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Improving the accuracy of outlook price forecasts

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Abstract

This study investigates the predictive ability of outlook hog price forecasts released by Iowa State University relative to alternative time-series and market forecasts. Under root mean squared error (RMSE), the futures market forecast is most accurate at the first and second horizon but less accurate than Iowa outlook and the other forecast methods at the third horizon. In terms of the individual time-series models, some vector autoregressions (VARs) and Bayesian VARs flexible in specification and estimation and model averaging tend to perform better than Iowa outlook forecasts. Evidence from encompassing tests, more stringent tests of forecast performance, indicates that many price forecasts can add incremental information to the Iowa forecast. Simple combinations of these models and outlook forecasts are able to reduce forecast errors by economically significant levels. Overall, the results indicate that it is possible to provide more accurate forecasts than Iowa outlook at every horizon.

JEL classifications: Q11, Q13

Keywords: Forecasting; Hog prices; Time-series models; Futures; Composite forecasts

1. 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 forecasts of price in the future can influence production, marketing, and inventory decisions, there has been interest in the ability of outlook forecasts to accurately reflect market conditions. Research has compared outlook price forecasts to predictions from a variety of econometric and time-series models (e.g., Bessler and Brandt, 1981; Sanders and Manfredo, 2003). Similarly, outlook price forecasts have been compared to forecasts embedded in futures markets (e.g., Bessler and Brandt, 1992; Colino and Irwin, 2010; Irwin et al., 1994; Sanders and Manfredo, 2004, 2005). Overall, evidence on the accuracy of outlook price forecasts is mixed, but it suggests the forecasts often 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 Wang and Bessler, 2004, for an example). The lack of research is somewhat understandable since developing predictive models is challenging in an environment like agriculture where markets are subject to large changes. For instance, the U.S. hog industry has faced significant transformations during the last two decades, as the industry has become more industrialized, highly concentrated, and vertically coordinated by production contracts (McBride and Key, 2003). 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 economic value.

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Data Appendix Available Online

A data appendix to replicate main results is available in the online version of this article. Please note: Wiley-Blackwell, Inc. is not responsible for the content or functionality of any supporting information supplied by the author. Any queries (other than missing material) should be directed to the corresponding author for the article.

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This absence of recent research becomes more notable 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 based on 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, 2006b), and Elliott and Timmermann (2008) are representative of the recent and extensive research on forecasting found in the economics literature.

The purpose of this paper is to investigate the predictive accuracy of hog price forecasts provided by the Iowa State University outlook program relative to alternative time-series and market 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 2010). Outlook price forecasts are compared to forecasts from ARIMA, vector autoregression (VAR), and Bayesian vector autoregression (BVAR) models, as well as specifications designed to allow for instabilities in market relationships. A futures-based market forecast also is considered as a comparison. 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 some VARs and BVARs that are flexible in specification and estimation and model averaging tend to perform better 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. Even with the use of simple time-series models, the findings highlight the efficacy of improving Iowa's price forecasting performance via composite procedures.

2. Literature review

Early research by Leuthold et al. (1970) initiated the use of time-series models in 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 a 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 a univariate model, a Bayesian VAR (BVAR), and a VAR based on Hsiao's (1979) specification approach provide accurate forecasts for all variables examined. 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) and Wang and Bessler (2004), address nonstationarity 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 1970s and 1980s for model specification and estimation and relatively small sample periods for out-of-sample forecast evaluation. Model coefficients are commonly 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 (1984). Overall the weight of the evidence suggests that unrestricted VARs perform poorly when forecasting livestock prices (Bessler and Kling, 1986; Brandt and Bessler, 1984; Kling and Bessler, 1985; Kaylen, 1988). An exception is the work by Zapata and Garcia (1990) who find an unrestricted VAR(2) in first differences is the most accurate model. They argue that a small model size, with proper lag-specification, and proper treatment of nonstationarity 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 over-parameterization of the basic VAR seem to have provided more effective forecasting structure than univariate models (Bessler and Kling, 1986; Zapata and Garcia, 1990). 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 VARs and BVARs, an important component of the literature focuses on developing flexible and combinatory methods that 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 that 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, semi-parametric, and nonparametric procedures. While semi-parametric 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 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 that can bias coefficients and forecasts. Researchers have addressed this issue in numerous ways (Pesaran and Timmermann, 2002, 2004; Stock and Watson, 1996, 2003, 2004; Tashman, 2000), 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. There is a clear trade-off between efficiency and bias when using partial windows for estimation (Clark and McCracken, 2004), but in the presence of large changes in levels and volatility of economic variables this method may 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 postbreak 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 (Clark and McCracken, 2004, 2006a; Stock and Watson, 2003). Similarly the alternative approach of using discounted least squares for estimation was found to work well in some studies (Stock and Watson, 2004) but poorly in others (Clark and McCracken, 2006a). Using only postbreak data for model 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 postbreak 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 postbreak 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 the 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 diversification 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 others adapt more slowly, combining forecasts may provide a type of insurance for breaks or other nonstationarities in the future. Numerous procedures have been developed to generate the appropriate combinatory weights for alternative forecasts (Bates and Granger, 1969; 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 can be readily estimated. 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 (Clemen, 1989).

In the presence of instability, researchers have also developed an interest in nonlinear models to describe and forecast economic phenomena (e.g., Balagtas and Holt, 2009; Terasvirta, 2006). The number of nonlinear models is unlimited in theory, but in practice smooth transition regression, Markov-switching, and artificial neural network models have been used to investigate economic behavior. While nonlinear models may have been shown to fit in-sample data better, their forecast

[1] Extensive surveys of the forecasting literature in economics exist. For example, see De Gooijer and Hyndman (2006), Clark and McCracken (2006a), and Elliott and Timmermann (2008).

performance is often meager relative to linear models (e.g. Ramsey, 1996; Terasvirta, 2006). This inability to forecast well has been attributed to the models explaining features in the data that do not arise often, which in turn means the models can be highly sensitive to outliers (leading to extreme forecasts), prone to over-fitting, and generate superior forecasts only during periods that occur infrequently (Elliott and Timmermann, 2008). Evidence suggests these problems are exacerbated in relatively short data samples, hampering the precise estimation of models, and adversely affecting forecasts. While most comparisons between linear and nonlinear models have only included a limited number of alternatives, the available evidence indicates that it is difficult to identify an appropriate nonlinear specification and this can lead to over-fitting and forecasting problems.

3. Data

The 1975.I–1999.IV time period serves as the in-sample estimation period and the 2000.I–2007.IV period as the out-of-sample evaluation period for the time-series and market forecasting models considered in this study (see next section). The U.S. hog industry has undergone considerable structural change during the two last decades. The effects of new technologies and capital concentration provoked a significant production expansion especially during the 1990s. 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-ahead forecast horizons are evaluated for each model.

Quarterly hog price forecasts are collected from various issues of *Iowa Farm Outlook* for the 1975.I–2007.IV period. One-, two-, and three-quarter-ahead forecasts of the cash price for Iowa–Minnesota barrows and gilts are available. Iowa State analysts do not use econometric models to generate price forecasts, but instead employ a "spreadsheet" approach based on price flexibilities and estimates of percentage changes in per capita consumption of pork, beef, and poultry, consumer income, and population (Lawrence, 2008). The resulting point estimates may be subjectively adjusted by the analyst based on expected market conditions.

Plots of the Iowa hog price forecast errors over 1975.I–2007.IV are shown in Fig. 1. These plots suggest a stable pattern of errors centered on zero and no obvious increase or decrease in variability over time. This is confirmed in Table 1, which shows descriptive statistics for the forecast errors over the entire sample period, the in-sample period, and the out-of-sample

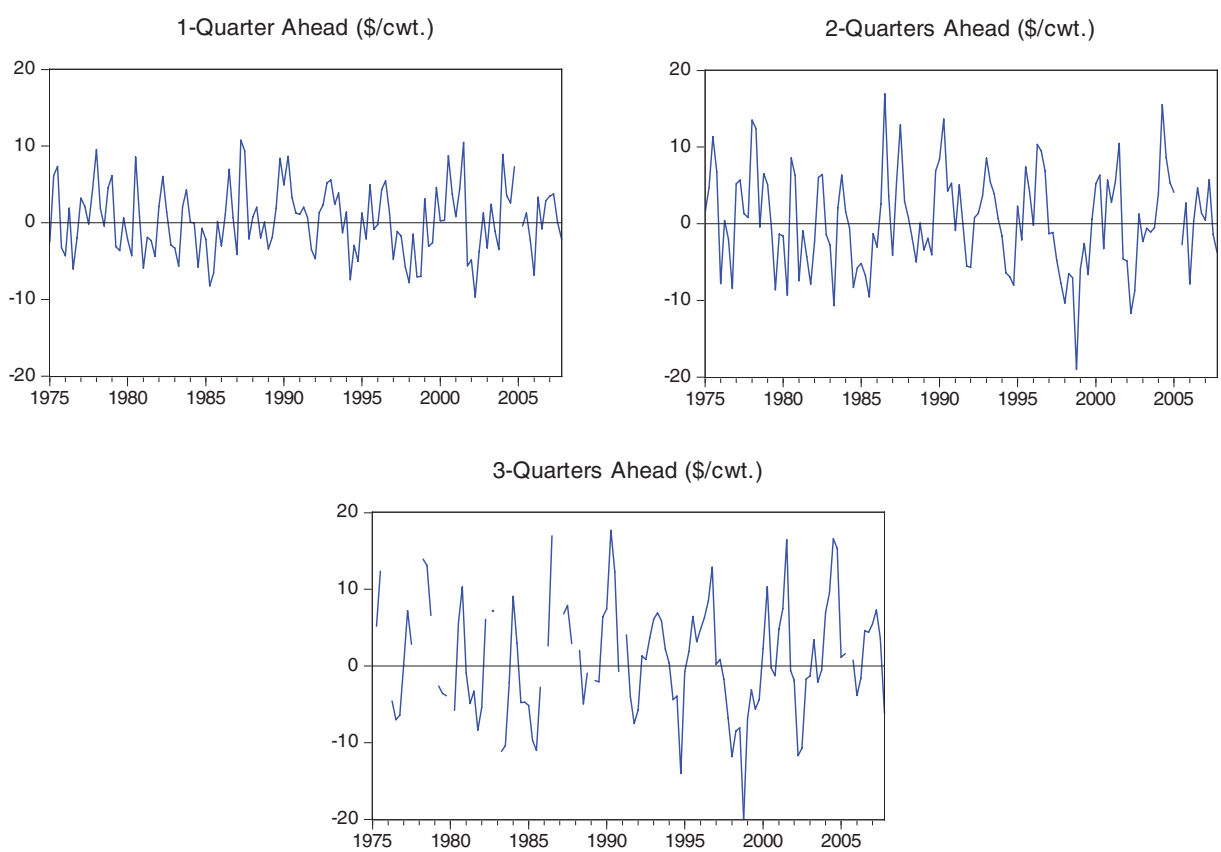

Fig. 1. Time-series plots of quarterly errors for Iowa outlook forecasts of U.S. hog prices, 1975.I–2007.IV.

Table 1
Descriptive statistics for hog price forecast errors of the Iowa outlook program, 1975.I–2007.IV

Sample period	Forecast horizon	Number of observations	Average	Standard deviation	Minimum	Maximum
1975.I–2007.IV	1-qtr.	131	0.32	4.42	−9.68	10.80
	2-qtr.	131	0.42	6.30	−19.01	16.98
	3-qtr.	116	0.81	7.24	−20.01	17.69
1975.I–1999.IV	1-qtr.	100	0.16	4.35	−8.24	10.80
	2-qtr.	101	0.23	6.45	−19.01	16.98
	3-qtr.	87	0.32	7.32	−20.01	17.69
2000.I–2007.IV	1-qtr.	31	0.82	4.66	−9.68	10.48
	2-qtr.	30	1.06	5.79	−11.68	15.54
	3-qtr.	29	2.26	6.80	−11.68	16.60

Notes: All descriptive statistics on forecast errors are reported as $/cwt.

period.[2] At a given forecast horizon, the standard deviation of forecast errors varies relatively little across the three periods. However, there is a tendency for the average error to be somewhat larger in the out-of-sample period compared to the in-sample period. Overall, the plots and descriptive statistics indicate that the forecasting errors over 2000.I–2007.IV are representative of the longer-run track record of the Iowa outlook program.

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 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 with 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 knowledge of the market.

As shown in Fig. 2, the set of variables selected for VAR specifications include live hog prices, corn prices, sows farrowing, pork production, and fed cattle prices. The five variables are highly consistent with the variables used in previous VAR models of the hog market (e.g., Brandt and Bessler, 1984; Kaylen, 1988). Since we are interested in assessing the performance of outlook price forecasts from Iowa State University, Iowa–Minnesota barrows and gilts cash prices are used in the analysis. These prices are reported in $/cwt. and collected by the Agricultural Marketing Service of the U.S. Department of Agriculture (USDA). The total number of sows farrowing in the U.S. is measured in thousand head and obtained from the National Agricultural Statistic Service (NASS) of the USDA. U.S. commercial pork production is measured in million pounds and also obtained from NASS. The price of corn is the central Illinois cash corn price in $/bushel as released by Illinois Ag Market News-Agricultural Marketing Service. Finally, the fed cattle price is the Omaha or Nebraska direct choice steer price in $/cwt. as reported by the Livestock, Dairy, and Poultry reports from the USDA. All data are expressed in calendar quarters to be consistent with the cash hog price series. For most variables this simply involves averaging monthly or daily observations. However, the number of sows farrowing is provided in "hog" quarters that begin in December; consequently, 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 nonstationarity is found for pork production and fed cattle prices in all ADF regressions (see Fig. 2), indicating that both variables are integrated of order one. The other variables were stationary. As result, pork production and fed cattle prices are both incorporated into the analysis in first difference form.

4. Alternative forecasting models

We generate a number of forecasts to evaluate performance relative to outlook forecasts released by Iowa State University, and to assess whether the forecasts provide incremental information when combined with outlook forecasts. Table 2 provides a list of models and their respective acronyms. The time-series models are limited to linear specifications for several reasons. First, as discussed previously, the available evidence suggests that it is difficult to identify an appropriate nonlinear specification and this can lead to over-fitting and poor forecast

[2] One observation is missing from each series of Iowa outlook price forecasts for the out-of-sample period. Hence, the sample of Iowa forecasts over 2000.I–2007.IV includes 31 one-quarter-ahead forecasts, 30 two-quarter-ahead forecasts, and 29 three-quarter-ahead forecasts. Market and time-series model forecasts for the quarters with missing observations for Iowa are excluded in forecasting evaluations.

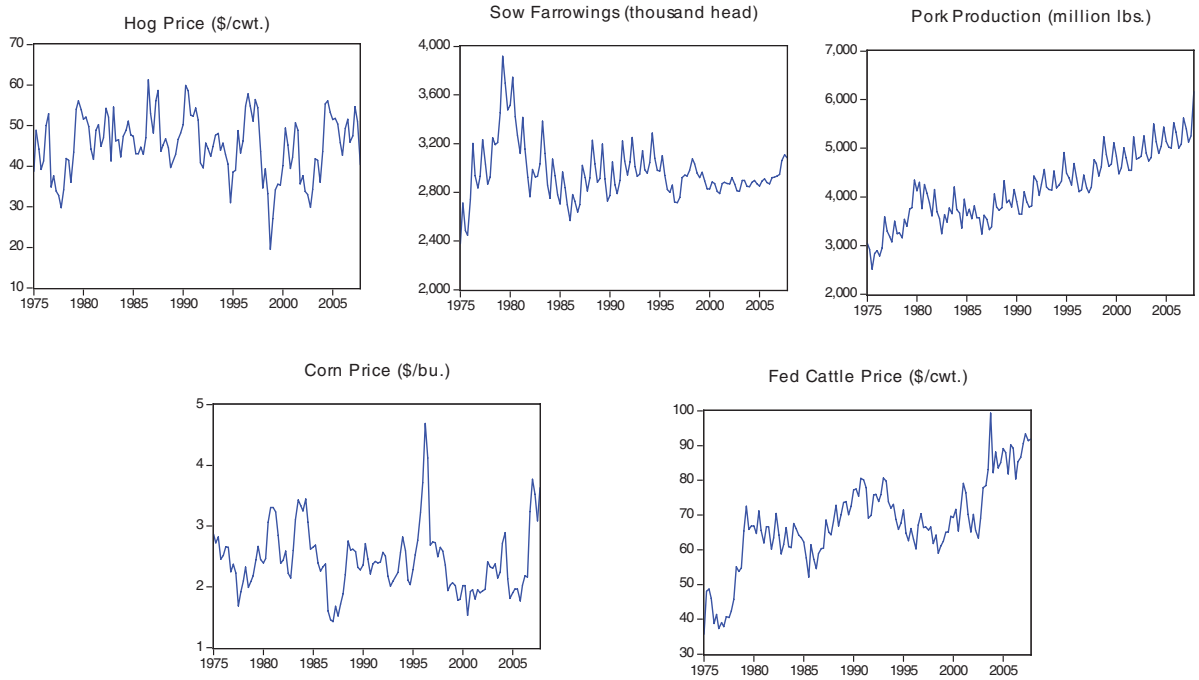

Fig. 2. Time-series plots of variables used in VAR models of U.S. hog prices, 1975.I–2007.IV.

Table 2
List of alternative hog price forecasting models

#	Forecasting Model	Abbreviation
1	Iowa State University outlook forecasts	Iowa
2	Futures-based forecasts	Futures
3	Univariate model—AR(5)—no parameter update	AR(5)
4	Unrestricted VAR(5)—no parameter update	VAR(5)-no update
5	Unrestricted VAR(5)—parameter update	VAR(5)-update
6	VAR—optimal lag structure by AIC—parameter update	VAR-AIC
7	VAR—optimal lag structure by BIC—parameter update	VAR-BIC
8	VAR(5)—rolling window estimation—60 obs.	VAR(5)-rolling window60
9	VAR(5)—rolling window estimation—100 obs.	VAR(5)-rolling window100
10	Bayesian VAR(5)—parameter update	BVAR(5)
11	Bayesian VAR—optimal lag structure by AIC—parameter update	BVAR-AIC
12	Bayesian VAR—optimal lag structure by BIC—parameter update	BVAR-BIC
13	Bayesian VAR(5)—rolling window estimation—60 obs.	BVAR(5)-rolling window60
14	Bayesian VAR(5)—rolling window estimation—100 obs.	BVAR(5)-rolling window100
15	VAR based on Hsiao-Kaylen's procedure—no parameter update	VAR-Kaylen-no update
16	VAR based on Hsiao-Kaylen's procedure—parameter update	VAR-Kaylen-update
17	Average forecast (all VARs: #4—#16)	Average 1
18	Average forecast (VARs: #4—#9)	Average 2
19	Average forecast (BVARs: #10—#14)	Average 3
20	Average forecast (VAR and BVARs: #9, #10, #16)	Average 4
21	Average forecast (all market and time-series models: #2—#16)	Average 5

performance. Second, our main interest is determining whether recent innovations in the forecasting literature have the potential to substantially improve the accuracy of outlook price forecasts. These innovations have focused on strategies to improve the forecast accuracy of relatively simple linear models when the underlying data series are subject to instabilities. Third, linear models are easier to estimate and manipulate, and therefore, more practical from an outlook program perspective.

When available, futures prices are usually considered the "gold standard" for evaluating forecast accuracy within agricultural markets.[3] However, lean hog futures contracts reflect a particular set of delivery markets, and consequently, a set of assumptions must be applied to convert the available array of lean

[3] 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).

Table 3
Examples of futures model computations for one- and two-quarter ahead Iowa hog forecasts, 2005.II and 2005.III

	One-quarter ahead Forecast quarter: 2005.II Iowa outlook release date: 03/31/2005					Two-quarters ahead Forecast quarter: 2005.III Iowa outlook release date: 3/31/2005			
	April 2005	May 2005	June 2005	July 2005	August 2005	July 2005	August 2005	September 2005	October 2005
Futures prices									
(1) Settlement price by contract observed the day of Iowa outlook report release			79.27		75.20		75.20		64.22
(2) Monthly average price based on futures contract prices	79.27	79.27	75.20			75.20	64.22	64.22	
(3) Quarterly futures price (average)		77.91					67.88		
(4) Lean-live adjustment [(3)*1/1.35]		57.71					50.28		
Basis (cash-futures)									
(5) basis (ARMA forecast)		−3.11					2.16		
(6) **Quarterly futures-based forecast** [(4)+(8)]		**54.60**					**52.44**		
(7) Actual quarterly price		52.09					49.79		

Notes: All figures are reported as $/cwt.

hog futures prices to a quarterly average cash price forecast that is comparable to the Iowa outlook program forecasts. For this reason, a futures-based forecast is constructed following the model developed by Hoffman (2005) and recently applied to livestock outlook forecasts by Colino and Irwin (2010). Table 3 provides examples of the construction of one- and two-quarter-ahead price forecasts based on Hoffman's model. The examples are keyed to the release of Iowa hog price forecasts on March 31, 2005. Data on timing of release is critical in order to correctly match the release date of outlook forecasts to lean hog futures forecasts. A mismatch could create an informational advantage for either outlook or lean hog futures forecasts. Fortunately, the Iowa outlook publication provides the exact release date.

The first step in constructing the futures forecasts is to match each of the forecast months in a quarter with the nearest-to-maturity contracts that do not expire in the target calendar month. In the one-quarter-ahead example shown in Table 3, the June 2005 contract is matched to April and May 2005 and the August 2005 contract is matched to June 2005. This procedure assures that the horizon of the futures contracts approximately matches the horizon of the Iowa outlook forecast. Next, a simple average of the daily settlement prices for the three futures contracts is taken to represent the average price forecast by the futures market as of the release date of the Iowa forecast. The quarterly average futures price also must be converted from lean to live hog units in order to be comparable to outlook forecasts, which are reported in live weight terms.[4] The final step is to add a basis forecast to the quarterly average futures price to obtain the futures model forecast. Historical basis levels are computed by averaging daily futures prices for each quarter and subtracting the quarterly Iowa–Minnesota cash price. Univariate ARMA models with seasonal (quarterly) dummy variables are estimated using the historical basis data over a rolling 15-year window. Out-of-sample forecasts of lean hog basis are then made in the usual manner. Similar calculations to the examples shown in Table 3 are used to compute futures model forecasts for the third and fourth calendar quarters.[5]

Based on the literature, we specify a number of five-variable VAR models. As a relatively simple benchmark, we first specify an unrestricted VAR(5),

$$Y_t = \beta + \sum_{k=1}^{p} \varphi_k Y_{t-k} + \nu_t \quad t = 1, \ldots, T, \tag{1}$$

where Y_t denotes the 5×1 vector of variables included in the model for period t (live hog prices, corn prices, sows farrowing, pork production, and beef prices), β is the 5×1 vector of constant terms, and the φ_k are the 5×5 matrices of autoregressive coefficients, and ν_t is the 5×1 vector of error terms, assumed to be normally and independently distributed. This specification is unrestricted in the sense that all Y_t variables have the same lag order p and none of the coefficients in φ_k are set to zero a priori. A lag order of $p = 5$ was selected based on Akaike's Information Criteria (AIC), the Final Prediction Error (FPE), and

[4] An estimated ratio of 0.73673 is applied to lean-hog futures prices. This factor is obtained by dividing an average weight for lean hogs (180.5) by an average weight for live hogs (245).

[5] Third quarter forecasts are based on August and October contracts and fourth quarter forecasts are based on December and February (following calendar year) contracts. Settlement prices for lean hog futures contracts are obtained from the Chicago Mercantile Exchange (CME).

Hannan and Quinn's 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.

We also specify a Bayesian VAR(5) using "Minnesota-style priors." As first proposed by Doan et al. (1984), a random walk prior is applied to the VAR model in Eq. (1). This assumes coefficients in the φ_k matrices are normally and independently distributed as follows:

$$\begin{aligned} \varphi_{ii}(k) &\sim N\left(1, \sigma^2_{\varphi_{ii}}\right) \\ \varphi_{ij}(k) &\sim N\left(0, \sigma^2_{\varphi_{ii}}\right) \end{aligned}, \tag{2}$$

where $\varphi_{ii}(k)$ is the autoregressive coefficient for variable i in equation i at lag k, $\sigma^2_{\varphi_{ii}}$ is the variance of the autoregressive coefficient for variable i in equation i at lag k, $\varphi_{ij}(k)$ is the autoregressive coefficient for variable i in equation j at lag k, and $\sigma^2_{\varphi_{ij}}$ is the variance of the autoregressive coefficient for variable i in equation j at lag k. The prior mean of lagged dependent variables in each VAR equation is set to one based on the belief that autoregressive effects of the dependent variable should be most important, while the prior mean of other variables in each equation is set to zero based on the view that these variables should be less important. The prior variance determines the uncertainty in the prior mean.[6] For all BVAR models, parameters are updated with each new observation.

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. Two window sizes are selected for comparison, 100 and 60 observations. The first window size (100) is selected in order to be the same as the size of the initial estimation sample. The second window size (60) is the minimum sample we consider reasonable for estimating the time-series models. 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).

We estimate two models based on the Kaylen–Hsiao exclusion-of-variables approach that has been shown in previous studies to work reasonably well in the hog market. This approach attempts to overcome degree of freedom problems that tend to plague unrestricted VAR models by excluding lags of variables. The first step is to group variables considered for inclusion in the VAR model into sets and to order the groups. Then the best set of lags out of all possible combinations of lags is determined via a fit criterion, proceeding in a sequential manner from the highest to the lowest ordered group. When the lag structure for the first group in the ordering is determined, this lag structure is fixed and the lag structure for the second group is considered in an additive fashion, and so on. The identification procedure is completed when the lag structure for the final group of variables is determined.

In the present study, we determine the ordering of series for each equation based on prior knowledge of the hog market, and in a couple of situations, on the strength of simple correlations. Table 4 provides the optimal specification obtained for the five-variable VAR following Kaylen's exclusion-of-variables approach. Despite differences in some of the variables selected, ordering of the series, and sample periods, the lag structure of the optimal specification is similar to Kaylen's (1988) specification. Two versions of the model are estimated; one where the model does not update parameter estimates as the forecast period progresses and a second version where parameters are re-estimated for each new forecast.

As another method to allow for instability, simple combined forecasts also are developed. Five different averaging models are computed using equal weights for the forecasts in each case. The first is an average of all (non-Bayesian) VARs and BVARs (#4–#16 in Table 2). The second is an average of all VARs except those using Kaylen's procedure (#4–#9 in Table 2), while the third is an average of all BVARs (#10–#14 in Table 2). To maximize diversification against model uncertainty, the fourth averages the VAR(5) with a rolling estimation window of 100 observations, the BVAR(5) with parameter updating, and the VAR based on Kaylen's approach with parameter updating (#9, #10, and #16 in Table 2). The fifth averages all market and time-series models (#2–#16 in Table 2).

Table 4
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, 3, 5	1, 2, 3, 4	3	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

[6] Doan et al. (1984) specify prior uncertainty based on a formula that is a function of three hyper-parameters: $\sigma_{ij}(k) = \frac{\lambda w}{k^d}(\frac{\hat{\sigma}_i}{\hat{\sigma}_j})$. The tightness parameter λ is assumed to equal 0.1, which implies a constant standard deviation for the first lag of the dependent variable in each equation. The rate of decay parameter d is assumed to equal 1, which controls the decline in the standard deviation of coefficients on further lags. The weight parameter w is assumed to equal 0.5, which allows the standard errors on lags of other series to be smaller (tighter) than those on own-lags. Note that $\hat{\sigma}_i$ and $\hat{\sigma}_j$ are the standard errors of the residuals from a univariate autoregression for equations i and j, respectively. The ratio of these two standard errors is a scaling factor to adjust for different magnitudes of the two variables.

Table 5
ME and RMSE for hog price forecasts during the out-of-sample evaluation period, 2000.I–2007.IV

Forecast model	Forecast horizon					
	1-qtr.-ahead		2-qtr.-ahead		3-qtr.-ahead	
	ME	RMSE	ME	RMSE	ME	RMSE
Iowa	0.82	4.66	1.06	5.84	2.26*	7.13
Futures	**0.21**	**3.45***	1.59	**5.62**	2.86**	7.24
AR(5)	−0.35	5.68	−1.32	7.01	−2.01	7.79
VAR(5)-no update	−1.74**	4.87	−2.32**	6.07	−2.32*	7.34
VAR(5)-update	−1.04	4.92	−1.15	6.19	−0.86	7.65
VAR-AIC	**−0.31**	**4.12**	−0.81	6.72	−1.12	7.23
VAR-BIC	−0.49	4.65	−0.53	6.72	−0.78	**6.87**
VAR(5)-rolling window-60	1.56	5.36	2.69**	7.10	3.88**	9.70*
VAR(5)-rolling window-100	−0.51	5.22	−0.54	6.46	**−0.30**	8.08*
BVAR(5)	−0.67	4.82	−0.91	5.95	−0.91	7.10
BVAR-AIC	−0.46	4.59	−0.57	6.51	−0.49	7.13
BVAR-BIC	−0.62	4.77	**−0.29**	6.59	**−0.30**	7.10
BVAR(5)-rolling window-60	0.56	4.36	1.14	**5.63**	1.61	7.28
BVAR(5)-rolling window-100	−0.47	4.76	−0.64	5.87	−0.70	7.10
VAR-Kaylen-no update	−1.39	5.32	−2.19*	6.42	−2.60*	7.83
VAR-Kaylen-update	−0.73	5.21	−0.99	6.14	−1.10	7.58
Average 1	−0.49	4.42	−0.55	**5.82**	−0.46	7.05
Average 2	−0.42	4.35	**−0.44**	5.89	**−0.25**	7.14
Average 3	**−0.33**	4.46	**−0.25**	5.86	**−0.16**	**6.91**
Average 4	−0.64	4.92	−0.81	6.02	−0.77	7.48
Average 5	−0.43	**4.30**	−0.48	**5.73**	−0.36	**6.90**

Notes: All figures are reported as $/cwt. One, two, and three asterisks indicate significant differences from zero for ME and from the Iowa forecast for RMSE at the 10%, 5%, and 1% level, respectively, using the MDM test and the *t*-test for the RMSEs and MEs, respectively. The figures in bold are the three lowest values at each forecast horizon. Sample sizes are 31, 30, and 29 observations at one-, two-, and three-quarter forecast horizons, respectively.

VARs based on Kaylen's procedure were estimated with the *STATA 8* econometric software package. All other VARs and BVARs were estimated with the *Econometrics Toolbox* for *MATLAB 6.b* software package (LeSage, 1999).

5. Results

Mean error (ME) and root mean square error (RMSE) for the price forecasts are presented in Table 5. ME and RMSE for a price forecast at a given horizon are computed as,

$$ME = \frac{1}{n}\sum_{t=1}^{n} e_t$$

$$RMSE = \left[\frac{1}{n}\sum_{t=1}^{n} e_t^2\right]^{1/2}, \tag{3}$$

where $e_t = p_t - f_t$ is the forecast error ($/cwt.), 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 ME values in terms of absolute value and three smallest RMSE values for each horizon are highlighted in bold font. A standard t-test is used to test the significance of ME.

Statistical significance of differences in RMSEs between Iowa outlook and alternative forecasts is assessed using the modified Diebold-Mariano (MDM) test proposed by Harvey et al. (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 outlook (e_{1t}) and an alternative forecast (e_{2t}) at a given horizon,

$$d_t = g(e_{1t}) - g(e_{2t}) = e_{1t}^2 - e_{2t}^2. \tag{4}$$

The MDM test is then specified as follows,

$$MDM = \left[\frac{n + 1 - 2h + n^{-1}h(h-1)}{n}\right]^{1/2} \left[V\left(\bar{d}\right)\right]^{-1/2}\left[\bar{d}\right] \tag{5}$$

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

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), $\gamma_0 = n^{-1}\sum_{t=1}^{n}(d_t - \bar{d})^2$ 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 kth auto-covariance of d_t, $(k = 1, ..., h-1)$. 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.

The ME results in Table 5 provide little evidence of significant bias at the one-quarter-ahead forecast horizon for Iowa, futures, or the time-series models. More evidence is found at the two- and three-quarter-ahead horizons. MEs are statistically significant for three of the VAR models at the second and third horizons and Iowa and futures forecasts at the third horizon. The magnitude of the tendency of Iowa and futures to under-forecast at the third horizon averages over \$2/cwt. It is interesting to note that averaging forecasts is one of the better strategies in terms of reducing forecast bias. The ME of the averages generally is small and at least one of the averages at each horizon is among the three smallest MEs across all of the forecasting alternatives.

The RMSE results in Table 5 show that the futures market forecast at the one-quarter horizon (RMSE = \$3.45/cwt.) is the most accurate by a substantial margin.[7] At the two-quarter horizon, the futures market continues to provide the most accurate forecast (RMSE = \$5.62), but by a much smaller margin than at the first horizon. At the three-quarter horizon, the futures market (RMSE = \$7.24/cwt.) is less accurate than both Iowa outlook and the other forecast methods. The pattern of relative decline in forecast accuracy of futures across horizons is consistent with the findings in two recent studies. Sanders and Manfredo (2005) report that the accuracy of Class III milk futures prices relative to USDA and simple time-series forecasts declines rather markedly moving from a one-quarter to a three-quarter horizon. Alquist and Kilian (2010) report that crude oil futures are less accurate relative to a variety of alternative forecasts at longer horizons compared to shorter horizons. They argue that fluctuations in precautionary demand are the underlying reason for the relatively poor forecasting performance of futures prices at longer horizons.

In terms of the individual time-series models, the RMSE results in Table 5 indicate that the Bayesian specification with rolling window estimation and the VAR(5) with lag structure selected by AIC and BIC generally performs well across horizons. In contrast, the AR(5), the unrestricted VAR(5) models, the VAR(5) with rolling windows estimations, and the VARs estimated by Kaylen's procedure have RMSEs larger than those from Iowa at all horizons. Averaging forecasts provides smaller RMSEs than Iowa in several cases. Overall, the RMSE results indicate that it is possible to provide more accurate forecasts than Iowa outlook at every horizon.

We find it difficult to detect statistical differences among forecast models based simply on out-of-sample RMSEs. Only three cases are found. Differences between Iowa forecast errors and the two VAR models with rolling window estimation are statistically significant at the third horizon, in favor of Iowa. The only case where an alternative model provides a statistically smaller RMSE than Iowa is the futures market at the one-quarter horizon. Forecast errors for Iowa and the alternative models tend to track one another relatively closely over the out-of-sample period. This degree of correlation makes it difficult for statistical tests to distinguish between the accuracy of Iowa and alternative model forecasts with the sample sizes considered here. As an example of this correlation, Fig. 3 plots the errors of Iowa and the best alternative model at each forecast horizon. Elliot and Timmerman (2008) note that this type of result is not unusual in studies of economic forecasting.

The plots in Fig. 3 also indicate that the forecast accuracy advantage of the best alternative model tends to be greater when the Iowa outlook forecast is too low (positive error) in contrast to too high (negative error). Sorting based on the sign of the Iowa forecast error reveals that when Iowa forecasts are too low the RMSE of the best alternative model is \$1.40/cwt. lower on average across the three forecast horizons. In contrast, when Iowa forecasts are too high the RMSE of the best alternative model is \$0.46/cwt. higher on average across the three forecast horizons. These results suggest that the forecasting methods used by Iowa outlook analysts are most inferior in periods of rising as opposed to falling hog prices.

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. Sanders and Manfredo (2005) argue that conditional efficiency, or encompassing, represents a more stringent and powerful criterion for evaluating the performance of alternative forecasts. Following this criterion, Harvey et al. (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,

$$e_{1t} = \lambda(e_{1t} - e_{2t}) + \xi_t, \quad t = 1, ..., n, \tag{6}$$

where e_{1t} is the error of the preferred forecast (outlook) and e_{2t} is the error of the alternative forecast. The null hypothesis for the encompassing test is $\lambda = 0$, which implies zero covariance between e_{1t} and $e_{1t} - e_{2t}$. Harvey et al. (1998) recommend testing the null hypothesis of $\lambda = 0$ in equation (6) using a version of the MDM test. This is accomplished by re-defining d_t in equation (4) to equal $e_{1t}(e_{1t} - e_{2t})$ and then computing the MDM test statistic in the usual manner. Rejection of the null hypothesis indicates that a composite forecast can be constructed based on the two forecast series that has a smaller RMSE than the preferred forecast. In other words, rejection of the null implies that a combination of Iowa forecasts and the alternative forecast will provide a smaller RMSE than obtained by Iowa alone.

[7] Forecast errors also were computed in percentage form. RMSE comparisons of percentage errors were similar to those reported in Table 5 except that Iowa and the futures market performed better at the two- and three-quarter-ahead horizons. Encompassing test results based on percentage errors were quite similar to those reported in Tables 6 and 7. These results are available from the authors upon request.

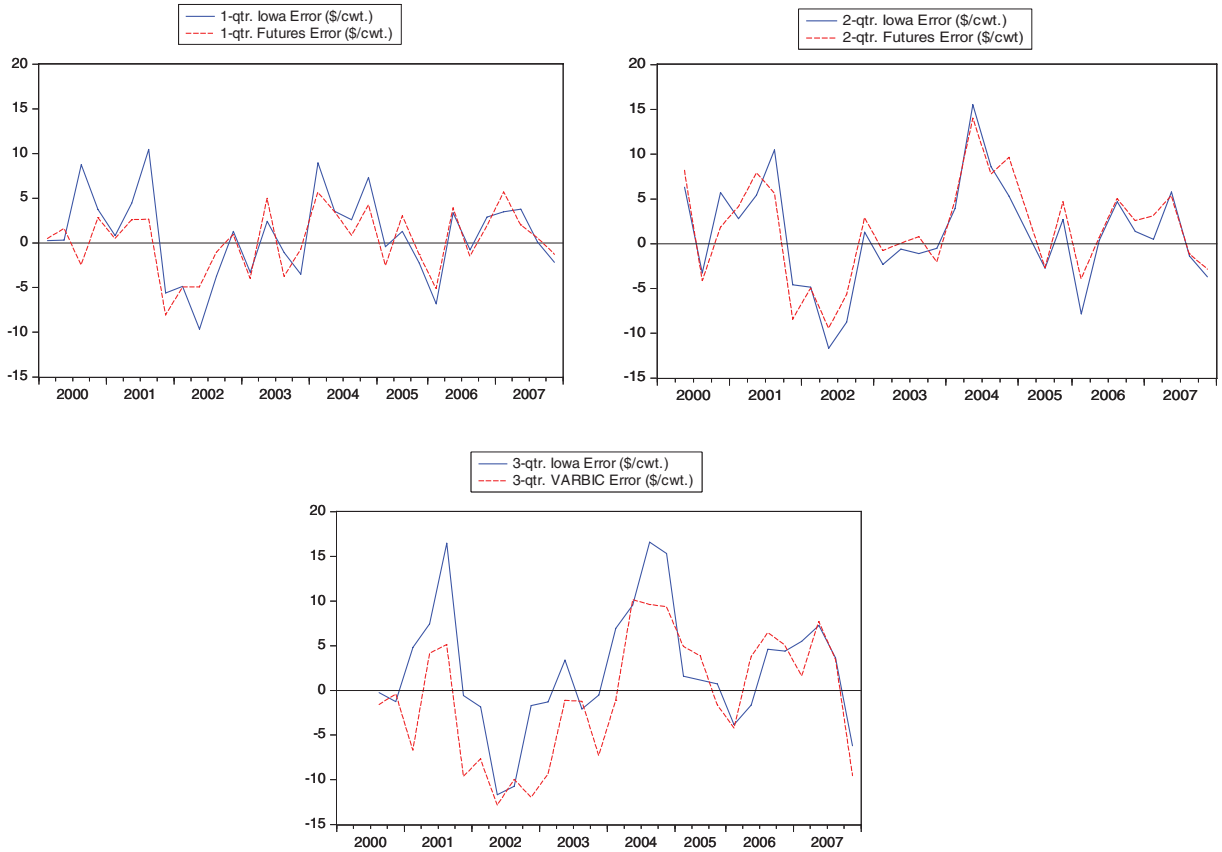

Fig. 3. Hog price forecast errors for the Iowa outlook program and most accurate alternative model during the out-of-sample evaluation period, 2000.I–2007.IV.

Encompassing test results are shown in Table 6. The table provides the regression λ-estimate for each horizon and the significance of the estimate based upon the MDM test discussed earlier. The tests reject the null hypothesis that Iowa outlook forecasts encompass futures and time-series models ($\lambda = 0$) in 37 of 54 cases. On average, alternative models receive a weight of 0.51, 0.45, and 0.45 at one-, two-, and three-quarter-ahead horizons, respectively. Based on individual models, the most important is the futures price at the first and second horizons with weights of 1.01 and 0.76, respectively. After that it becomes difficult to identify which model consistently has a larger weight. Averaging across forecast models again helps, generating among the larger weights. The AR(5) model has the smallest weight averaged across the horizons. Overall, the evidence shows that a combination of outlook forecasts released by Iowa and alternative time-series and futures forecasts generate a lower RMSE than Iowa alone.

Using the results from Table 6, composite forecasts are constructed by assigning a weight $\hat{\lambda}$ to the alternative forecast and $(1-\hat{\lambda})$ to the outlook forecast. The RMSE of the resulting composite forecasts are then compared to the RMSE of Iowa alone, and their performance is ranked. To highlight the value of the composite forecasts, the RMSE of Iowa is also compared to the RMSE of each individual forecast model, and performance is ranked. Results of this analysis are shown in Table 7. Positive (negative) values for percent change indicate RMSE for the given composite forecast or individual model is higher (lower) than the RMSE for Iowa outlook. The three best forecasts for each horizon and comparison are in bold. On average, the composite forecasts reduce the RMSE of the Iowa forecasts more than the reduction that would arise from the use of individual alternative forecasts alone. The RMSE reductions obtained from the composite forecast average −14.5%, −10.0%, and −7.4% at the one-, two-, and three-quarter horizons, respectively, across all the alternative models considered.[8] This represents declines of −$0.68/cwt., −$0.58/cwt., and −$0.53/cwt. at the one-, two-, and three-quarter horizons, respectively. Previous research on the value of improved forecast information in livestock markets suggests that the magnitude of compos-

[8] To investigate the source of improvement in the Iowa outlook forecasts, MSE decompositions ($\text{MSE} = \text{BIAS}^2 + \text{VAR}$) are analyzed. For the first and second horizons, percent reductions in the Iowa MSEs with the use of the composite models are primarily due to a reduction of the variance of the forecast error. For example, at the first horizon, with the composite based on a VAR(5)-update model, 89.2% of the reduction in the Iowa MSE was due to a decline in the variance of the forecast error. At the more distant horizon, the importance of variance reduction declines. At the third horizon, with use of the same model, 43.8% of the reduction in Iowa MSE was due to a decline in the variance of the forecast error. In part this pattern is a reflection of a larger relative bias in Iowa hog price forecasts at the third horizon.

Table 6
Forecast encompassing test results between Iowa outlook and alternative hog price forecasts during the out-of-sample evalution period, 2000.I–2007.IV

Forecast model	Forecast horizon		
	1-qtr.-ahead λ-estimate	2-qtr.-ahead λ-estimate	3-qtr.-ahead λ-estimate
Futures	1.01**	0.76*	0.42***
AR(5)	0.32	0.31	0.40
VAR(5)-no update	0.47**	0.47**	0.47*
VAR(5)-update	0.46**	0.47**	0.44
VAR-AIC	0.61**	0.38*	0.46
VAR-BIC	0.50*	0.33*	0.56
VAR(5)-rolling window-60	0.38*	0.33	0.15
VAR(5)-rolling window-100	0.41*	0.41*	0.33
BVAR(5)	0.47*	0.48**	0.50*
BVAR-AIC	0.52*	0.37	0.50
BVAR-BIC	0.48*	0.33	0.51
BVAR(5)-rolling window-60	0.56**	0.54**	0.47*
BVAR(5)-rolling window-100	0.48*	0.49**	0.50
VAR-Kaylen-no update	0.38	0.41**	0.40
VAR-Kaylen-update	0.39	0.44**	0.41
Average 1	0.55*	0.50**	0.52
Average 2	0.56**	0.49**	0.50
Average 3	0.54*	0.50**	0.56
Average 4	0.45*	0.47**	0.43
Average 5	0.58**	0.52**	0.56

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. One, two, and three asterisks indicate statistical significance at the 10%, 5%, and 1% level, respectively, using the MDM test of encompassing. Sample sizes are 31, 30, and 29 observations at one-, two-, and three-quarter forecast horizons, respectively.

ite RMSE reductions is economically significant (Adam et al., 1996; Antonovitz and Roe, 1984).

It is interesting to note that the most accurate forecast models in a conventional RMSE comparison are not necessarily the forecasts that generate the largest RMSE reductions when combined with the Iowa forecast. Rankings based on the effectiveness of RMSE reduction of the Iowa forecast change depending on whether an individual model or a composite is used. This pattern arises at all horizons, but becomes more prominent for two- and three-quarter-ahead horizons. For example, at the two-quarter horizon, the futures market leads to the largest individual error reduction compared to Iowa (−3.7%), but when combined with Iowa forecasts an unrestricted VAR provides the most accurate forecasts (−16.8%). A similar result is found at the three-quarter horizon.

Overall, forecasts based on the average of several VARs perform among the best, individually or in combination with Iowa, at all forecast horizons. Results also suggest that simple VARs, and even a univariate model, may help reduce forecast errors considerably when combined with Iowa forecasts, despite stand-alone RMSE performance that is moderate to poor. For instance, basic VARs with or without parameter updates are able to reduce RMSE between −7.9% and −17.4% when combined with the Iowa forecasts. Further details are provided in Fig. 4, which compares the out-of-sample performance of Iowa two-quarter-ahead forecasts to a composite forecast made up of Iowa and the VAR(5) model with updating.[9] The left plot illustrates the substantial dampening effect on forecast errors from combining Iowa forecasts with the VAR model, while the right plot shows that the benefits of combining are not limited to a few quarters, but instead, are positive almost two-thirds of the time. The most dramatic evidence of the benefit of combining occurred in 2004.II. The Iowa two-quarter ahead forecast was $15.54/cwt. below the actual market price for this quarter (positive error), while the composite was only $7.99/cwt. below the market.[10]

6. Summary and conclusions

The predictive ability of outlook hog price forecasts released by Iowa State University is compared to alternative time-series and market forecasts in this study. The time-series models include ARIMA, VAR, and Bayesian vector autoregression (BVAR) models with no updating, as well as other specifications designed to allow for instabilities in market relationships. A futures-based market forecast also is considered. The 2000.I–2007.IV time period serves as the out-of-sample evaluation period for the outlook, time-series, and market forecasts.

Under RMSE, the futures market forecast at the one-quarter horizon is most accurate by a substantial margin. At the two-quarter horizon, the futures market continues to provide the most accurate forecast, but by a much smaller margin than at the first horizon. At the three-quarter horizon, the futures market is less accurate than Iowa outlook and the other forecast methods. The pattern of relative decline in forecast accuracy of futures across horizons is consistent with the findings in other recent studies and suggests that the value of market forecasts of hog prices lies primarily in the short to intermediate-run.

In terms of the individual time-series models, some VARs and Bayesian VARs flexible in specification and estimation and model averaging tend to perform better than Iowa outlook forecasts. Evidence from encompassing tests, more stringent tests of forecast performance, indicates that many price forecasts can add incremental information to the Iowa forecast. Simple combinations of these models and outlook forecasts are able to reduce forecast errors by economically significant levels. For instance, basic VARs with or without parameter updates are able to reduce RMSE between –7.9% and –17.4% when

[9] Qualitatively similar results are also found at the one-quarter-ahead and two-quarter-ahead horizons for the VAR(5) model with updating.

[10] Given this single large observation it is not surprising that the benefits to forming a composite forecast between Iowa and the VAR(5) are heavily skewed towards quarters when the Iowa forecast was too low (positive error) as compared to quarters when the forecast was too high (negative error). When this observation is removed from the sample the benefits of combining are still weighted towards quarters when the Iowa forecast is too low, but the difference is sharply reduced.

Table 7
Performance comparisons of individual hog price forecasts and composite forecasts between Iowa outlook and alternative hog price forecasts during the out-of-sample evalution period, 2000.I–2007.IV

Forecast model	Forecast horizon											
	1-qtr. ahead				2-qtr. ahead				3-qtr. ahead			
	Composite model		Individual model		Composite model		Individual model		Composite model		Individual model	
	% Change	Rank	% Change	Rank	% Change	Rank	% Change	Rank	% Change	Rank	% Change	Rank
Iowa outlook RMSE ($/cwt.)	***4.66***				***5.84***				***7.13***			
Futures	**−26.0**	1	**−26.0**	1	−4.1	20	−3.7	1	−1.8	19	1.5	11
AR(5)	−6.9	20	22.0	20	−6.0	17	20.0	19	−7.6	12	9.2	17
VAR(5)-no update	−17.4	5	4.5	13	**−16.8**	**1**	3.9	10	**−11.4**	**1**	3.0	13
VAR(5)-update	−15.6	8	5.6	14	**−14.7**	**2**	6.1	12	−7.9	11	7.3	16
VAR-AIC	**−20.1**	**2**	**−11.6**	**2**	−10.0	12	15.1	17	−8.2	10	1.4	10
VAR-BIC	−14.0	10	−0.3	9	−5.2	18	15.1	18	**−9.5**	**2**	**−3.6**	**1**
VAR(5)-rolling window-60	−9.6	18	15.1	19	−7.2	15	21.6	20	−1.3	20	36.0	20
VAR(5)-rolling window-100	−12.8	14	12.1	17	−11.2	11	10.6	14	−4.8	18	13.4	19
BVAR(5)	−13.3	13	3.4	12	−11.6	7	1.9	8	**−9.2**	**3**	−0.4	6
BVAR-AIC	−13.4	12	−1.4	8	−6.3	16	11.5	15	−7.3	13	0.1	8
BVAR-BIC	−12.3	16	2.5	11	−4.3	19	12.9	16	−6.2	17	−0.4	7
BVAR(5)-rolling window-60	−17.6	4	−6.4	5	−12.8	4	**−3.6**	**2**	−7.1	15	2.1	12
BVAR(5)-rolling window-100	−13.9	11	2.1	10	−11.3	9	0.4	6	−8.5	8	−0.4	5
VAR-Kaylen-no update	−9.8	17	14.3	18	−11.2	10	10.0	13	−9.2	4	9.8	18
VAR-Kaylen-update	−8.9	19	11.8	16	−9.3	14	5.1	11	−6.8	16	6.4	15
Average 1	−16.2	7	−5.2	6	−11.9	5	**−0.3**	**4**	−8.7	6	−1.2	4
Average 2	**−17.9**	**3**	−6.6	4	**−13.1**	**3**	0.9	7	−8.3	9	0.2	9
Average 3	−15.4	9	−4.4	7	−10.0	13	0.3	5	−8.7	7	**−3.1**	**3**
Average 4	−12.4	15	5.6	15	−11.4	8	3.1	9	−7.1	14	4.9	14
Average 5	−16.7	6	**−7.6**	**3**	−11.9	6	**−1.8**	**3**	−9.0	5	**−3.3**	**2**
Average % change	−14.5		1.5		−10.0		6.4		−7.4		4.1	

Notes: For composite models, the % change represents the change in RMSE of a composite forecast consisting of the given model and Iowa outlook relative to Iowa alone. For individual models, the % change represents the change in RMSE of the given model relative to Iowa outlook. Positive (negative) values for % change indicate RMSE for the given model or composite forecast is higher (lower) than the RMSE for Iowa outlook. Rank orders the % change from largest RMSE reduction (1) to smallest reduction (20). The figures in bold are the three largest RMSE reductions for each forecast horizon and comparison. Sample sizes are 31, 30, and 29 observations at one-, two-, and three-quarter forecast horizons, respectively.

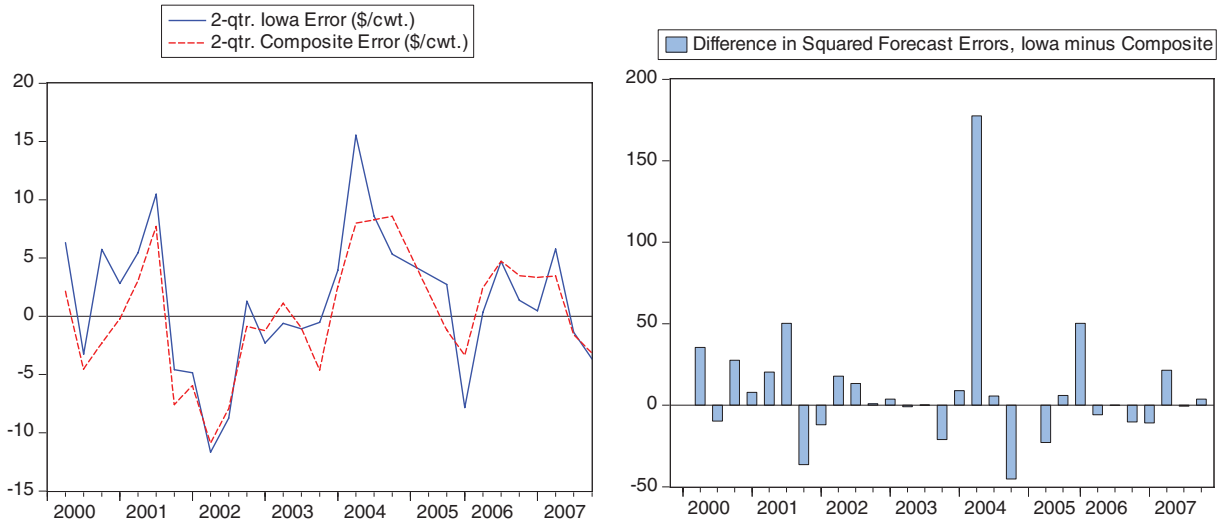

Fig. 4. Hog price forecast errors for the Iowa outlook program and VAR(5) with updating composite during the out-of-sample evaluation period, 2000.I–2007.IV.

combined with the Iowa forecasts. RMSE reductions obtained from composite forecasts average –14.5%, –10.0%, and –7.4% at the one-, two-, and three-quarter horizons, respectively, across all the alternative models considered. Overall, the results indicate that it is possible to provide more accurate forecasts than Iowa outlook at every horizon.

In a forecasting context, our findings are consistent with several lessons from the recent literature (Elliot and Timmerman, 2008). 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 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. Consistent with the literature, which highlights the benefits of forecast combination, significant forecast error reductions are obtained from combining Iowa and alternative models, even with simpler time-series forecasts. It is difficult to identify which model is preferred, but from a practical perspective, combining Iowa outlook and a simple unrestricted VAR could be a useful and low-cost approach to improving performance.

It appears that recent innovations in the forecasting literature have the potential to substantially improve the accuracy of outlook price forecasts. As per the usual caveat, one should be cautious in generalizing from results for Iowa hog price forecasts to other outlook programs or commodities. There is also a need to investigate whether the results are sensitive to adding the last several years to the analysis, a period of historically large price instability. Nevertheless, our findings are important 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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