinois/Purdue outlook program in April 2008.

Price forecasts generated from futures prices are constructed using a procedure developed by Hoffman (2005).[1] For each calendar month, the model uses the nearest-to-maturity contract. On the day outlook forecasts are released, the average of monthly futures prices over the forecast quarter is used to represent the quarterly average futures price. Lean hog futures prices are then converted to live hog units to make them comparable to outlook forecasts, which are reported in live weight terms.[2]

The third and fourth forecast models are an AR(5) and an unrestricted VAR(5).[3] These models have been widely used in the livestock forecasting literature, are relatively easy to compute, and performed well in the composite analysis conducted by Colino, Irwin, and Garcia (2011). The VAR(5) specification is highly consistent with previous hog price forecasting models and is the result of a through process of examining potential variables, structural changes undergone in the industry, and preliminary estimations of reduced VARs. It is a five-variable system with a five fixed-lag structure, which was determined by the Akaike's Information Criteria (AIC), Final Prediction Error (FPE), and Hannan and Quinn's Information Criterion (HQIC). The variables used in this VAR(5) are live-hog prices, corn prices, number of sows farrowing, pork production, and fed cattle prices. More information about the VAR specification and variables selected are available in Colino, Irwin, and Garcia (2011).

[1] The future forecast differs by programs since the forecast is adjusted by a program-related basis. Also the futures-based forecast is constructed using the futures price on the day that the outlook forecast was released, which is different across programs.

[2] An estimated ratio of 0.73673 is applied to lean-hog futures prices. This factor is obtained by dividing the average weight of lean hogs (180.5) by the average weight of live hogs (245) (Sutton and Albrecht, 1996). The adjustment is necessary because the Chicago Mercantile Exchange shifted the hog contract delivery terms from a live weight to carcass weight basis beginning with the February 1997 contract.

[3] For each outlook programs, the AR(5) and VAR(5) models are different since the target cash price for each program is different (the target cash price is the sole input of AR(5) model, and one of the variables included in the VAR(5) model).

The fifth individual forecast model is the naïve no-change forecast based on the previous period price. Alquist and Kilian (2010) find that under the mean-squared error (MSE) framework, the no-change forecast generally outperforms various futures-based forecasts in the crude oil market. They attribute the inferiority of oil futures forecasts to futures price variability about the spot price that is captured by the oil futures spread. In this study, the forecasting performance of the no-change forecast is compared to other individual forecasts to test whether the same hypothesis holds in the livestock market.

Each outlook forecast has a different target cash price, which also has varied over time. To allow for the different program-related target cash prices, futures prices are adjusted by a program-related basis. Historical basis levels are computed by averaging daily futures prices for each quarter and subtracting the quarterly target cash price specified by the outlook forecast. Following Garcia and Sanders (1996), ARMA basis forecasts are estimated and the futures prices are adjusted. Time-series models are specified and estimated for cash prices of the specific program.

Forecast Combination Methods

Theoretical and empirical research on forecast composites is extensive (Timmermann, 2006). A key question is whether to use simple averages or estimate forecast combination weights. Empirical evidence has shown that it is difficult to outperform simple procedures such as an arithmetic average (Clemen, 1989; Makridakis and Hibon, 2000; Stock and Watson, 2004). The effect of parameter estimation error can be a significant determinant of the performance of composite forecasting models. For instance, least-square weight (slope) estimation procedures (e.g., Granger and Ramanathan, 1984) require the estimation of covariances among forecast errors, which can introduce an additional source of error in weight estimation. Simple combination schemes like arithmetic averages, although perhaps biased, do not require the estimation of covariances across model errors, so they offer a potentially attractive option (Timmermann, 2006). This question can be viewed as a tradeoff between imposing equal weights for each individual forecast, which could lead to bias (clearly a suboptimal scheme), and estimating the weights, which could lead to a loss in efficiency. This bias-efficiency trade-off gives rise to the so-called *forecast combination puzzle* recently analyzed by Smith and Wallis (2009) and Issler and Lima (2009).

After reviewing available approaches, we follow Capistrán and Timmermann (2009), who assess nearly all categories of composite procedures outlined in Timmermann (2006). All approaches assume that the combination rule takes a linear additive form:

(1) $$f^c_{t+h|t}(p) = \sum_{i=1}^{K} w^i_t \hat{p}^i_{t+h|t},$$

where, w^i_t is the estimated weight on model i at time t, K is the number of h-step-ahead forecasts of the hog price p, $\hat{p}^i - t + h|t$ is the ith forecast model available at time t for price at $t+h$, and $f^c_{t+h|t}$ is the composite forecast. The task is to derive the optimal weight to be assigned to each forecast.

The first approach follows a naïve decision rule using the best-previous forecast. For each forecast made at t, we identify the individual forecast with the most accurate historical performance and use it to forecast into the future (Clark and McCracken, 2006; Capistrán and Timmermann, 2009). In other words, the forecast with the lowest mean-squared error (MSE) receives all the weight:

(2) $$f^c_{t+h|t} = \hat{p}^{i^*_t}_{t+h|t},$$

where:

(3) $$i^*_t = \text{argmin}_{i=1,\ldots,K} t^{-1} \sum_{\tau=1}^{t} (p_\tau - \hat{p}^i_{\tau|\tau-h})^2.$$

A second composite forecast uses an arithmetic average of the four individual forecasts. It is also called the equal-weighted composite forecast:

(4) $$\overline{p}_{t+h|t} = K^{-1} \sum_{i=1}^{K} \hat{p}^{i}_{t+h|t}.$$

A third composite uses a projection of the equal-weighted combination:

(5) $$\tilde{p}_{t+h|t} = \hat{a}_t + \hat{\beta}_t \overline{p}_{t+h|t}.$$

This regression on the equal-weighted forecast includes a constant to adjust for potential biases in individual forecasts as well as in the aggregate and allows the slope coefficient to differ from unity. The combination is an extension of equation (4) and only requires the estimation of α and β. This is a potentially useful technique because it uses information from all forecasts in the average but adjusts for possible bias and noise in the aggregate forecast. Capistrán and Timmermann (2009) find this procedure possesses good overall forecast performance.

Probably the most common procedure for estimating combination weights is least squares regressions (Bates and Granger, 1969; Nelson, 1972; Granger and Ramanathan, 1984). In matrix notation, the K-dimension weight vector at forecast period T, W_T, is estimated by regressing the actual values of the target variable, $\boldsymbol{P}_{t+h}$ on the K-vector of forecasts, $\hat{\boldsymbol{P}}_{N+h|N}$ over the period $t = 1, \ldots, T$,

(6) $$\hat{\boldsymbol{W}}_T = (\sum_{t=1}^{T-1} \hat{\boldsymbol{P}}_{t+h|t} \boldsymbol{P}'_{t+h})^{-1} \sum_{t=1}^{T-1} \hat{\boldsymbol{P}}_{t+h|t} \boldsymbol{P}'_{t+h}.$$

Following Granger and Ramanathan (1984), three versions of the procedure are examined:

(7) $$\boldsymbol{P}_{t+h|t} = \boldsymbol{W}'_T \hat{\boldsymbol{P}}_{t+h|t} + \boldsymbol{E}_{t+h} \rightarrow s.t. \boldsymbol{W}'_T \mathbf{1} = 1;$$

(8) $$\boldsymbol{P}_{t+h} = \boldsymbol{W}^0_T + \boldsymbol{W}'_T \hat{\boldsymbol{P}}_{t+h|t} + \boldsymbol{E}_{t+h};$$

(9) $$\boldsymbol{P}_{t+h} = \boldsymbol{W}'_T \hat{\boldsymbol{P}}_{t+h|t} + \boldsymbol{E}_{t+h};$$

where in equation (7), $\mathbf{1}$ is a K-dimension vector of ones. Equation (7) is essentially a constrained regression requiring composite weights to sum up to unity and individual forecasts to be unbiased in order to guarantee that the combined forecast is also unbiased. This procedure has been used in many studies and is directly related to Harvey, Leybourne, and Newbold's (1998) encompassing test. Equation (8) is an unconstrained regression since it allows for bias in the individual forecasts, which can be corrected by the constant W^0_T, and does not require the weights to sum to unity. Equation (9) is a simple variation of equation (8) without a constant. The equations are estimated using standard OLS procedures.

As mentioned, errors in the combination weights tend to be high in procedures—like least squares regressions—that require the estimation of the covariance matrix of forecast errors. An alternative is to ignore the correlations among forecast errors and to weight each forecast by some measure of relative performance. Consider equation (10), where the weight for each forecast is determined by the inverse of its MSE relative to the sum of the inverse MSE values for all the models (Bates and Granger, 1969; Newbold and Granger, 1974):

(10) $$w^i_t = \frac{MSE_i^{-1}}{\sum_{i=1}^{K} MSE_i^{-1}}.$$

Gupta and Wilton (1987, 1988) propose a non-parametric odds matrix approach based on a matrix of pair-wise odds ratios to incorporate prior forecast accuracy. Specifically, let π_{ij} be the probability that forecast model i will outperform forecast j in the next realization. Then, each element of the matrix $\boldsymbol{O}$, $o_{ij} = \pi_{ij}/\pi_{ji}$, can be viewed as the odds that forecast i will outperform forecast j. Combination weights are the solution to the system of equations:

$$(\boldsymbol{O} - \boldsymbol{KI})\boldsymbol{W} = \boldsymbol{0}, \tag{11}$$

where $\boldsymbol{I}$ is the identity matrix and $\boldsymbol{W}$ is the weight vector. The solution (the estimated weight vector) is given by the eigenvector corresponding to the largest positive eigenvalue that solves $\boldsymbol{OW} = \tau_{max}\boldsymbol{W}$; it is unique when normalized. To estimate the pair-wise probabilities, π_{ij}, we follow Gupta and Witlon's (1987) empirical application:

$$\pi_{ij} = \frac{a_{ij}}{a_{aj} + a_{ji}}, \tag{12}$$

where a_{ij} is the number of times forecast i had a smaller absolute error than forecast j in the past. This approach has been shown to be superior to many methods particularly in small samples.

Shrinkage methods are a set of combination approaches widely and rather successfully used in the macroeconomic literature. Shrinkage methods offer a trade-off between the bias in averaging weights and parameter error when estimating weights (Timmermann, 2006). The most common shrinkage approach usually shrinks towards equal-weights or the average of forecasts (Stock and Watson, 2004; Diebold and Pauly, 1990) Let $\hat{w}_t^i$ be the least-squares weight estimator for model i from regression (7) up to period t. Stock and Watson's combination weights take the form:

$$\tilde{w}_t^i = \phi_t \hat{w}_t^i + (1 - \phi_t)(\frac{1}{K}), \tag{13}$$

where:

$$\phi_t = \max(0, 1 - \frac{\theta K}{N - 1 - K - 1}), \tag{14}$$

and θ is the shrinkage parameter. For fixed values of K and N, as the values of θ become larger (lower ϕ_t), the greater the shrinkage towards equal-weights. As the sample size N increases relative to the number of forecast models K, more weight is given to the least-squares estimate. Following Capistrán and Timmermann (2009), we consider two values for the θ shrinkage parameter, 0.25 and 1, to assess forecast performance.

Finally, for composite techniques that require historical data for each forecast, weights are recursively estimated using two procedures. The first uses all the data available to the time of the prediction. Weights are also estimated using a fixed-rolling window of sixty observations to allow estimated weights to reflect only information in the most recent fifteen-year period.

Data and Estimation Procedures

The data are divided into three periods: initial fitting, weight determination, and final assessment. In the second period, we develop the composite weights that are used to forecast in the last period. An exception to this process is the equally-weighted composite, which averages the forecasts for each period. Four individual forecasts are used for composite forecasting, outlook forecasts, futures forecasts, ARMA and VAR forecasts.[4]

Quarterly data for outlook forecasts, hog prices, and related variables are available for 1975.I-2007.IV (Illinois/Purdue) and 1975.I-2010.IV (Iowa, Missouri, and USDA). Following Ashley (2003), a sample size of at least fifty observations for the out-of sample evaluation was first specified

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[4] Due to their markedly poor performance relative to the other individual forecasts, the no-change forecast is not used when constructing composite forecasts. Also, note that hog prices are stationary as discussed in Colino, Irwin, and Garcia (2011).

at the end of the data. Next, a composite identification period of thirty-two observations was used to establish the initial weights. The remaining data starting from the beginning of the study period were used for initial fitting of the models. Chronologically, models are initially specified and estimated for the 1975.I-1984.IV sub-period. Individual model forecasts are generated recursively (by adding the next observation to the estimation window for each forecast date) for 1985.I-1993.IV sub-period and used to estimate the combination weights. For the 1994.I-2010.IV period (or 1994.I-2007.IV for Illinois/Purdue), out-of-sample forecasts for the individual and composite models are also estimated, in which the weights are allowed to change at each forecast based on specified procedures. In the last period, composite forecasts are computed recursively using all data and a rolling window specifying a fixed number of observations. The performance of all composite forecasts is compared to the performance of the individual forecasts for the 1994.I to 2010.IV period (1994.I-2007.IV for Illinois/Purdue).

As an example of the estimation procedure, univariate and VAR models are initially specified and estimated over 1975.I to 1984.IV. Next, their out-of-sample forecasts are generated recursively for the period 1985.I-1993.IV. Combined with the ex-ante outlook and futures forecasts for the same period, initial optimal composite weights are estimated. These weights are used for the first out-of-sample composite forecast of 1994.I. For the 1994.II composite forecast, weights are re-estimated using data from 1985.I to 1994.I. The process is repeated period-by-period adding the latest observation and generating a forecast for the subsequent period. Once the combined number of out-of-sample forecasts reaches sixty observations (beginning in 1985.I), weights are re-estimated both recursively and by fixing a rolling window of sixty observations. One-, two-, and three-quarter ahead price forecasts are analyzed for all outlook programs except the USDA, where availability is limited to one- and two-quarter ahead forecasts.

Results

Overall, the forecast combination analysis applied to the four outlook programs yields strong similarities. For brevity, we focus on forecasts released by Iowa State University and identify important similarities and differences found in other outlook programs.

RMSE Analysis

Table 1 presents the RMSE over 1994.I-2010.IV for the individual and composite models compared to the Iowa outlook forecasts. RMSE for a forecast model i at a given horizon h is computed as:

$$(15) \qquad RMSE_i^h = \left[\frac{1}{N}\sum_{t=1}^{N}(p_{t+h} - \hat{p}^i_{t+h|t})^2\right]^{1/2},$$

where, as before, p_{t+h} is the actual cash price in quarter $t+h$, $\hat{p}^i_{t+h}$ is the ith forecast price evaluated for quarter $t+h$ made at period t, and N is the number of forecast observations. For each forecast horizon the three forecast models with the smallest RMSEs are in bold. When compared individually, Iowa forecasts are generally superior to those from the time series models, except at the two-quarter ahead horizon. Iowa outperforms the AR(5) and VAR(5) models by 0.61%-12.88% across horizons. However, futures forecasts beat the Iowa forecast at all horizons by 10.68% on average. The naïve forecasts based on the previous period performs significantly worse than the Iowa forecasts, with RMSEs that are 34.73%, 36.39% and 23.36% higher than the RMSEs of the Iowa forecasts at the one-, two-, and three-quarter horizons. The naïve no-change forecasts perform even worse when compared to the futures forecasts at all three forecasting horizons. The superiority of no-change forecasts found in the crude oil market by Alquist and Kilian (2010) thus cannot be established in the hog market. For the first and second horizons, when Iowa is combined with other forecasts significant

Table 1: Out-of-Sample RMSEs of Hog Price Forecasts, Iowa State University, 1994.I-2010.IV

		Forecast Horizon		
	Forecast model	**1-qtr.-ahead**	**2-qtr.-ahead**	**3-qtr.-ahead**
#1	Iowa State University	4.87	6.97	8.19
#2	Futures	**3.72*****	6.57	7.97
#3	VAR(5)	4.90	6.38	8.36
#4	ARMA(5,0)	5.59	7.75	**8.45**
#5	No change	6.56**	9.50***	10.11**
#6	Best previous model	**3.72*****	6.38	8.62
#7	equal-weight composite	4.15**	6.07**	**7.40**
#8	MSE-weight composite	4.01***	6.06**	**7.45**
#9	MSE-weight composite - rolling window	4.01***	6.06**	7.46
#10	Unrestricted OLS composite	3.74***	6.06	8.16
#11	Unrestricted OLS composite - rolling window	3.71***	**5.95**	8.01
#12	Unrestricted OLS composite -noconstant	3.67***	6.03	7.96
#13	Unrestricted OLS composite -noconstant - rolling window	3.68***	6.06	8.07
#14	Restricted OLS composite	**3.65*****	6.05	7.84
#15	Restricted OLS composite - rolling window	3.66***	6.05	7.86
#16	Projection on the equal-weight composite	4.17**	6.05*	7.72
#17	Projection on the equal-weight composite - rolling window	4.19**	6.06*	7.70
#18	Shrinkage - 0.25 composite	**3.66*****	6.04	7.83
#19	Shrinkage - 0.25 composite - rolling window	3.67***	6.04	7.84
#20	Shrinkage - 1 composite	3.67***	**6.02***	7.77
#21	Shrinkage - 1 composite - rolling window	3.68***	**6.02***	7.80
#22	Odds matrix composite	4.03**	6.06**	**7.43**
#23	Odds matrix composite - rolling window	4.01**	6.04**	7.45

Notes: All figures are reported as $/cwt. At each horizon, the three forecasts with the smallest RMSEs are in bold font. Single, double, and triple asterisks (*, **, ***) represent significance in the RMSE differences between outlook forecast and the alternative forecast model at the 10%, 5% and 1% level based on the Modified Diebold-Mariano (MDM) test.

improvements in forecast accuracy emerge. On average, Iowa RMSE is reduced by 20.99%, 13.26%, and 5.40% at one-, two-, and three-quarter ahead through combining. Notably at the three-quarter ahead horizon, the equal-weighted composite forecast has the smallest RMSE compared to all other forecasts.

To analyze whether differences in RMSEs are statistically different among the various forecasts, we use the modified Diebold-Mariano (MDM) test proposed by Harvey, Leybourne, and Newbold (1997). The MDM statistic tests the null hypothesis of equality of forecast performance between forecasts i and j based on a specified loss function, $E\left(g(e^i_{t+h|t} - g(e^j_{t+h|t})\right) = 0$, where $e^i_{t+h|t}$ and $e^j_{t+h|t}$ are forecast errors of models i and j at period t for price at period $t+h$. Assuming a quadratic loss function, the test is based on the difference in squared errors for two forecasts at a given horizon h:

$$d_{t+h|t} = g(e^i_{t+h|t}) - g(e^j_{t+h|t}) = (e^i_{t+h|t})^2 - (e^j_{t+h|t})^2. \tag{16}$$

The MDM test is then specified as:

$$MDM = \left[\frac{N+1-2h+N^{-1}h(h-1)}{N}\right]^{\frac{1}{2}} [V(\overline{d})]^{-\frac{1}{2}}[\overline{d}],$$

(17)

$$V(\overline{d}) = \left[N^{-1}\left(\gamma_0 + 2\sum_{s=1}^{h-1}\gamma_s\right)\right],$$

where $\overline{d}$ is the sample mean $d_{t+h|t}$, $h = 1,2,3$ is the forecast horizon, $\gamma_0 = N^{-1}\sum_{t=1}^{N}(d_{t+h|t} - \overline{d})^2$ is the variance of $d_{t+h|t}$, and $\gamma_s = N^{-1}\sum_{t=s+1}^{N}(d_{t+h|t} - \overline{d})(d_{t+h-s|t-s} - \overline{d})$ is the sth auto-covariance of $d_{t+h|t}$ $(s = 1,\ldots,h-1)$. Auto-covariance terms are included to account for the overlap in two- and three-quarter ahead forecasts. The MDM test statistic follows a t-distribution with $N-1$ degrees of freedom.

Table 2 presents results from the MDM test applied to Iowa for one-, two-, and three-quarter horizons.[5] The MDM test of significantly different RMSEs is computed for each pair of forecast comparisons to analyze not only the statistical improvement of forecast combination relative to outlook but also to assess meaningful differences among alternative composite approaches. The non-empty cells in the upper part of a matrix correspond to those comparisons between the particular row- and column-forecasts that are statistically different from zero. The number in the parenthesis identifies the forecast with smaller RMSE. Results show that at one-quarter ahead, futures forecasts (#2), all composite forecasts (#7 - #23), and even the simple approach of following the best previous model (#6) provide statistically smaller RMSEs than those from Iowa alone. At more distant horizons, using futures and composite forecasts becomes less attractive. The equal-weighted approach, the composite forecasts based on the odds matrix, the shrinkage methods with the shrinkage parameter equal to 1, and those based on the historical MSE show a statistically significant superiority that tends to increase at longer horizons. Notably no composite forecast is statistically superior to the Iowa forecast at the three-quarter ahead horizon.

To better understand the successful performance of forecast combination, the evolution of Iowa forecast errors over time is compared to those from the equal-weighted composite approach and the constrained- (or restricted) OLS regression. The constrained-OLS regression is of interest not only because of its connection to encompassing tests, but also because it reflects those approaches that require the estimation of error covariances. In contrast, the equal weighted composite reflects combinatory techniques that ignore any correlation between individual forecasts. They also perform well, as shown in other studies and in table 2, particularly across horizons. Examination of the forecast errors at one-, two-, and three-quarter ahead provided insights into these relationships.[6] While all errors move closely together through time, forecast errors of the equal-weighted composite approach tend to fall inside the range of the outlook and OLS-regression errors. Equal-weighted composite forecast errors tend to be less variable and to provide more precise estimates. This tendency becomes even more evident at two- and three-quarter horizons. Specifically, the forecast errors of the equal-weighted composite approach fall inside the range of the outlook and the OLS-regression errors in 28 out of 67, 33 out of 66, and 34 out of 65 cases for the one-, two-, and three-quarter ahead forecasts.

Examination of the RMSEs for the other outlook programs reveals several significant results (tables 3, 4, and 5). First, futures forecasts exhibit lower RMSEs than the other three outlook forecasts at all horizons, except for Missouri at three-quarter ahead. Second, the naïve no-change forecasts based on the previous period prices perform much worse than the Illinois/Purdue and Missouri forecasts and, in fact, their RMSEs are much larger than any other forecasts at all horizons. However, the no-change forecast outperforms the USDA forecast at the one-quarter horizon. Third, while a variety of composite forecasts have significantly smaller RMSEs than the other outlook forecasts, the equal-weighted approach is always smaller than outlook forecasts and significantly outperforms all outlook forecasts at all forecast horizons, except for Missouri at one- and three-quarter ahead. Fourth, composites generated using OLS regressions perform well in several programs, particularly at the first and second horizons; however, their ability declines at the most distant horizon, where the forecast errors are largest for all procedures. Added estimation error during periods of high variability may explain the decline in forecast ability relative to equal-weighting, inverse MSE, and posterior odds. These last results are consistent with previous findings

[5] MDM test results for the other three outlook forecasts are available from the authors upon request.
[6] These figures are available on request from the authors upon request.

(Clemen, 1989; Makridakis and Hibon, 2000; Stock and Watson, 2004; Capistrán and Timmermann, 2009), which point to the use of an equal-weighted composite procedure. Overall, results suggest that most of the forecast combination models significantly improve the performance of outlook forecasts in isolation, with an average percentage reduction in RMSEs across all four programs of -19.80%, -17.22%, and -6.19% across horizons.

Table 6 summarizes the benefits of pooling the four individual hog price forecasts using an equal-weighted approach, which exhibited relative superiority among the forecast combination approaches. The table presents the percentage RMSE reductions (increments) obtained from the combinations relative to futures forecasts alone and to outlook forecasts alone. Percentage RMSE changes from futures forecasts are also of interest, since they are usually considered as the "gold standard" for comparison in agricultural price forecasting. At one-quarter ahead, the average composite forecast does not provide smaller RMSEs than the futures in isolation, except for the USDA outlook forecast. Excluding the USDA, average forecast errors across the three other programs are 9.26% larger than those from futures. Average equal-weighted forecasts do a better job at two- and three-quarter ahead. RMSE reductions relative to futures forecasts average -9.79% across outlook programs and horizons. Reductions at these horizons are statistically significant in two out of seven cases.

The usefulness of equal-weighted forecasts is more noticeable when outlook forecasts are the benchmark. Regardless of the outlook program, the equal-weighted composite forecast consistently provides smaller RMSEs than those obtained from outlook alone. Across programs, the average forecast error reductions are -13.73%, -16.44%, and -14.67% at one-, two-, and three-quarter ahead. Furthermore, reductions versus outlook are significant in all but three cases. Within programs, the largest reduction is obtained for the USDA, while Missouri receives the fewest benefits from the combinations. On average, the equal-weighted composite reduces the Missouri, Iowa, Illinois/Purdue, and the USDA forecast errors by -10.55%, -12.45%, -14.08%, and -26.74%.

The overall benefit of the equally-weighted forecasts is consistent with extensive literature and the forecast combination puzzle, which identifies that it is difficult to outperform simple average combinatorial procedures. Clearly, relevant information for different sources can improve forecast accuracy. The finding that the equally-weighted forecasts are often better than procedures estimating weights by statistical procedures supports the idea that any bias in using simple averages is less than the loss in efficiency from estimation (Timmermann, 2006). Another potential reason for the performance of the equally-weighted forecasts is that outlook experts have changed with the passage of time in most cases. Only at Illinois/Purdue did the same expert remain for the entire period, but the program stopped generating outlook forecasts in 2008 (Colino and Irwin, 2010). The changes in outlook experts, who form the basis of the judgmental component of the composites, likely resulted in different sources of objective information and subjective insights affecting outlook forecasts over time. These differences can make it difficult to clearly identify the systematic effect of the experts in the composite forecasts and may have influenced the relatively superior performance of the simple equal-weight procedure.[7]

Analysis of Economic Benefits

A model with smaller RMSE may not be a sufficient condition for generating positive economic opportunities (e.g., Brandt and Bessler, 1983; Garcia et al., 1988; Park, Garcia, and Leuthold, 1989). To assess the economic benefits of using composite forecast procedures, trading activities in the futures market are simulated using the forecast information from the forecasting models for the out-of-sample evaluation period. Following a similar approach used by Gerlow, Irwin, and Liu (1993),

[7] We would like to thank a reviewer for this suggestion.

Table 2: Modified Diebold-Mariano (MDM) Test Results, Iowa State University, 1994.I-2010.IV

Model	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14	#15	#16	#17	#18	#19	#20	#21	#22	#23
1-Quarter Ahead																						
#1	(2)			(1)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
#2		(2)	(2)	(2)		(2)*									(2)*	(2)						
#3			(3)	(3)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)*	(17)*	(18)	(19)	(20)	(21)	(22)	(23)
#4				(4)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
#5					(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
#6						(6)*									(6)*	(6)						
#7							(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)			(18)	(19)	(20)	(21)	(22)	(23)
#8											(12)	(13)	(14)	(15)			(18)	(19)	(20)	(21)		
#9											(12)	(13)	(14)	(15)			(18)	(19)	(20)	(21)		
#10															(10)	(10)					(10)*	
#11															(11)	(11)					(11)*	
#12															(12)	(12)					(12)	(12)
#13															(13)	(13)					(13)	(13)
#14															(14)	(14)					(14)	(14)
#15															(15)	(15)					(15)	(15)
#16																	(18)	(19)	(20)	(21)		
#17																	(18)	(19)	(20)	(21)		
#18																					(18)	(18)
#19																					(19)	(19)
#20																					(20)	(20)
#21																					(21)	(21)
#22																						(23)
2-Quarter Ahead																						
#1				(1)		(7)	(8)	(9)							(16)*	(17)*			(20)*	(21)*	(22)	(23)
#2				(2)																		
#3			(3)	(3)																		
#4				(4)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
#5					(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
3-Quarter Ahead																						
#1				(1)																		
#2				(2)																		
#3				(3)		(7)	(8)	(9)					(14)	(15)*			(18)	(19)	(20)	(21)	(22)	(23)
#4				(4)																		
#5					(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
#6						(7)	(8)	(9)			(12)*		(14)	(15)*			(18)	(19)*	(20)	(21)*	(22)	(23)
#8											(8)*	(8)*										
#9											(9)*	(9)*										
#12																					(22)*	(23)*
#13																					(22)*	
#14																	(18)*		(20)*			
#15																		(19)*		(21)*		
#18																			(20)*			

Notes: Numbers in parentheses represent the superior forecast model. Unless otherwise noted by a single asterisk (*), all entries are significant at the 5% level based on the MDM test. A single asterisk (*) indicates significance at the 10% level. No statistically significant differences between forecasts were found for the models not included.

Table 3: Out-of-Sample RMSEs of Hog Price Forecasts, University of Missouri, 1994.I-2010.IV

		Forecast horizon		
	Forecast model	**1-qtr.-ahead**	**2-qtr.-ahead**	**3-qtr.-ahead**
#1	University of Missouri	4.27	6.76	7.96
#2	Futures	3.96	6.49	8.18
#3	VAR(5)	4.72	6.45	8.46
#4	ARMA(5,0)	6.12***	7.92*	8.57
#5	No change	6.29***	9.24***	9.71***
#6	Best previous model	3.96	6.38	8.62
#7	equal-weight composite	4.17	6.12*	**7.47**
#8	MSE-weight composite	3.99	6.08*	**7.50**
#9	MSE-weight composite - rolling window	3.98	6.09*	7.51
#10	Unrestricted OLS composite	3.79	6.11	8.14
#11	Unrestricted OLS composite - rolling window	3.75	6.08	8.05
#12	Unrestricted OLS composite -noconstant	3.73	**5.98**	7.96
#13	Unrestricted OLS composite -noconstant - rolling window	3.69*	**6.06**	8.07
#14	Restricted OLS composite	3.72*	6.09	7.95
#15	Restricted OLS composite - rolling window	**3.67***	6.10	7.97
#16	Projection on the equal-weight composite	4.05	6.12	7.62
#17	Projection on the equal-weight composite - rolling window	4.05	6.11	7.57
#18	Shrinkage - 0.25 composite	3.73*	6.08	7.93
#19	Shrinkage - 0.25 composite - rolling window	**3.67***	6.09	7.96
#20	Shrinkage - 1 composite	3.73*	**6.07**	7.88
#21	Shrinkage - 1 composite - rolling window	**3.67***	6.08	7.90
#22	Odds matrix composite	4.07	6.14*	**7.50**
#23	Odds matrix composite - rolling window	4.04	6.12*	7.51

Notes: All figures are reported as \$/cwt. At each horizon, the three forecasts with the smallest RMSEs are in bold font. Single, double, and triple asterisks (*, **, ***) represent significance in the RMSE differences between outlook forecast and the alternative forecast model at the 10%, 5% and 1% level based on the Modified Diebold-Mariano (MDM) test.

the trading signal $S^i_{t+h|t}$ for forecast i at t for h-period ahead forecast are defined as follows:

$$S^i_{t+h|t} = \begin{cases} 1, & | \quad \text{buy if} \quad \hat{p}^i_{t+h|t} > F_{t+h|t} \\ -1, & | \quad \text{sell if} \quad \hat{p}^i_{t+h|t} \leq F_{t+h|t} \end{cases}, \tag{18}$$

where $\hat{p}^i_{t+h|t}$ is defined as before and $F_{t+h|t}$ is the futures forecast for quarter $t+h$ made at t. If the forecasted price exceeds the futures forecast, a long position in the nearby contract is established at the opening price on the next trading day. The long position is liquidated at the closing price on the last trading day of the forecast quarter. If the forecasted price is less than or equal to the futures forecast, a short position is established on the next trading day and the position is later offset by buying back the contract. The trading profit $R^i_{t|t+h}$ for forecast i made at t for price at $t+h$ is defined as:

$$R^i_{t|t+h} = S^i_{t|t+h}[FP_{nt} - FP_{mt}], \tag{19}$$

where $S^i_{t|t+h}$ is the trading signal defined as in equation (16), FP_{mt} is the futures price on the first trading day m for quarter t at the open, and FP_{nt} is the futures price on the last trading day n at the close.[8]

[8] Here the April contract is used for the first quarter, the July, October, and February contracts are used for the second, third, and fourth quarter.

Table 4: Out-of-Sample RMSEs of Hog Price Forecasts, University of Illinois/Purdue, 1994.I-2007.IV

		Forecast horizon		
	Forecast model	**1-qtr.-ahead**	**2-qtr.-ahead**	**3-qtr.-ahead**
#1	Illinois/Purdue	4.55	6.87	7.78
#2	Futures	3.76	5.78**	7.30
#3	VAR(5)	4.70	5.95	7.59
#4	ARMA(5,0)	5.07	6.81	7.37
#5	No change	6.15***	8.66**	9.28**
#6	Best previous model	3.76	5.95	7.70
#7	equal-weight composite	3.89**	5.54***	**6.65*****
#8	MSE-weight composite	3.75**	5.46***	**6.65****
#9	MSE-weight composite - rolling window	3.75**	5.45***	6.66***
#10	Unrestricted OLS composite	3.69*	**5.32***	6.96
#11	Unrestricted OLS composite - rolling window	3.75	**5.32***	7.04
#12	Unrestricted OLS composite -noconstant	**3.61****	**5.29****	7.06*
#13	Unrestricted OLS composite -noconstant - rolling window	**3.65****	5.35**	7.28
#14	Restricted OLS composite	3.71**	5.45**	7.04
#15	Restricted OLS composite - rolling window	3.72*	5.49**	7.07
#16	Projection on the equal-weight composite	3.92*	5.66**	6.86**
#17	Projection on the equal-weight composite - rolling window	3.94*	5.72**	6.97**
#18	Shrinkage - 0.25 composite	3.70**	5.44**	7.03
#19	Shrinkage - 0.25 composite - rolling window	3.71**	5.49**	7.06
#20	Shrinkage - 1 composite	**3.69****	5.44**	6.99*
#21	Shrinkage - 1 composite - rolling window	3.70**	5.48**	7.01*
#22	Odds matrix composite	3.79**	5.49***	**6.65*****
#23	Odds matrix composite - rolling window	3.79***	5.48***	6.67***

Notes: All figures are reported as $/cwt. At each horizon, the three forecasts with the smallest RMSEs are in bold font. Single, double, and triple asterisks (*, **, ***) represent significance in the RMSE differences between outlook forecast and the alternative forecast model at the 10%, 5% and 1% level based on the Modified Diebold-Mariano (MDM) test.

Table 7 presents the trading profits of outlook programs and equal-weighted composite forecasts, as well as the maximum trading profits or "best" produced by the composite forecasts generated.[9] The sample size ranges from 52 to 68 for different programs and different forecast horizons. On average, using the Iowa forecast one would incur negative trading profits at all forecast horizons; for the two-quarter-ahead forecast, the mean trading profit is significantly different from zero. The equal-weighted composite forecast, on the other hand, consistently generates positive trading profits in all cases except for Illinois/Purdue at the two-quarter horizon. Excluding the Illinois/Purdue two-quarter horizon and the Missouri one-quarter horizon, the equal-weighted composite forecast generates higher economic benefits than outlook forecasts. The trading profits generated by the equal-weighted composite forecast are statistically significantly different from zero for the USDA at both one- and two-quarter horizons and the Missouri at the two- and three-quarter horizons. Across the outlook programs and forecast horizons, statistically significant positive economic benefits can be generated using the "best" composite forecasting procedures, as evidenced by the largest mean trading profits presented in table 8. Overall, the analysis of economic benefits highlights the advantage of using equal-weighted composite forecast and other composite procedures over the outlook forecasts, consistent with the results from RMSE analysis.

[9] The maximum trading profits are the largest mean trading profit per contract by any of the forecasts assessed. The trading profits for all forecast methods are available from the authors upon request.

Table 5: Out-of-sample RMSEs of the hog price forecasts, USDA, 1994.I-2010.IV

	Forecast model	Forecast horizon	
		1-qtr.-ahead	**2-qtr.-ahead**
#1	USDA	6.62	8.20
#2	Futures	5.26**	7.16
#3	VAR(5)	4.63***	6.10**
#4	ARMA(5,0)	5.20**	7.10
#5	No change	6.23	9.13
#6	Best previous model	4.63***	6.38**
#7	equal-weight composite	4.67***	6.23***
#8	MSE-weight composite	4.55***	6.08***
#9	MSE-weight composite - rolling window	4.58***	6.09***
#10	Unrestricted OLS composite	4.53***	6.09**
#11	Unrestricted OLS composite - rolling window	4.58***	6.10**
#12	Unrestricted OLS composite -noconstant	4.51***	**6.02****
#13	Unrestricted OLS composite -noconstant - rolling window	4.56***	6.06**
#14	Restricted OLS composite	**4.52*****	6.06**
#15	Restricted OLS composite - rolling window	4.62***	6.18**
#16	Projection on the equal-weight composite	4.75***	6.36***
#17	Projection on the equal-weight composite - rolling window	4.76***	6.33***
#18	Shrinkage - 0.25 composite	**4.52*****	**6.06****
#19	Shrinkage - 0.25 composite - rolling window	4.61***	6.17**
#20	Shrinkage - 1 composite	**4.50*****	**6.05****
#21	Shrinkage - 1 composite - rolling window	4.59***	6.15**
#22	Odds matrix composite	4.56***	6.08***
#23	Odds matrix composite - rolling window	4.56***	6.09***

Notes: All figures are reported as $/cwt. At each horizon, the three forecasts with the smallest RMSEs are in bold font. Single, double, and triple asterisks (*, **, ***) represent significance in the RMSE differences between outlook forecast and the alternative forecast model at the 10%, 5% and 1% level based on the Modified Diebold-Mariano (MDM) test.

Summary and Conclusions

This study analyzes whether the accuracy of outlook hog price forecasts can be improved through composite forecasts in a realistic out-of-sample context. Data are divided into three periods for individual model fitting, composite forecast training, and final evaluation. Price forecasts from four well-recognized outlook programs are combined with futures-based forecasts, an ARMA model, and an unrestricted VAR model using different combining techniques.

For the out-of-sample 1994.I-2010.IV period (1994.I-2007.IV for Illinois/Purdue), futures outperform outlook forecasts at most horizons. Based on the MDM test of significance in RMSE differences, futures are statistically significantly superior to outlook in five out of eleven cases. The naïve no-change forecast is inferior to the outlook forecasts except for the USDA one-quarter ahead horizon. A variety of composite procedures also provide smaller RMSEs than outlook forecasts, with numerous statistically significant differences. Performance of futures and composite forecasts decreases at longer horizons, with the exception of the equal-weighted composite. The equal-weighted composite always has a smaller RMSE than outlook forecasts and is significantly superior in eight out of eleven cases. On average, the equal-weighted composite forecast reduces outlook RMSEs by -13.73%, -16.44%, and -14.67% at first, second, and third horizon. While it is difficult for the equal-weighted composite forecast to outperform futures at the first horizon, it reduces futures forecast errors by an average of -9.79% at the second and third horizons and is statistically smaller in two of the seven cases. Finally, methods including the equal-weighted approach, the odds matrix,

Table 6: Summary of RMSE Reductions for Illinois/Purdue (1994.I-2007.IV) and Other Outlook Programs (1994.I-2010.IV)

		1-qtr.-ahead			2-qtr.-ahead			3-qtr.-ahead		
		RMSE	RMSE reduction from futures	RMSE reduction from outlook	RMSE	RMSE reduction from futures	RMSE reduction from outlook	RMSE	RMSE reduction from futures	RMSE reduction from outlook
#1	Iowa	4.87			6.97			8.19		
#2	Futures	3.72			6.57			7.97		
#3	Equal-weight	4.15	11.56%	−14.78%***	6.07	−7.61%	−12.91%**	7.40	−7.15%	−9.65%
#1	Missouri	4.27			6.76			7.96		
#2	Futures	3.96			6.49			8.18		
#3	Equal-weight	4.17	5.30%	−2.34%	6.12	−5.70%	−9.47%*	6.38	−22.00%	−19.85%
#1	Illinois/Purdue	4.55			6.87			7.78		
#2	Futures	3.76			5.78			7.30		
#3	Equal-weight	4.17	10.90%	−8.35%**	5.54	−4.15%	−19.36%***	6.65	−8.90%*	−14.52%***
#1	USDA	6.62			8.20					
#2	Futures	5.26			7.16					
#3	Equal-weight	4.67	−11.22%*	−29.46%***	6.23	−12.99%*	−24.02%***			

Notes: RMSEs are reported as $/cwt. Single, double, and triple asterisks (*, **, ***) represent significance in RMSE differences between futures and the equal-weighted composite or outlook and the equal-weighted composite at the 10%, 5%, and 1% level based on the Modified Diebold-Marino (MDM) test. Statistical differences between the outlook and alternative forecasts are presented in the earlier tables.

Table 7: Summary of Trading Profits for Illinois/Purdue (1994.I-2007.IV) and Other Outlook Programs (1994.I-2010.IV)

		1-qtr.-ahead			2-qtr.-ahead			3-qtr.-ahead		
		\$/cwt/qtr	**SD**	**\$/contract**	**\$/cwt/qtr**	**SD**	**\$/contract**	**\$/cwt/qtr**	**SD**	**\$/contract**
#1	Iowa	−0.57	6.04	−226.54	−2.01*	8.46	−802.39	−0.64	10.64	−257.02
#2	Equal-weight	0.00	6.07	0.99	0.99	8.63	397.55	1.69	10.53	675.11
#3	Best forecast	1.40*	5.90	559.49	2.20***	8.41	878.58	2.63***	10.33	1,053.51
#1	Missouri	1.16	5.82	464.06	0.83	8.93	332.27	1.82	10.51	727.97
#2	Equal-weight	0.08	5.93	31.53	2.28***	8.67	912.33	4.00***	9.88	1,601.78
#3	Best forecast	1.43***	5.76	571.12	3.48***	8.26	1,393.04	4.51***	9.66	1,804.53
#1	Purdue/Illinois	0.65	5.72	259.16	−0.04	7.98	−15.26	1.18	9.42	471.66
#2	Equal-weight	1.04	5.67	414.00	−0.32	7.98	−127.11	1.85	9.31	738.83
#3	Best forecast	1.94***	5.42	775.89	2.95***	7.42	1,181.63	3.63***	8.77	1,452.49
#1	USDA	−0.08	7.97	−33.62	0.61	10.28	243.94			
#2	Equal-weight	2.84***	7.45	1,136.97	4.05***	9.44	1,647.76			
#3	Best forecast	4.18***	6.79	1,671.03	6.18***	8.21	2,486.93			

Notes: \$/cwt/qtr refers to the mean trading profits per hundred weight per quarter and \$/contract refers to the mean trading profits per contract. One contract consists of 40,000 pounds, or 400 cwt. The SD refers to the standard deviation of \$/cwt/qtr. The best forecast refers to forecast with the largest mean trading profit per contract. Single, double, and triple asterisks (*, **, ***) represent significance at the 10%, 5% and 1% level based on the two-tailed *t* test.

Table 8: Summary of Trading Profits for the Illinois/Purdue (1994.I-2007.IV) and for the other Outlook Programs (1994.I-2010.IV)

		1-qtr.-ahead			2-qtr.-ahead			3-qtr.-ahead		
		$/cwt/qtr	SD	$/contract	$/cwt/qtr	SD	$/contract	$/cwt/qtr	SD	$/contract
#1	Iowa	−0.57	6.04	−226.54	−2.01*	8.46	−802.39	−0.64	10.64	−257.02
#2	Equal-weight	0.00	6.07	0.99	0.99	8.63	397.55	1.69	10.53	675.11
#3	Best forecast	1.40*	5.90	559.49	2.20***	8.41	878.58	2.63***	10.33	1,053.51
#1	Missouri	1.16	5.82	464.06	0.83	8.93	332.27	1.82	10.51	727.97
#2	Equal-weight	0.08	5.93	31.53	2.28***	8.67	912.33	4.00***	9.88	1,601.78
#3	Best forecast	1.43***	5.76	571.12	3.48***	8.26	1,393.04	4.51***	9.66	1,804.53
#1	Purdue/Illinois	0.65	5.72	259.16	−0.04	7.98	−15.26	1.18	9.42	471.66
#2	Equal-weight	1.04	5.67	414.00	−0.32	7.98	−127.11	1.85	9.31	738.83
#3	Best forecast	1.94***	5.42	775.89	2.95***	7.42	1,181.63	3.63***	8.77	1,452.49
#1	USDA	−0.08	7.97	−33.62	0.61	10.28	243.94			
#2	Equal-weight	2.84***	7.45	1,136.97	4.05***	9.44	1,647.76			
#3	Best forecast	4.18***	6.79	1,671.03	6.18***	8.21	2,486.93			

Notes: $/cwt/qtr refers to the mean trading profits per hundred weight per quarter and $/contract refers to the mean trading profits per contract. One contract consists of 40,000 pounds, or 400 cwt. The SD refers to the standard deviation of $/cwt/qtr. The best forecast refers to forecast with the largest mean trading profit per contract. Single, double, and triple asterisks (*, **, ***) represent significance at the 10%, 5% and 1% level based on the two-tailed t test.

and the composite based on the historical MSE that do not require estimation of OLS regressions to generate the weights are significantly superior at the most distant horizon.

The forecast evaluations based on the simulated trading activities provide evidence of the economic importance of the forecast information. The equal-weighted forecasts generally produce larger trading profits (all positive) than the forecasts generated by outlook programs. The statistically significant positive trading profits generated by using the best composite procedures across all horizons for all outlook programs may be indicative of further untapped economic opportunities for use of the forecast information.

Overall, results favor the use of composite forecasting methods to reduce outlook programs' forecast errors. For short-term forecasting, it is difficult to outperform futures forecasts, but composite procedures perform well at more distant horizons in terms of forecast-error reduction. Our evidence on the trade-off between bias and efficiency in estimating composite weights suggests that losses from inefficiency outweigh potential bias. At most distant horizons, where predictive accuracy is more problematic, forecasts generated by OLS regressions do not perform as well as composite forecasts generated by other, less-statistical procedures. These results are of value to decision-makers in agricultural markets. In contrast to much of the previous research in agricultural markets, and particularly within the context of outlook forecasts, our findings solidly establish the effectiveness of futures and composite methods in a more realistic context. Further, the forecast and composite methods used are easy to implement and require only minimal upkeep to provide reductions in forecast errors.

[Received June 2009; final revision received March 2012.]

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