NCCC-134
APPLIED COMMODITY PRICE ANALYSIS, FORECASTING AND MARKET RISK MANAGEMENT

# How Much Can Outlook Forecasts be Improved?

# An Application to the U.S. Hog Market

by

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Suggested citation format:

Colino, E. V., S. H. Irwin, and P. Garcia. 2008. "How Much Can Outlook Forecasts be Improved? An Application to the U.S. Hog Market." Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. St. Louis, MO. [http://www.farmdoc.uiuc.edu/nccc134].

# How Much Can Outlook Forecasts be Improved? An Application to the U.S. Hog Market

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*Paper presented at the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management*
*St. Louis, Missouri, April 21-22, 2008*



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# How Much Can Outlook Forecasts be Improved? An Application to the U.S. Hog Market


## Practitioner's Abstract

*This study investigates the predictability of outlook hog price forecasts released by Iowa State University relative to alternative market and time-series forecasts. The findings suggest that predictive performance of the outlook hog price forecasts can be improved substantially. Under RMSE, VARs estimated with Bayesian procedures that allow for some degree of flexibility and model averaging consistently outperform Iowa outlook estimates at all forecast horizons. Evidence from the encompassing tests, which are highly stringent tests of forecast performance, indicates that many price forecasts do provide incremental information relative to Iowa. Simple combinations of these models and outlook forecasts are able to reduce forecast errors by economically significant levels. The value of the forecast information is highest at the first horizon and then gradually declines.*



**Key words:** forecast, futures, models, prices, time-series, vector autoregression


## Introduction

Public situation and outlook programs are cooperative efforts between the U.S. Department of Agriculture (USDA) and land-grant universities. These programs provide producers and market participants with extensive information on the current market situation, including estimates of supply, demand, and future cash prices. Because estimates of future price can influence production, marketing, and inventory decisions, there has been interest in the ability of outlook forecasts to reflect accurately market conditions. Research has compared outlook price forecasts to predictions from a variety of econometric and time-series models (Bessler and Brandt 1981; Elam and Holder 1985; Gerlow, Irwin and Liu 1993; Sanders and Manfredo 2003). Similarly, outlook forecasts have been widely compared to forecasts embedded in futures markets (Just and Rausser 1981; Bessler and Brandt 1992; Irwin, Gerlow, and Liu 1994; Hoffman 2005; Sanders and Manfredo 2004, 2005; Colino and Irwin 2007). Overall, evidence on the accuracy of outlook forecasts is mixed, but suggests that they contain valuable information.

Despite its importance, little recent research exists on price forecasting in agricultural markets and how outlook forecasts compare to alternatives. Few papers have been published in the last 15 years that focus on the specification and estimation of price forecasting methods for crop and livestock markets and their efficiency relative to outlook (see Foster, Havenner, and Walburger 1995 and Wang and Bessler 2004 for examples). The lack of research is somewhat understandable since developing predictive models is challenging in an environment like agriculture in which markets are subject to large changes. For instance, the U.S. hog industry has faced significant transformations during the last two decades (Boehlje 1992; Rhodes 1995; McBride and Key 2003). The industry has become more industrialized, highly concentrated, and vertically coordinated by production contracts. Technological innovations in nutrition, reproductive management, breeding and genetics also have contributed to changes in the production process. Further challenging to forecasters is the highly volatile environment seen in recent years, due to demand growth from developing nations, the diversion of row crops to biofuel production, and U.S. monetary policy (Trostle 2008). Nevertheless, it is precisely during these periods of change when accurate forecasts take on added value (Falk and Orazem 1985).

This absence of recent research becomes more noticeable in light of the forecasting techniques and procedures recently developed in other fields that have not been tested in agricultural markets. New procedures and strategies have been designed to improve forecast accuracy when underlying series are subject to instabilities. Many procedures have emerged from the notion that a forecasting model is a simple approximation to reality that is changing due to shifts in institutions and technology. In this context, flexible and combinatory methods may be useful for representing the true but unknown data generating process. In practice, this calls for the estimation of a variety of flexible models that allow for different weighting schemes between old and new data, and for averaging or weighting of individual forecasts. Recent papers by Clark and McCracken (2006a,b) and Elliott and Timmermann (2008) are representative of the extensive research on forecasting found in the economics literature.

The purpose of the paper is to investigate the predictive accuracy of cash hog prices provided by the Iowa State University outreach program relative to alternative market and time-series price forecasts. We focus on the cash hog market because of its importance and a well-documented background with respect to earlier forecasting models. We investigate the Iowa State program because of its reputation for providing sound fundamental analysis, its long and well-documented history of price forecasts, and forecasting performance that is representative of other prominent outlook programs (Colino and Irwin 2007). Outlook forecasts are compared to time-series approaches that worked reasonably well in past studies of forecasting prices in agricultural markets, as well as predictions from estimation procedures designed to allow for instabilities in market relationships that have emerged recently in the economics literature. Models are fit over the 1975.I-1999.IV sample period and evaluated over 2000.I-2007.IV. Efforts are also made to combine forecasts to improve cash price predictive accuracy and to identify the most relevant sources of forecast information for outlook economists.

Results show that Bayesian procedures and model averaging consistently do a better job than outlook forecasts, but differences are not statistically robust in a mean squared error context. However, results from the encompassing tests strongly support the benefits of combining information from market outlook specialists and time-series models.

## Literature Review

Early research by Leuthold et al. (1970) and Nerlove et al. (1979) initiated the use of time-series models for forecasting livestock prices. Subsequent investigations were stimulated by the development of VAR models (Sims 1980) that permitted forecasting in a multivariate context. Brandt and Bessler (1984) were the first to develop and evaluate a VAR model to forecast hog prices. Despite using Tiao and Box's (1981) pre-testing procedure to reduce the number of parameters, they find the VAR is consistently outperformed by a univariate ARIMA model for all accuracy measures considered. Comparing a variety of time-series models in the hog market, Kling and Bessler (1985) find that an exponential smoothing model and a VAR estimated with Parzen's (1977) procedure forecast poorly, while a univariate model, a Bayesian VAR (BVAR), and a VAR based on Hsiao's (1979) specification approach provide accurate forecasts for all variables within their specification. Following Litterman's (1986) procedures, Bessler and Kling (1986) generate a BVAR model to forecast hog prices. They compare the accuracy of two BVARs with symmetric and general priors, a univariate model, and an unrestricted VAR, and find the BVAR with general priors yields the best predictions and the unrestricted VAR the worst.

Kaylen (1988) proposes an alternative approach to reduce the number of parameters in a VAR model based on a modification of Hsiao (1979). His results indicate that the model based on Hsiao's modified approach outperforms all other VARs at most forecast horizons and for most variables. A BVAR with general priors is the alternative best option. Other studies, including Zapata and Garcia (1990), Fanchon and Wendel (1992), and Wang and Bessler (2004), address non-stationarity and cointegration in other livestock markets, introducing Vector Error Correction Models (VECM) and finding that any forecast improvement only emerges at distant horizons.

Not surprisingly, these studies have several characteristics in common. Most use data through the 1970's and 1980's for model specification and estimation, and relatively small sample periods for the out-of-sample forecast evaluation. Model coefficients are usually re-estimated using all of the data available up to the time of forecast construction. For the hog market, the variables used in the VARs are generally similar and based on Brandt and Bessler's 1984 study. Overall the weight of the evidence suggests that unrestricted VARs perform poorly when forecasting livestock prices (Brandt and Bessler 1984; Kling and Bessler 1985; Bessler and Kling 1986, Kaylen 1988). An exception is the work by Zapata and Garcia (1990) who find an unrestricted VAR(2) in differences is the most accurate model. They argue that a small model size, with proper lag-specification, and proper treatment of non-stationarity may have contributed to the results. In contrast, BVARs have performed well, especially with asymmetric prior distributions (Bessler and Kling 1986; Kaylen 1988; Zapata and Garcia 1990). While ARIMA models showed early success (Brandt and Bessler 1981, 1984; Kling and Bessler 1985), BVARs and procedures to reduce the overparameterization of the basic VAR seem to have provided more effective forecasting structure than univariate models (Zapata and Garcia 1990, Bessler and Kling 1986). Among the exclusion-of-variables approaches applied to forecast livestock markets, Hsiao's (1979) approach and an improved version of it developed by Kaylen (1988) have shown some efficiency relative to others.

Outside of agriculture, there has been a "virtual revolution" in the forecasting literature, focusing on different methods to compute, apply, and evaluate forecasts (Elliott and Timmermann 2008).[1] While the mainstays of practical applications continue to be VAR models (Sims 1980) and Bayesian VARs (Litterman 1986), an important component of the literature focuses on developing flexible and combinatory methods which may be useful for representing the true but unknown data generating process. This focus has emerged from the notion that a forecasting model is a simple approximation to reality that is changing due to shifts in institutions and technology. In practice, this calls for the estimation of a variety of flexible models which allow for different weighting schemes between old and new data, and for averaging or weighting of individual forecasts.

Forecasting models can be characterized into parametric, semiparametric, and nonparametric procedures. While semiparametric and nonparametric procedures offer a high degree of flexibility, they require considerable data and are less attractive when the set of variables is large. Elliott and Timmermann (2008) argue that flexible parametric models are often the best that can the analyst can hope to achieve. Flexibility can arise in a number of ways, including allowing for variable lag lengths that change as new information is incorporated, estimating different models with alternative priors, and using different methods to select the specification of the forecasting model.

Regardless of the specification procedures used, evidence has grown that models are subject to instabilities which can bias coefficients and forecasts. Researchers have addressed this issue in numerous ways (Stock and Watson 1996 2003 2004; Tashman 2000; Pesaran and Timmermann 2002, 2004), but the most prevalent and practical involve the use of rolling windows for estimation and combining forecasts from various models. The use of rolling windows keeps the length of the estimation period constant, and after each new prediction the model is re-estimated adding the most recent observation and removing the oldest. Clearly, there is trade off between efficiency and bias when using partial windows for estimation (Clark and McCracken 2004), but in the presence of large changes in the levels and volatility this method is likely to be preferred to expanded window forecasts that are based on all available data up to the forecast. Numerous studies have been performed to assess the effect of rolling window estimation relative to other procedures including the expanded window, discounted least squares in which recent observations are fully weighted while decreasing weights are given to more distant observations (Stock and Watson 2004), and the possibility of using only post-break windows for estimation (Pesaran and Timmermann 2004) .

Evidence on the performance of these techniques is mixed. Certainly, the performance of rolling windows for estimation is not uniform (Swanson and White 1997; Stock and Watson 2003; Clark and McCracken 2004 2006a). Similarly, the alternative approach of using discounted least squared for estimation was found to work well in some studies (Stock and Watson 2004; Branch and Evans 2006) but poorly in others (Clark and McCracken 2006a). Using only post-break data for models fit and estimation was found to be superior to using rolling and expanded windows when the variance of the pre-break data is higher than the post-break variance (Pesaran and Timmermann 2004). What does emerge is that the relative performance of the procedures depends in large part on the characteristics of underlying series and nature of the change. For instance, Elliott and Timmermann (2008) find that for series characterized by a high noise to signal ratio (e.g., financial stock returns), estimation error can be large and there is no evidence to suggest that shortening the estimation window can improve forecasts. Conversely, more systematic series can benefit from rolling window estimation provided the window is appropriately defined to reflect the nature of the change. Further, it appears that large abrupt data breaks are best handled by fitting post-break data while rolling windows may work more effectively when changes are more gradual.

The issue of change, model selection, and specification are also linked. Tashman (2000) argues strongly for recalibration, or re-optimization, rather than simply updating parameters as new data become available. Similarly, Stock and Watson (2003) suggest that the lag structure of the model should be updated over time. In essence, as forecasting moves forward through time, the optimal lag-length of the model is periodically updated based on standard information criteria. Keating (2000) also identifies an approach that allows different lag order for each variable in each equation selected by same criteria and regularly updating the optimal lag structure. Again the evidence is mixed, but clearly the emphasis has been to allow for flexibility.

An alternative method to allow for model instability is to combine forecasts. The argument often used to explain combining forecasts is that they diversify against model uncertainty. Since some models may adapt more quickly (or even over respond) to a change in the behavior of the predicted variable, while other adapt more slowly, combining forecasts may provide a type of insurance for breaks or other non-stationarities in the future. Numerous procedures have been developed to generate the appropriate combinatory weights for alternative forecasts (Bates and Granger 1969; Geweke and Whiteman 2006; Timmermann 2006). Clements and Hendry (1998) propose an encompassing method to determine the weights which is particularly attractive since it focuses on forecast errors and is readily estimable. Empirical evidence suggests that forecast combinations tend to outperform predictions from single models, but strategies used to determine the optimal weights perform no better than a simple average forecast in which all forecasts receive equal weight.

Two recent studies (Clark and McCracken 2006a; and Elliott and Timmermann 2008) use a variety of models to develop forecasts of different series. Their findings reinforce many of the points already made, but several other lessons emerge. First, they conclude that it is difficult to differentiate among many models in terms of their out-of-sample forecast performance even when models are derived very different approaches. Second, it is difficult to out perform simple autoregressive models that provide stable forecasts with limited estimation error. In contrast, highly nonlinear models can generate poor forecasts due to their sensitivity to outliers and susceptibility to estimation error. Third, forecast findings should be assessed in context of loss functions which are most relevant for the decision maker. In certain cases, evaluations of forecast performance can vary based on the loss function used. Fourth, in the presence of instabilities, rolling windows estimation and Bayesian estimations can perform well, but their ultimate effectiveness depends on the source of the instability. Finally, the use of economic theory is useful to determine the nature of the forecasts most relevant to the decision maker, and to guide in variable selection and model restrictions.

## Alternative Price Forecasts

We generate a number of forecasts to evaluate their performance relative to outlook forecasts released by Iowa State University, and to assess whether they provide incremental information that when combined with outlook forecasts will improve prediction of hog prices.
When available, futures prices are usually considered the "gold standard" for evaluating forecast accuracy within agricultural markets.[2] For this reason, a futures-based forecast is constructed following the model developed by Hoffman (2005). For each calendar month, the model uses the nearest-to-maturity contract. A simple average of the three futures prices represents the quarterly average futures price. We then convert the price from lean to live hog units to make it comparable to outlook forecasts which are reported in live weight terms.[3] A three-year moving average of historical basis is then added to the computed futures price. Historical basis levels are computed on a daily basis using the futures prices in the first step and the target cash price

specified by the outlook forecast. As another standard of comparison, an univariate time series model is estimated; an AR (5) was found to fit best.

Based on the literature, we specify a number of five-variable VAR models. The five variables are identified in Table 1 and are highly consistent with previous hog models. While not shown to perform well except by Zapata and Garcia (1990), we first specify an unrestricted VAR with 5 fixed lags. The lag structure was determined using Akaike's Information Criteria (AIC), Final Prediction Error (FPE), and Hannan and Quinn' Information Criterion (HQIC). We construct two forecasts from this structure: a forecast in which the parameters are updated with each new observation, and another forecast with no parameter updates. A Bayesian VAR(5) is computed using the "Minnesota-style priors," where the standard priors assume an overall tightness ($\lambda$) value of 0.1, a lag decay (*d*) value of 1, and a general weight (*w*) of 0.5. Parameters of the BVAR are also updated.

To permit structural instabilities, VARs with a dynamic lag structure are considered where the optimal lag length is updated (Stock and Watson 2003). Four models are constructed using this approach. The first two models are a VAR and BVAR that select the optimal lag structure for each new forecast value based on AIC. The other two models are a VAR and a BVAR that select the optimal lag length for each new forecast based on the Bayesian Information Criteria (BIC).

As a further allowance for structural instabilities, we also estimate several models using a rolling window. The window size selected 100 observations, which is the size of the initial estimation sample. The number of observations should permit sufficient flexibility without increasing estimation error, and should work reasonably well since most of the changes in the hog industry have been longer term institutional changes and gradual changes in genetic production technology that have led to increasing litter size and animal weights. The rolling window estimation approach is applied to the unrestricted VAR(5) and to the Bayesian VAR(5).

As another method to allow for instability, we develop combined forecasts. Three different averaging models are computed, using equal weights in each case. The first model considered is an average of all VARs and the univariate model. The second is an average of the two VARs that allow for optimal updating of the lag structure (VAR-AIC, VAR-BIC), and the VAR(5) with a rolling window, and the unrestricted VAR with and without updating. The mean of all Bayesian VARs is the third averaging method.

Finally, we estimate two models based on the Kaylen-Hsiao exclusion-of-variables approach which has been shown to work reasonably well in the hog market. The first version of the model does not update parameter estimates as forecast period progresses. The second version re-estimates parameters for each new forecast. Here, we determine the ordering of series for each equation based on our prior knowledge of the hog market, and in a couple of situations on the strength of simple correlations. Table 1 provides the optimal specification obtained for the five-variable VAR following Kaylen's exclusion-of-variables approach.

## Data and Model Specifications

Since we are interested in assessing the performance of the Iowa State outlook price forecasts, Iowa-Southern Minnesota Barrows and Gilts cash prices are used in the analysis. The selection of variables for the time-series representation of the market is an important issue. Here, we base our selection on the literature and examination of the several variables that could affect both demand and supply. Focusing on the in-sample period of 1975.I-1999.IV, variables were plotted to investigate cycles, trends, shifts, and seasonality in the series. Variables associated to the production process clearly reflect the changes over time in genetics, health, nutrition and operational management so they become important determinants of future production and prices. Alternative variables for feeding costs were also investigated. Most variables for the demand side showed the same markedly upward trend over the last three decades. Preliminary estimation of reduced VARs were also made, and variables were checked for signs and magnitude and lag lengths based on consistency with previous findings and our knowledge of the market.

The set of variables selected for the basic VAR specification are: live-hog prices (HP), corn prices (CP), number of sows farrowing (SF), pork production (PP), and beef prices (BP). The Iowa-Southern Minnesota Barrows and Gilts price is in $/cwt. and is collected by USDA-Economic Research Service (ERS) and USDA-Agricultural Marketing System (AMS). U.S. total number of sows farrowing measured in thousand head is obtained from USDA-National Agricultural Statistic Service (NASS) database. Pork production is the U.S. commercial pork production measured in million pounds also obtained from the USDA-NASS. Corn price is the Central Illinois cash corn price in $/bushel as released by the USDA-AMS. Finally, the beef price is the retail beef prices in $/lb released by the USDA-ERS. All the data are expressed in calendar quarters to be consistent with the cash hog price series. For most variables this simply involved using monthly or daily averages. However, for sows farrowing which is provided in hog quarters that begin in December, the values were adjusted by using two-thirds of a hog quarter plus one-third of the next hog quarter.

Stationarity of each series was assessed using the Augmented Dickey-Fuller (ADF) test. ADF regressions with and without a constant and with a trend and a constant were considered. Optimal lag lengths were selected by AIC (up to 8 lags). Strong evidence of non-stationarity is found for pork production and beef prices in all ADF regressions, indicating that both variables are integrated of order one. The other variables were stationary. As result, the pork production and beef prices are both incorporated into the analysis in first differences.

Models are fit over the 1975.I-1999.IV quarterly period and out-of-sample forecasting evaluation is performed for 2000.I-2007.IV. The U.S. hog industry has undergone structural changes during the last decades. The effects of new technologies and capital concentration provoked a significant production expansion, especially during the 90's. For this reason, the sample period for model estimation extends through 1999. A modeling effort that takes into account this information is more likely to provide valuable forecasts than an effort that ignores this information. One-, two-, and three-quarter forecast horizons are evaluated.[4]

## Results

Table 2 provides a list of models and their respective acronyms, and root mean squared errors (RMSE) for the price forecasts are presented in Table 3. RMSE for a price forecast at a given horizon is computed as,

(1)
$$RMSE = \left[ \frac{1}{n} \sum_{t=1}^{n} \left( p_t - f_t \right)^2 \right]^{1/2}$$

where $p_t$ is the actual cash price in quarter $t$, $f_t$ is the price forecast under evaluation for quarter $t$, and $n$ is the number of forecast observations. The three smallest RMSE for each horizon are in bold font. Statistical significance of differences in RMSEs between Iowa outlook and alternative forecasts is assessed using 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 based on a specified loss function, $E[g(e_{1t}) - g(e_{2t})] = 0$. Assuming a quadratic loss function, the test is based on the difference in squared errors for futures and outlook forecasts at a given horizon,

(2)
$$d_t = g(e_{1t}) - g(e_{2t}) = e_{1t}^2 - e_{2t}^2.$$

The MDM test is then specified as follows,

(3)
$$MDM = \left[ \frac{n + 1 - 2h + n^{-1}h(h-1)}{n} \right]^{1/2} \left[ V\left(\bar{d}\right) \right]^{-1/2} \left[ \bar{d} \right]$$

(4)
$$V\left(\bar{d}\right) = \left[ n^{-1} \left( \gamma_0 + 2 \sum_{k=1}^{h-1} \gamma_k \right) \right]$$

where $\bar{d}$ is the sample mean of $d_t$, $h = 1,2,3$ is the forecast horizon (e.g., 1 = one-quarter ahead forecast), $\gamma_0 = n^{-1} \sum_{t=1}^{n} \left( d_t - \bar{d} \right)^2$ is the variance of $d_t$, and $\gamma_k = n^{-1} \sum_{t=k+1}^{n} (d_t - \bar{d})(d_{t-k} - \bar{d})$ is the $k^{th}$ auto-covariance of $d_t$, $\left( k = 1,...,h-1 \right)$. 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.

Overall, the results suggest that it is possible to provide more accurate forecasts than the outlook estimates using almost every model for every horizon. However, only at the one-quarter horizon does the futures market forecast provide a smaller and statistically significant RMSE ($3.44/cwt.). The superiority of futures prices relative to Iowa outlook and relative to the other forecast methods decreases considerably at the second and third forecast horizon. Among the individual models, Bayesian specifications that allow for updating, identification of lag structures, and rolling window estimation generally tend to perform well, and consistently better than the AR(5), Kaylen-procedure, and VAR(5) with no updating. In fact, the AR(5) model and the VARs estimated by Kaylen- procedure have on average RMSEs larger than those from Iowa outlook forecasts at all horizons. Without question, averaging forecasts provide rather consistently small RMSEs.

Table 4 shows the mean absolute percentage errors (MAPE) of price forecasts for each horizon. The MAPE for a price forecast at a given horizon is computed as,

(5)
$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{p_t - f_t}{p_t}\right|$$

and differs from the RMSE in that it places less emphasis on large errors. Again the three best forecasts are in bold font. Here, the findings change to some degree. The accuracy of futures prices is consistently high for every horizon. No less impressive is the performance of Iowa, especially for two- and three-quarter horizons. Among the individual models, the Bayesian models and those models that provide some flexibility continue to do better than the AR(5), the Kaylen procedure, and VAR(5) without updating. However, the superiority of a specific model is less clear. Averaging reduces the errors but not to the same degree as with RMSE which is understandable since one would expect that averaging would have a larger effect in a loss function that squares forecast errors.

As first identified by Granger and Newbold (1973), it is possible for a forecast to have a larger MSE than another forecast but still provide useful information. Granger and Newbold define a forecast as conditionally efficient if alternative forecasts do not add incremental information to the forecast. Following this criterion, Harvey, Leybourne, and Newbold (1998) develop a test of forecast encompassing based on the principle that one forecast encompasses another if the optimal weight of the inferior forecast in a composite forecast is zero. This can be formalized in the following regression equation:

(6)
$$e_{1t} = \lambda(e_{1t} - e_{2t}) + \xi_t \qquad t = 1,\ldots,n$$

where $e_{1t}$ is the error of the preferred forecast (futures) and $e_{2t}$ is the error of the alternative forecast (outlook). The null hypothesis for the encompassing test is $\lambda = 0$, which implies zero covariance between $e_{1t}$ and $e_{1t} - e_{2t}$. Rejection of the null hypothesis indicates that a composite forecast can be constructed based on the two forecast series that has a smaller MSE than the preferred forecast. In other words, rejection of the null implies that a combination of Iowa forecasts and the alternative forecast considered will provide smaller MSE than those obtained from Iowa by itself. Note that Newey-West standard errors are estimated for two- and three-quarter ahead horizons to account for the overlapping inherent in forecast errors at these horizons.

Encompassing test results are shown in Table 5. The table shows, for each horizon, the p-value and the λ-estimates of the test that Iowa encompasses the forecast presented at each row. The tests reject the null hypothesis that Iowa encompass futures and all time-series models $(\lambda = 0)$ in 42 of a total of 48 cases over all horizons. Regression estimates of $\lambda$ indicate that composite weights for the time-series and futures models are significantly large. On average, alternative models receive a weight of 0.56, 0.49, and 0.50 at one-, two-, and three-quarter ahead, respectively. Based on individual models, the most important is the futures prices at the first horizon which has a weight of 1.03. After that it becomes difficult to identify which model consistently has a larger weight. Averaging again here helps, generating the largest weights. Overall, the evidence shows that a combination of outlook forecasts released by Iowa and alternative time-series and futures prices generate lower MSE than Iowa alone.

The economic significance of these results can be analyzed by examining the magnitude of reduction in RMSEs from combining outlook and the optional forecasts. Composite forecasts are built by giving the weight to the alternative forecast equivalent to the $\lambda$ estimate and a weight equivalent to $(1-\lambda)$ to the outlook forecast. The RMSE of the resulting composite forecasts are then compared to the RMSE of Iowa alone. Results of the composite forecast analysis are shown table 6 and are of a considerable large magnitude. For one-quarter ahead, if Iowa is combined with futures the average RMSE reduction is -24.2%, while if combined with any of the multiple VAR forecast models considered, RMSE is reduced, on average, by -23.9%. Interestingly, if Iowa is combined with the AR(5) model an average reduction of -15.2% is obtained. For two- and three-quarters ahead, the average achievable reduction of combining Iowa and any of the alternative price forecasts is -10.4% and -8.5%, respectively.

## Summary and Concluding Remarks

We investigate the predictability of outlook hog price forecasts released by Iowa State University to alternative market and time-series forecasts. The models include a univariate time-series representation, VARs and BVARs with no updating, as well as other specifications designed to allow for instabilities in market relationships. A futures-based forecast also is considered as a comparison.

Overall the findings suggest that predictive performance of the outlook hog price forecasts can be improved. Under RMSE, VARs estimated with Bayesian procedures that allow for some degree of flexibility and model averaging consistently outperform Iowa outlook estimates at all forecast horizons. Under MAPE, the value of forecast information beyond the first forecast horizon is questionable. Evidence from encompassing tests, which are highly stringent tests of forecast performance, indicates that many price forecasts do provide incremental information relative to Iowa. Simple combinations of these models and outlook forecasts are able to reduce forecast errors by economically significant levels. The reductions in RMSE average 25%, 10.4%, and 8.5% at the one-, two-, and three-quarter horizons, respectively. While averaging does reduce forecast errors at all horizons, Iowa outlook forecasts clearly perform better at two- and three-quarter horizons compared to the one-quarter horizon.

In a forecasting context, our findings are consistent with several lessons from the recent literature. We find it difficult to differentiate among forecast models based simply on their out-of-sample mean squared errors. Nevertheless, Bayesian models and other representations that allow for flexibility through updating, optimizing lag structure, or through rolling window estimation do tend to perform better than simple univariate and basic VARs. Encompassing test comparisons show that most of these models provide information relative to outlook forecasts, but it is difficult to identify which would be preferred. In this situation, it appears that averaging of the forecasts from diverse models would be the most judicious strategy to follow.

In conclusion, the results of this study indicate that recent innovations in the forecasting literature have the potential to substantially improve the accuracy of outlook forecasts. This is an important finding since the agricultural economics profession has largely abandoned traditional price forecasting work in the last 15 years. Given the mixed track record of previous modeling efforts and the negative implications of the Efficient Market Hypothesis for the likelihood of forecasting success, the decline in resources devoted to the development and testing of price forecasting models is not entirely surprising. Nonetheless, Timmerman and Granger (2004) argue that innovation in forecasting methods is an integral component of market efficiency, in the sense that markets are always in a "race for innovation" to adopt new generations of forecasting methods. The dearth of research on price forecasting models over the last 15 years raises the issue of whether the pendulum has swung too far. That is, has the agricultural economics profession under-invested in price forecasting research during recent years?

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## Endnotes

[1] For extensive surveys of the forecasting literature in economics see Granger and Newbold (1986), De Gooijer and Hyndman (2006), Clark and McCracken (2006a), Fildes (2006), and Elliott and Timmermann (2008).

[2] A futures prices in an efficient market should provide forecasts of subsequent spot prices that are at least as accurate as any other forecast (Tomek 1997).

[3] 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) (e.g., 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.

[4] Iowa outlook forecasts are generated for one through three quarters ahead.

**Table 1. Variables and lags chosen using Kaylen's exclusion-of-variable approach**

| Dependent variable | Hog prices | Sows farrowing | Pork production | Corn prices | Beef prices |
|---|---|---|---|---|---|
| Hog prices | 1,4,5 | 1,2,5 | 1,2,3,4 | 1,2 | 3,4,5 |
| Sows farrowing | 1,3,4 | 1,2,4,5 | - | 2,4 | 4 |
| Pork production | 1,2,3,4 | 2,3,4,5 | 2,3,4,5 | - | 3 |
| Corn prices | - | 3,5 | 3,4 | 1,2,3,5 | 5 |
| Beef prices | 3,4 | 5 | - | 2,4,5 | 2,3,4,5 |

**Table 2. List of alternative hog price forecast models**

| Forecasting Model | Abbreviation |
|---|---|
| Iowa State University outlook forecasts | Iowa |
| Futures-based forecasts | Futures |
| Univariate model - AR(5) - no parameters update | AR(5) |
| VAR based on Hsiao-Kaylen's procedure - no parameters update | VAR-Kaylen-no update |
| VAR based on Hsiao-Kaylen's procedure - parameters update | VAR-Kaylen-update |
| Unrestricted VAR(5) - no parameters update | VAR(5)-no update |
| Unrestricted VAR(5) - parameters update | VAR(5)-update |
| Bayesian VAR(5) - parameters update | BVAR(5) |
| Bayesian VAR(5) - rolling window estimation | BVAR(5)-roll. window |
| VAR(5) - rolling window estimation | VAR(5)-roll. window |
| VAR - optimal lag structure by AIC - parameters update | VAR-AIC |
| VAR - optimal lag structure by BIC - parameters update | VAR-BIC |
| Bayesian VAR - optimal lag structure by AIC - parameters update | BVAR-AIC |
| Bayesian VAR - optimal lag structure by BIC - parameters update | BVAR-BIC |
| Average forecast (all Time-Series models) | Average 1 |
| Average forecast (VARs) | Average 2 |
| Average forecast (BVARs) | Average 3 |

**Table 3. Root mean squared errors (RMSE) for hog price forecasts during the out-of-sample evaluation period, 2000.I-2007.IV**

| Forecast model | 1-qtr.-ahead | 2-qtr.-ahead | 3-qtr.-ahead |
|---|---|---|---|
| Iowa | 4.54 | 5.86 | 7.00 |
| Futures | **3.44** ** | 5.86 | 7.11 |
| AR(5) | 4.98 | 6.54 | 7.28 |
| VAR-Kaylen-no update | 4.88 | 6.09 | 7.45 |
| VAR-Kaylen-update | 4.70 | 5.86 | 7.14 |
| VAR(5)-no update | 4.50 | 5.84 | 7.08 |
| VAR(5)-update | 4.14 | 5.66 | 7.08 |
| BVAR(5) | 4.14 | **5.49** | 6.69 |
| BVAR(5)-roll. window | 4.10 | **5.43** | 6.73 |
| VAR(5)-roll. window | 4.53 | 6.00 | 7.58 |
| VAR-AIC | 3.98 | 6.43 | 6.85 |
| VAR-BIC | 4.42 | 6.60 | 6.75 |
| BVAR-AIC | 4.29 | 6.14 | 6.90 |
| BVAR-BIC | 4.43 | 6.37 | 6.94 |
| Average 1 | **3.91** | **5.51** | **6.55** |
| Average 2 | **3.84** | 5.52 | **6.60** |
| Average 3 | 4.08 | 5.65 | **6.67** |

Notes: All figures are reported as $/cwt. One, two, and three stars indicate statistical significance at the 10%, 5% and 1% level, respectively, based on the Modified Diebold-Mariano (MDM) test.

**Table 4. Mean absolute percentage errors (MAPE) for hog price forecasts during the out-of-sample evaluation period, 2000.I-2007.IV**

| Forecast model | 1-qtr.-ahead | 2-qtr.-ahead | 3-qtr.-ahead |
|---|---|---|---|
| Iowa | 8.8 | 10.6 | 11.7 |
| Futures | 6.9 | 10.4 | 12.6 |
| AR(5) | 9.6 | 13.2 | 14.7 |
| VAR-Kaylen-no update | 9.2 | 12.0 | 15.4 |
| VAR-Kaylen-update | 8.9 | 11.5 | 14.5 |
| VAR(5)-no update | 8.4 | 11.4 | 14.9 |
| VAR(5)-update | 7.7 | 11.2 | 14.5 |
| BVAR(5) | 8.0 | 11.0 | 13.5 |
| BVAR(5)-roll. window | 7.5 | 10.6 | 13.6 |
| VAR(5)-roll. window | 8.2 | 11.6 | 14.8 |
| VAR-AIC | 7.5 | 12.7 | 14.2 |
| VAR-BIC | 8.6 | 13.1 | 13.5 |
| BVAR-AIC | 8.0 | 12.3 | 14.0 |
| BVAR-BIC | 8.5 | 12.7 | 13.8 |
| Average 1 | 7.6 | 10.9 | 13.4 |
| Average 2 | 7.3 | 11.0 | 13.7 |
| Average 3 | 7.8 | 11.2 | 13.5 |

Notes: All figures are reported as %.

**Table 5. Forecast encompassing test results between Iowa outlook and alternative hog price forecasts during the out-of-sample evalution period, 2000.I-2007.IV**

| | 1-qtr.-ahead | | 2-qtr.-ahead | | 3-qtr.-ahead | |
|---|---|---|---|---|---|---|
| **Forecast Model** | **λ-estimate** | ***p*-value** | **λ-estimate** | ***p*-value** | **λ-estimate** | ***p*-value** |
| Futures | 1.03 | (0.030) | 0.50 | (0.267) | 0.43 | (0.000) |
| AR(5) | 0.41 | (0.072) | 0.38 | (0.095) | 0.44 | (0.183) |
| VAR-Kaylen-no update | 0.45 | (0.047) | 0.49 | (0.039) | 0.44 | (0.056) |
| VAR-Kaylen-update | 0.47 | (0.051) | 0.56 | (0.028) | 0.48 | (0.038) |
| VAR(5)-no update | 0.52 | (0.014) | 0.54 | (0.022) | 0.50 | (0.047) |
| VAR(5)-update | 0.54 | (0.014) | 0.55 | (0.019) | 0.49 | (0.041) |
| BVAR(5) | 0.56 | (0.040) | 0.54 | (0.030) | 0.53 | (0.063) |
| BVAR(5)-roll. window | 0.57 | (0.037) | 0.56 | (0.023) | 0.53 | (0.071) |
| VAR(5)-roll. window | 0.49 | (0.023) | 0.48 | (0.023) | 0.38 | (0.046) |
| VAR-AIC | 0.59 | (0.032) | 0.41 | (0.089) | 0.52 | (0.098) |
| VAR-BIC | 0.51 | (0.064) | 0.34 | (0.121) | 0.55 | (0.098) |
| BVAR-AIC | 0.53 | (0.059) | 0.43 | (0.110) | 0.51 | (0.090) |
| BVAR-BIC | 0.50 | (0.064) | 0.36 | (0.111) | 0.50 | (0.102) |
| Average 1 | 0.62 | (0.031) | 0.55 | (0.041) | 0.57 | (0.075) |
| Average 2 | 0.62 | (0.022) | 0.55 | (0.034) | 0.56 | (0.058) |
| Average 3 | 0.59 | (0.046) | 0.52 | (0.049) | 0.55 | (0.078) |

Notes: The null hypothesis for the encompassing test is that the "preferred" forecast (outlook) encompasses the alternative forecast (models). The λ estimates are based on a regression of the outlook forecast error on the difference between the outlook and model forecast errors without an intercept. Newey-West standard error estimates are used for the two- and three-quarter ahead horizons.

**Table 6. Composite forecast comparisons between Iowa outlook and alternative hog price forecasts during the out-of-sample evalution period, 2000.I-2007.IV**

| | 1-qtr.-ahead | | 2-qtr.-ahead | | 3-qtr.-ahead | |
|---|---|---|---|---|---|---|
| **Forecast models** | **RMSE** | **% Reduction** | **RMSE** | **% Reduction** | **RMSE** | **% Reduction** |
| Iowa outlook | 4.54 | | 5.86 | | 7.00 | |
| Composite forecasts with Iowa: | | | | | | |
| Futures | 3.44 | -24.2 | 5.71 | -2.5 | 6.86 | -2.1 |
| AR(5) | 3.85 | -15.2 | 5.44 | -7.2 | 6.27 | -10.4 |
| VAR-Kaylen-no update | 3.77 | -17.1 | 4.91 | -16.1 | 6.23 | -11.1 |
| VAR-Kaylen-update | 3.71 | -18.3 | 5.07 | -13.4 | 6.36 | -9.2 |
| VAR(5)-no update | 3.27 | -27.9 | 4.62 | -21.1 | 6.01 | -14.1 |
| VAR(5)-update | 3.27 | -28.0 | 4.87 | -16.9 | 6.33 | -9.5 |
| BVAR(5) | 3.42 | -24.7 | 5.09 | -13.0 | 6.31 | -10.0 |
| BVAR(5)-roll. window | 3.39 | -25.4 | 5.12 | -12.6 | 6.36 | -9.2 |
| VAR(5)-roll. window | 3.50 | -22.9 | 5.15 | -12.0 | 6.80 | -2.9 |
| VAR-AIC | 3.33 | -26.7 | 5.48 | -6.4 | 6.42 | -8.4 |
| VAR-BIC | 3.62 | -20.3 | 5.86 | 0.0 | 6.43 | -8.1 |
| BVAR-AIC | 3.52 | -22.5 | 5.48 | -6.4 | 6.51 | -7.0 |
| BVAR-BIC | 3.64 | -19.8 | 5.74 | -2.0 | 6.62 | -5.5 |
| Average 1 | 3.30 | -27.4 | 5.09 | -13.1 | 6.30 | -10.0 |
| Average 2 | 3.24 | -28.8 | 5.02 | -14.3 | 6.30 | -10.0 |
| Average 3 | 3.41 | -25.0 | 5.26 | -10.2 | 6.43 | -8.2 |

Notes: RMSE denotes root mean squared error, which is reported as \$/cwt. Composite forecasts are based on λ estimates from encompassing regressions of outlook errors on the difference between outlook errors and model forecasts (see Table 5).