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Forecasting Fed Cattle, Feeder Cattle, and Corn Cash Price Volatility: The Accuracy of Time Series, Implied Volatility, and Composite Approaches

Mark R. Manfredo, Raymond M. Leuthold, and Scott H. Irwin

ABSTRACT

Economists and others need estimates of future cash price volatility to use in risk management evaluation and education programs. This paper evaluates the performance of alternative volatility forecasts for fed cattle, feeder cattle, and corn cash price returns. Forecasts include time series (e.g. GARCH), implied volatility from options on futures contracts, and composite specifications. The overriding finding from this research, consistent with the existing volatility forecasting literature, is that no single method of volatility forecasting provides superior accuracy across alternative data sets and horizons. However, evidence is provided suggesting that risk managers and extension educators use composite methods when both time series and implied volatilities are available.

Key Words: *composite forecasting, implied volatility, time series, volatility forecasting.*

Today, agribusiness managers have many risk management products available, including a plethora of derivatives and insurance products (e.g., Boehlje and Lins). As a result, many extension programs are re-orienting their focus towards risk management rather than traditional price forecasting. A good example is the AgRisk™ program developed at The Ohio State University and the University of Illinois at Urbana-Champaign. AgRisk™ is a tool that allows users to simulate harvest-time revenue distributions of grain farms with and without using a variety of risk management strategies. While many volatility forecasting procedures are available (e.g. time series forecasts), the program relies on implied volatilities from options on futures contracts to forecast the volatility of cash grain prices that is used in developing the revenue distributions.

Most volatility forecasting studies have focused on the accuracy of implied volatility versus time series forecasts. Implied volatility is often believed to provide the best prediction of future volatility since it is a forward looking, market-based forecast. However, GARCH models (Generalized Autoregressive Conditional Heteroskedasticity), in particular the GARCH (1,1) model, have been found to be good specifications of conditional volatility for both financial assets and agricultural price returns (e.g., Bollerslev, Chou, and Kroner; Yang

Manfredo is an assistant professor, Morrison School of Agribusiness and Resource Management at Arizona State University. Leuthold is professor emeritus and Director of the Office for Futures and Options Research and Irwin is a professor in the Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign.

and Brorsen). Despite fitting the data well, the forecasting performance of GARCH models, especially relative to simple time series models and implied volatility, is often debated (e.g. Brailsford and Faff; Figlewski; Jorion). Composite forecasts, which can potentially enhance accuracy relative to individual forecasts (e.g. Clemen; Granger and Ramanathan; Park and Tomek), have been used little to forecast volatility. Overall, the literature suggests that no one particular method of forecasting the volatility of asset returns performs best over a wide array of data series and alternative forecast horizons. Jackson, Maude, and Perraudin (p. 79) argue that "The forecastibility of volatilities and the sensitivity of the forecasts to different techniques depend very much on the return series in question."

Given this mixed evidence, it is important to understand the forecasting performance of different volatility forecasts over alternative price series important to agribusinesses. For instance, the profitability of cattle feeding enterprises is vulnerable to fluctuations in fed cattle, feeder cattle, and corn cash prices (Schroeder *et al.*, Jones *et al.*). Understanding how various volatility forecasts perform for these key prices could help livestock risk managers and extension educators develop comprehensive risk management strategies as well as simulation tools such as the AgRisk™ program. Therefore, the objective of this research is to determine the performance of alternative volatility forecasting techniques for fed cattle, feeder cattle, and corn cash price returns. Volatility forecasting methods tested include time series, implied volatility from options on futures contracts, and composite models over short and long horizons. Testing the performance of a variety of forecasting procedures over multiple horizons provides a rigorous test of procedures that have been advocated and debated in the literature. Thus, the results of this research should prove valuable to those managers and economists who rely on measures of commodity price volatility, especially those involved with the cattle feeding industry.

Price Volatility

In a comprehensive review of the volatility forecasting literature, Figlewski provides a theoretical description of price volatility which he describes as being "... the standard way to model asset price behavior, both for derivatives pricing and in financial applications generally" (Figlewski, p. 4). Under the assumption of market efficiency, asset price movements can be described as a random walk process:

$$(1) \qquad R_t = \frac{S_t - S_{t-1}}{S_{t-1}} = \mu_t + \epsilon_t$$

where S_t is the asset price, R_t is the proportional change in asset price (return), μ_t is the conditional mean, and ϵ_t is a serially uncorrelated random disturbance term (Figlewski). For option pricing purposes as well as risk measurement applications, equation (1) can be considered in a continuous time context where the time interval becomes infinitely small. The result is the well-known log diffusion process:

$$(2) \qquad \frac{dS}{S} = \mu dt + \sigma dz$$

where dS is the instantaneous asset price change, μ is the annualized mean return per time unit, dt is an infinitely small time interval, σ is the annualized instantaneous standard deviation or "volatility" of the return, and dz is geometric Brownian motion. Empirically, continuously compounded returns are defined as:

$$(3) \qquad R_t = \ln(S_t) - \ln(S_{t-1})$$

where R_t and S_t are defined as before. Figlewski states that for finite time horizons (h), the expected return of (2) is μh and the standard deviation (volatility) is $\sigma\sqrt{h}$. The important result here is that volatility increases by the square root of time (h).

In practical risk management applications, high frequency data (e.g. weekly) are often used to create estimates of volatility. Forecasters often rely on the time aggregation property of volatility (known as the $\sqrt{h}$ *rule*) to create long-horizon forecasts of volatility (Figlewski; *RiskMetrics*™). For example, if one was interested in the volatility of live cattle prices over the next four weeks, the estimate created from weekly data could be extended to a four-week horizon by multiplying it by $\sqrt{4}$. The time aggregation of volatility is also important when working with implied volatility. Since implied volatility represents the annualized standard deviation of the underlying asset over the remaining life of the option, implied volatility must be adjusted to match the desired forecast horizon.[1]

To assess forecast performance a measure of realized volatility is needed. Since true *ex-post* volatility is not directly observable (Anderson and Bollerslev), a proxy for realized volatility must be used. One commonly used measure that incorporates the time aggregation properties of volatility described above is:

$$(4) \qquad {}_t\sigma_{t-h,i} = \sqrt{\sum_{j=1}^{h} R^2_{t+j,i}}$$

where ${}_t\sigma_{t-h,i}$ is the realized (total) volatility of price returns for commodity i over the time horizon t to $t + h$ (e.g., 2 weeks, 4 weeks, etc.) and R^2_t is the squared return at time t of price return for commodity i consistent with the frequency of the data being used. This proxy of realized volatility is the variable of interest throughout this paper.

Data

In examining the performance of alternative volatility forecasting procedures, return series of the relevant cash prices are needed. Weekly return series are constructed from Wednesday cash prices of fed cattle, feeder cattle, and corn. These return series are the log price changes (continuously compounded rate of return) as defined in equation (3). Weekly price data are used since fed cattle and feeder cattle are actively traded only one day per week, with that day typically occurring mid week (Rob). If a Wednesday price is not available, then a Tuesday price is used. The three weekly price series span from January 1984 through December 1997, providing 14 years (729 observations) of returns for estimation and out-of-sample testing.

The following cash price data are taken from the *Wall Street Journal* and the Technical Tools Inc. *Database of Securities and Futures Prices.* Fed cattle prices (\$/cwt) reflect the Texas-Oklahoma direct market for 1100- to 1300-pound choice steers. Feeder cattle (\$/cwt) are for the Oklahoma City terminal market and represent 650- to 700-pound feeder steers (Miles). Corn prices (\$/bu) are for the Central Illinois market (number 2 yellow corn). Of course, each individual cattle feeding operation throughout the country is exposed to specific prices in its particular region which may or may not have different volatility than the specific price series examined here.

Futures and options price data as well as interest rate data are used to calculate forecasts based on implied volatilities. The futures and options prices span from approximately 1986 to 1997. Both live cattle and feeder cattle futures and options are traded on the Chicago Mercantile Exchange, while corn futures and options are traded on the Chicago Board of Trade. The source of the options prices for live cattle and feeder cattle is the Futures Industry Association historical database, while the source for corn options is the Chicago Board of Trade. The source for the live cattle, feeder cattle, and corn futures prices is the Technical Tools Inc. *Database of Securities and Futures Prices.* A proxy for the risk free rate of interest, needed when calculating implied volatilities, is the daily three-month T-bill rate for the particular day that an implied volatility estimate is needed. The source for interest rate data is the Federal Reserve Bank of Chicago (http://www.frbchi.org/).

Methods

Emphasis is placed on developing alternative time series as well as implied volatility forecasts. The appropriateness of using implied

[1] Although commonly used in risk-management applications, scaling procedures have recently been criticized. In particular, Christoffersen, Diebold, and Schuermann and Diebold et al. state that scaling volatility by $\sqrt{h}$ is theoretically valid only when returns are distributed *i.i.d.* and that scaling may actually increase volatility fluctuations over long horizons.

volatility from options on futures contracts in forecasting cash price volatility is discussed. Techniques for creating composite volatility forecasts which combine information from time series and implied volatility procedures are also delineated. Finally, methods for evaluating the various time series, implied volatility, and composite forecasts are outlined.

Time Series Forecasts

The time series models presented are of the general form where the estimate of variance is a function of the weighted average of past squared returns (Boudoukh, Richardson, and Whitelaw; Mahoney). All of the time series models outlined are weekly models consistent with the return series for fed cattle, feeder cattle, and corn defined in equation (3). In addition to explaining the mechanics of the models used, a description of how each of the forecasts is extended to horizons greater than one week is also provided.

Historical Averages.[2] A long-run historical average (HISTAVG) is developed such that:

$$(5)\qquad {}_t\hat{\sigma}_{t+1,i} = \sqrt{\frac{1}{T}\sum_{j=0}^{T-1} R^2_{t-j,i}}$$

where ${}_t\hat{\sigma}_{t+1,i}$ is the next period's (week) volatility forecast for commodity i, T is the number of past squared returns used in developing the forecast, $R^2_{t,i}$ is the realized return in week t for commodity i, and the mean return of the series is constrained to be zero.[3] Each time a forecast is made, HISTAVG uses all the data available to that point. This model is often considered a benchmark for more complex models, in particular GARCH (West and Cho). Hence, HISTAVG is used as a benchmark forecast in this study.

Historical moving averages (or moving windows) are similar to long-run historical averages; however, they incorporate a fixed number of data observations, dropping old observations at each period t. They are thought to be more sensitive to structural changes and observed time variation than models which use a growing sample size (e.g., HISTAVG); however, the literature provides little guidance about how many observations to use in creating these models. Because of this, three historical moving average models are used such that in equation (5) $T = 150$ (H150), $T = 100$ (H100), and $T = 50$ (H50). By construction, HISTAVG, H150, H100, and H50 are all weekly forecasts and extended to horizons greater than one week by multiplying the weekly forecast by the square root of the desired horizon (h) such that ${}_t\hat{\sigma}_{t+h,i}\sqrt{h}$.

Naive Forecast. Following Brailsford and Faff, a simple naive model (NAIVE) also is used:

$$(6)\qquad {}_t\hat{\sigma}_{t+h,i} = \sqrt{\sum_{j=0}^{h-1} R^2_{t-j,i}}$$

where ${}_t\hat{\sigma}_{t-h,t}$ is the forecast of volatility for commodity i and h is the desired forecast horizon. Therefore, when a forecast of volatility over a particular horizon is needed, it is calculated as the square root of the sum of the actual squared returns from time t to $h - 1$. This forecast can also be thought of as using the realized volatility for a period of given length as a forecast over the next period of equal length (see equation 4).

GARCH. Models of conditional volatility, in particular GARCH, have dominated the volatility forecasting literature (Bollerslev, Chou, and Kroner). The GARCH (1,1) specification has received considerable attention and has often been found to be the best specification for conditional volatility among alternative and more complex variants of GARCH. However, controversy exists as to whether any GARCH

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[2] Each of the forecasts developed and its abbreviation is listed in Table 1 or Table 2.

[3] It is commonplace in the volatility forecasting literature to constrain the mean return of a series to zero when creating volatility forecasts and defining realized volatility. Figlewski provides evidence that imposing a mean of zero often yields a much better estimate of the true mean than attempts at estimating the mean from the data, thus leading to more accurate volatility forecasts. Despite this, the seasonal nature of agricultural prices lends caution to this practice. However, regressions of the weekly returns on monthly dummy variables yielded R^2s of 0.040, 0.037, and 0.049 for fed cattle, feeder cattle, and corn returns, respectively, illustrating that any bias created from constraining the mean to zero is likely to be very small.

specification provides superior volatility forecasts to simpler time series alternatives, especially in light of the difficulty in estimating GARCH models.

Two GARCH specifications are examined in this study. First, a standard GARCH (1,1) model (GARCH) is defined such that:

$$(7)\qquad \sigma^2_{t,i} = \alpha_0 + \alpha_1 R^2_{t-1,i} + \beta_1\sigma^2_{t-1,i}$$

where $\sigma^2_{t,i}$ is the conditional variance at time t of commodity i, $\sigma^2_{t-1,i}$ is the conditional variance in the previous period of commodity i, $R^2_{t-1,i}$ is the squared return in the previous period, where the mean return is set to zero, and α_0, α_1, and β_1 are estimated via maximum likelihood procedures. Second, consistent with known leptokurtosis of financial asset price returns, as well as the findings of Yang and Brorsen that a GARCH (1,1) ~ t specification better represents the variance of several agricultural price returns (including corn), a GARCH (1,1) ~ t is also specified. This is done by using a Student's-t distribution instead of the normal distribution in the maximum likelihood estimation, which helps to better account for fat-tailed return distributions. Similar to HISTAVG, a growing sample size is used in estimating both GARCH and GARCH-t; that is, all data up to the forecast are used. This produces meaningful GARCH forecasts that conform to the constraints that α_1 and β_1 are non-negative and that $\alpha_1 + \beta_1 < 1$ ensuring long-run stability of the model.[4]

The forecasting equation used for developing multiperiod GARCH variance forecasts is:

$$(8)\qquad \hat{\sigma}^2_{t+h,i} = \begin{cases} \hat{\alpha}_0 + \hat{\alpha}_1 R^2_{t,i} + \hat{\beta}_1\sigma^2_{t,i} & \text{if } h = 1 \\ \hat{\alpha}_0 + (\hat{\alpha}_1 + \hat{\beta}_1)\hat{\sigma}^2_{t+h-1,i} & \text{if } h \geq 2 \end{cases}$$

where $\hat{\sigma}^2_{t+h,i}$ is the conditional variance forecast at time $t + h$ for commodity i. The above equation produces individual conditional variance forecasts at each point $t + h$ that revert to the unconditional mean at a rate of ($\hat{\alpha}_1 + \beta_1$) (Campbell, Lo, and MacKinlay, p. 484). Subsequently, Kroner, Kneafsey, and Claessens (pg. 82) show that to obtain a GARCH volatility forecast over the h-week horizon, the square root of the summation of these forecasts created from equation (8) is needed such that:

$$(9)\qquad {}_t\hat{\sigma}_{t+h,i} = \sqrt{\sum_{j=1}^{h} \hat{\sigma}^2_{t+j,i}}.$$

All GARCH models and forecasts are estimated using the BHHH (Berndt, Hall, Hall, and Hausman) algorithm in the S-Plus statistical package.

RiskMetrics™ (Exponentially Weighted Moving Average). In response to the need for simpler metrics for developing Value-at-Risk measures, JP Morgan, through their *RiskMetrics™* documentation, advocates the use of an exponentially weighted moving average model of asset return volatility incorporating a fixed decay factor. This model, known as the *RiskMetrics™* method, is touted for its ease of estimation and its ability to represent time-varying volatility without resorting to GARCH estimation (Mahoney). In this spirit, *RiskMetrics™* forecasts are developed such that:

$$(10)\qquad {}_t\hat{\sigma}_{t+1,i} = \sqrt{\lambda\hat{\sigma}^2_{t,i} + (1 - \lambda)R^2_{t,i}}$$

where ${}_t\hat{\sigma}_{t+1,i}$ is the one-week ahead volatility forecast for commodity i, $\hat{\sigma}^2_{t,i}$ is the *RiskMetrics™* forecast at time t for commodity i, $R^2_{t,i}$ is the squared return innovation, and λ is a fixed decay factor. Through their research, *RiskMetrics™* suggests using $\lambda = .97$ for monthly data and $\lambda = .94$ for daily data, however they do not recommend a value of λ for weekly data. Because of this, both the $\lambda = .97$ (RM97) and $\lambda = .94$ (RM94) are used as well as an optimal value estimated using the data (RMOPT). The optimized λ's used for RMOPT are estimated with the entire historical return series (January, 1984 to December, 1997) using maximum likelihood procedures such that the variance in the likelihood function is specified as in equation (10) (see Mar-

[4] GARCH forecasts using a moving sample size of 150 past return observations, similar to H150, were also tried. However, using a moving sample size produced coefficient estimates that violated the constraints that α_1 and β_1 be non-negative and that $\alpha_1 + \beta_1 < 1$.

tin et al., p. 71). Like the GARCH models, the maximum likelihood estimate of λ is solved using the BHHH algorithm in the S-Plus package. These optimized estimates of λ are of interest primarily for comparison to the decay factors suggested by *RiskMetrics*™ for daily and monthly data. These optimized estimates also provide insight into the degree of compatibility of *RiskMetrics*™ recommendations for λ, which are designed to be robust for a number of non-agricultural return series, to the prices examined in this study. The resulting optimized decay factors are $\lambda = .91$ (fed cattle), $\lambda = .99$ (feeder cattle) and $\lambda = .78$ (corn). Similar to the historical averages, all *RiskMetrics*™ forecasts are inherently one-period ahead (weekly) forecasts. Therefore, volatility forecasts are extended to longer horizons by multiplying the $t + 1$ forecast by $\sqrt{h}$ such that ${}_t\hat{\sigma}_{t+h,i} = {}_t\hat{\sigma}_{t+1,t}\sqrt{h}$.

Implied Volatility

It is a widely held notion, especially among academics, that implied volatility forecasts derived from option premia are superior to alternative volatility forecasts since they are the market's forecast of volatility (Figlewski). Despite this, enough evidence exists to fuel a controversy over the predictive accuracy of implied volatility forecasts compared to those of time series specifications (e.g., Figlewski; Day and Lewis, 1992, 1993; Lamoureux and Lastrapes). Because futures options derive their value from futures contracts, and futures contracts derive their value from underlying cash prices, it is intuitive that information regarding cash price volatility is included in observed futures options prices. While not theoretically appealing in the strictest sense, in the absence of exchange traded options contracts specifically written on cash commodities implied volatilities taken from options on futures should provide a practical, readily available, market-based forecast of cash price volatility. Therefore, it is assumed that implied volatilities derived from options on fed cattle, feeder cattle, and corn futures contracts provide a reasonable proxy of the market's assessment of future price volatility for these cash commodities.

In addition to the theoretical appropriateness of using implied volatilities in forecasting cash price volatility, several theoretical issues exist regarding the estimation of implied volatility that are beyond the scope of this paper (see Mayhew; Figlewski). Hence, this research takes a risk-management perspective where practicality in estimating implied volatilities is emphasized. The option pricing model used to derive the implied volatilities is the popular Black-1976 model for European options on futures contracts.[5] Since options on futures contracts are of the American type, the use of a European pricing model for eliciting implied volatilities can introduce a small upward bias in the volatility estimate due to the early exercise premium of American options. However, this bias has been found to be small for short-term (e.g., nearby) options that are at-the-money (Whaley; Shastri and Tandon). Furthermore, studies examining alternative estimation procedures (weighting schemes) for implied volatility, e.g. calculating implied volatility as the average implied volatility across various strike prices, have found that implied volatilities taken from the nearest at-the-money options provide the most accurate volatility estimates (Beckers; Mayhew). At- or near-the-money options tend to contain the most information regarding volatility because they are usually the most traded options (highest volume) and yield the largest vega (Mayhew).[6] Aditionally, Jorion (p. 512) notes that the averaging of implied volatilities from both puts and calls helps to reduce measurement error.

Therefore, in accordance with these observations, implied volatilities are computed as the simple average of the implied volatility derived from nearby at-the-money (or closest to at-the-money) call and put options. Since implied volatilities are annualized estimates of the volatility over the remaining life of the op-

[5] The implied volatilities from the Black-1976 model are estimated using the Financial CAD software package.

[6] Vega is the rate of change in the options price due to changes in the underlying asset volatility.

tion contract, they must first be converted to weekly estimates and then extended to the desired horizon such that:

$$(11)\quad {}_t\hat{\sigma}_{t+h,i} = IV_{t,i} \cdot \frac{\sqrt{h}}{\sqrt{52}}$$

where $IV_{t,i}$ is the implied volatility (annualized) at time t for commodity i. These implied volatility forecasts derived from nearby options prices are designated as (IV).

Composite Forecasts

Many hypotheses have been suggested to explain the success of composite forecasting (e.g. Park and Tomek; Makridakis). However, the use of composite forecasting methods is largely an issue of information, suggesting that superior forecasts can be developed by combining alternative forecasts elicited from different formulations or information sets (e.g., time-series vs. implied volatility). Therefore, in the spirit of Kroner, Kneafsey, and Claessens, both composite forecasting procedures used in this study focus on combining forecasts of conditional volatility (e.g., GARCH; *RiskMetrics*™) with implied volatility. Combining conditional volatility forecasts with implied volatility is intuitively appealing given the forward looking nature of implied volatility versus the backward looking, historical nature of time series approaches.

First, a simple averaging technique is used where the composite forecast is merely the average of individual forecasts at any time period t. Second, a method is used where the weights are generated by an OLS regression of past realized volatilities on respective volatility forecasts such that:

$$(12)\quad \sigma_{t,i} = \alpha_0 + \beta_1\hat{\sigma}_{1,t,i} + \beta_2\hat{\sigma}_{2,t,i} + \cdots + \beta_k\hat{\sigma}_{k,t,i} + \epsilon_{t,i}$$

where $\sigma_{t,i}$ is realized volatility at time t for commodity i and $\hat{\sigma}_{k,t,i}$ is an individual volatility forecast (k) corresponding to the realized volatility at period t for commodity i (Granger and Ramanathan). Thus, the resulting volatility forecast is defined as:

$$(13)\quad {}_t\hat{\sigma}_{t+1,i} = \hat{\alpha}_0 + \hat{\beta}_1\hat{\sigma}_{1,t+1,i} + \hat{\beta}_2\hat{\sigma}_{2,t+1,i} + \cdots + \hat{\beta}_k\hat{\sigma}_{k,t+1,i}.$$

Each of the composite forecasts developed, both simple average and regression composites, are one-week ($h = 1$) forecasts. Composite forecasts for $h > 1$ horizons are created by taking the resulting one-week composite forecast and multiplying it by $\sqrt{h}$. In order to provide a robust examination of the performance of composite volatility forecasts, several combinations of conditional volatility and implied volatility are used and outlined in Table 2.[7]

Estimation and Evaluation

Since an objective of this research is to evaluate volatility forecasts at various horizons, the forecasts listed in Tables 1 and 2 are created and evaluated for horizons of one week ($h = 1$), two weeks ($h = 2$), four weeks ($h = 4$), 16 weeks ($h = 16$), and 20 weeks ($h = 20$) consistent with the procedures outlined previously. These horizons correspond with characteristics of the cattle feeding industry (e.g., cattle usually on feed a maximum of five months) and provide a wide range of short-term and long-term horizons to examine. All time series and implied volatility forecasts start in January of 1987. Starting the forecasts in 1987 allows for 150 past return observations to be used to generate initial forecasts for the time series models. Also, options on the relevant futures contracts did not consistently start trading until 1987 (the start of feeder cattle options). Since some initial observations of the various time series and implied volatility forecasts as well as realized volatility are needed for computing regression

[7] Since implied volatilities are market based forecasts, it is possible that implied volatility reflects seasonality in volatility that is not represented in the time-series models. Therefore, it is possible that in the regression composite forecasts more weight is inherently placed on IV. However, when GARCH models that included monthly dummy variables were used in the regression composite models to control for seasonality, little if any difference in the parameter estimates (weights) from the non-seasonal models were realized.

Table 1. Volatility Forecast Key

Abbreviation	Forecast	Commodity
HISTAVG	Long-run historical average	all
NAIVE	Previous period's realized volatility for the respective horizon (h)	all
H150	Moving average (150 weeks)	all
H100	Moving average (100 weeks)	all
H50	Moving average (50 weeks)	all
GARCH	GARCH(1,1)	all
GARCH-t	GARCH (1,1) ~ t	all
RM97	*RiskMetrics™* with $\lambda = .97$	all
RM94 '	*RiskMetrics™* with $\lambda = .94$	all
RMOPT	*RiskMetrics™* using optimized λ	all
IV	Implied volatility taken from nearby options contract	all

forecasts, regression composite forecasts for live cattle and feeder cattle are first calculated in April of 1987 and in June of 1987 for corn.[8,9] Each of the various forecasts (time series, implied volatility, and composite) are then updated each week through October 1997. This process provides approximately 550 out-of-sample observations for each of the horizons examined.[10]

All volatility forecasts for each horizon are ranked based on a mean-squared error (MSE) framework. Although MSE evaluation is common in the volatility forecasting literature, researchers have often found that the differences in MSE (or RMSE) among competing volatility forecasts to be quite subtle. As a result, it is often difficult to distinguish superior forecast accuracy among several competing methodologies based on MSE rankings (Brailsford and Faff; West and Cho). In such cases, the differences in the size of MSE among forecasts may be due to chance. Also, since forecasts are developed for a variety of horizons and updated throughout the sample, forecast horizons are overlapping, creating autocorrelation in the forecast errors. While autocorrelation does not affect MSE rankings, it can affect tests used to determine if significant differences in MSE occur among competing forecasts.

Because of this, a test for equality in forecast performance is conducted using a method recommended by Harvey, Leybourne, and Newbold (HLN test), which is a modified version of a test statistic put forth by Diebold and Mariano. This test is designed specifically to correct for autocorrelation introduced by overlapping forecast horizons without restricting the number of out-of-sample observations which can be evaluated. The null hypothesis of equal forecast performance is defined such that the expectation of the difference of squared errors is zero. Therefore, the resulting test statistic (Harvey, Leybourne, and Newbold, pp. 282–283) is defined as:

$$(14) \quad S_1^* = \left[\frac{N + 1 - 2h + N^{-1}(h - 1)}{N}\right]^{1/2} S_1$$

[8] Regression composite forecasts for corn (Table 2) also contain dummy variables corresponding to the option contract month from which the implied volatility estimate is derived. The May corn contract is the base; thus it is represented by the constant. This follows from observing that large jumps existed in the nearby implied volatility series related to changes in the options contract month. This observation was not found with the live cattle and feeder cattle option contracts.

[9] Starting the regression composites for live cattle and feeder cattle in April of 1987 and corn in June of 1987 provides 13 and 22 initial observations respectively of the various volatility forecasts and realizations. Corn required 22 initial observations due to the regressions that incorporated dummy variables for the option contract months. The OLS regressions incorporate a maximum of 150 past observations of volatility forecasts and realizations to maintain recent information in the regression weights.

[10] In Tables 3 through 5 the number of forecast errors is smaller for the $h = 20$ horizon since towards the end of the sample data, it becomes impossible to create a proxy for realized volatility for $h = 20$. Furthermore, there are fewer forecast errors evaluated for corn since more initial observations were needed for the regression composite forecasts (see footnote 9).

Table 2. Composite Volatility Forecasts

Abbreviation	Forecast	Commodity
COMP1	Simple average composite of GARCH-t and IV	all
COMP2	Simple average composite of GARCH-t, IV, and HISTAVG	all
COMP3	Simple average composite of RM97 and IV	all
COMP4	Simple average composite of RM94 and IV	all
COMP5	Simple average composite of RMOPT and IV	all
COMP6	Simple average composite of NAIVE and IV	Feeder Cattle
COMP1-R	Composite of GARCH-t and IV using regression weights	all
COMP2-R	Composite of GARCH-t, IV, and HISTAVG using regression weights	all
COMP3-R	Composite of RM97 and IV using regression weights	all
COMP4-R	Composite of RM94 and IV using regression weights	all
COMP5-R	Composite of RMOPT and IV using regression weights	all
COMP6-R	Composite of NAIVE and IV using regression weights	Feeder Cattle
COMP1-R-DV	Composite of GARCH-t and IV using regression weights and dummy variables representing the option contact month	Corn
COMP2-R-DV	Composite of GARCH-t, IV, and HISTAVG using regression weights and dummy variables representing the option contract month	Corn
COMP3-R-DV	Composite of RM97 and IV using regression weights and dummy variables representing the option contract month	Corn
COMP4-R-DV	Composite of RM94 and IV using regression weights and dummy variables representing the option contract month	Corn
COMP5-R-DV	Composite of RMOPT and IV using regression weights and dummy variables representing the option contract month	Corn

where S_1^* is the HLN statistic, N is the number of squared error observations, and h is the forecast horizon. Furthermore, S_1 is defined as:

$$(15)\quad S_1 = [V(\bar{d})]^{-1/2}\bar{d}$$

where $\bar{d}$ is the sample mean of the difference in squared errors and $V(\bar{d})$ is variance of $\bar{d}$ which is asymptotically approximated as:

$$(16)\quad V(\bar{d}) \approx N^{-1}\left[\gamma_0 + 2\sum_{k=1}^{h-1}\gamma_k\right]$$

where γ_k is the kth autocovariance of $\bar{d}$ (Harvey, Leybourne, and Newbold, pp. 282–283). The HLN statistic (S_1^*) is compared to a critical value from a Student's t-distribution with $(N - 1)$ degrees of freedom.

Empirical Results

Tables 3 through 5 present the MSE rankings for fed cattle, feeder cattle, and corn volatility forecasts. As well as these rankings, the tables provide the MSE of each forecast relative to HISTAVG, which is used as a benchmark forecast.[11] Results of the HLN tests are also presented. HLN tests were conducted to determine equality in forecast performance between the benchmark forecast HISTAVG and all forecasts that ranked higher than HISTAVG at each horizon. The HLN test is also conducted between the top-ranking forecast (rank = 1) and all subsequent forecasts for a particular horizon. Considering all the alternative volatility forecasts examined over these three commodity return series as well as the five different horizons, 350 unique forecasts are evaluated, providing a rigorous examination of forecast performance.

[11] Actual MSE's are not shown, but can be calculated from the data presented in each Table. Also, to save space results for $h = 16$ are not shown but are included in the discussion. These results are available from the authors.

Table 3. MSE Rankings of Fed Cattle Volatility Forecasts

Rank	$h = 1$[a] Forecast	$N = 553$ REL[b,c]	$h = 2$ Forecast	$N = 553$ REL	$h = 4$ Forecast	$N = 553$ REL	$h = 20$ Forecast	$N = 540$ REL
1	COMP3-R	0.782*[d]	COMP1	0.758*	COMP1	0.715*	COMP2	0.823
2	COMP1-R	0.783*	COMP5-R	0.763*	COMP5	0.723*	COMP3	0.845
3	COMP5-R	0.786*	COMP1-R	0.764*	COMP4	0.734*##	COMP4	0.863
4	COMP2-R	0.787*	COMP3-R	0.768*	COMP2	0.759*	COMP1	0.881
5	COMP4-R	0.788*	COMP4-R	0.771*	COMP3	0.760*	COMP5	0.891
6	COMP1	0.825*##[g]	COMP5	0.772*	GARCH-t	0.767*	H150	0.915
7	COMP5	0.844*#[f]	COMP4	0.783*##	COMP5-R	0.800	RM97	0.915
8	COMP4	0.850*	COMP2-R	0.786*	COMP1-R	0.802	GARCH-t	0.916
9	IV	0.853*	COMP2	0.804*#	IV	0.808*#	H100	0.937
10	GARCH-t	0.861*	GARCH-t	0.805*	COMP4-R	0.814	GARCH	0.985#
11	COMP2	0.862*	COMP3	0.805*	COMP3-R	0.819	H50	0.990
12	COMP3	0.864*	IV	0.812*	GARCH	0.827**[e]	HISTAVG	1.000
13	RMOPT	0.920*	GARCH	0.866*	RMOPT	0.840	RM94	1.029
14	RM94	0.925*	RMOPT	0.869*	RM94	0.841	IV	1.040
15	GARCH	0.927*	RM94	0.876*	RM97	0.854**	RMOPT	1.125
16	RM97	0.936*	RM97	0.895*	COMP2-R	0.877	COMP5-R	1.176
17	H50	0.958*	H50	0.936	H50	0.919	COMP1-R	1.195
18	H100	0.976	H100	0.964	H100	0.943	COMP4-R	1.195
19	H150	0.982	H150	0.966	H150	0.947	COMP3-R	1.229
20	HISTAVG	1.000	HISTAVG	1.000	HISTAVG	1.000	NAÏVE	1.302
21	NAÏVE	1.541	NAÏVE	1.316	NAÏVE	1.127	COMP2-R	1.399

[a] $h = 1$, $h = 2$, $h = 4$, and $h = 20$ represent 1-week, 2-week, 4-week, and 20-week forecast horizons, respectively.
[b] REL = MSE/HISTAVG.
[c] MSE of HISTAVG for $h = 1$ is 0.0220; $h = 2$ is 0.0274; $h = 4$ is 0.0370; $h = 20$ is 0.0989.
[d] * Indicates MSE is significantly different from the benchmark forecast (HISTAVG) at the 5% level.
[e] ** Indicates MSE is significantly different from the benchmark forecast (HISTAVG) at the 10% level.
[f] # Indicates the first MSE that is significantly different from the top ranking forecast at the 5% level.
[g] ## Indicates the first MSE that is significantly different from the top ranking forecast at the 10% level.

Table 4. MSE Rankings of Feeder Cattle Volatility Forecasts

	$h = 1$[a]	$N = 553$	$h = 2$	$N = 553$	$h = 4$	$N = 553$	$h = 20$	$N = 540$
Rank	Forecast	REL[b,c]	Forecast	REL	Forecast	REL	Forecast	REL
1	COMP1	0.894*[d]	COMP5	0.925*	COMP5	0.969	H150	0.950
2	COMP2	0.904*	COMP2	0.928*	COMP3	0.974	RMOPT	0.963
3	COMP5	0.904*	COMP3	0.929*	COMP2	0.977	GARCH	0.980
4	COMP3	0.910*	COMP4	0.940**	RMOPT	0.980	HISTAVG	1.000
5	COMP4	0.918*#[f]	COMP1	0.955##[g]	H150	0.982	H50	1.009
6	GARCH-t	0.921*	GARCH-t	0.959	COMP4	0.994	RM97	1.028
7	IV	0.923*	RMOPT	0.986	H50	0.996	H100	1.062
8	COMP6-R	0.959	H150	0.989	RM97	0.997	RM94	1.199
9	COMP1-R	0.971	RM97	0.997	HISTAVG	1.000	COMP5	1.234
10	COMP2-R	0.982	H50	1.000	GARCH	1.002	COMP2	1.254
11	COMP5-R	0.991	HISTAVG	1.000#	H100	1.011	COMP3	1.269
12	RMOPT	0.993	GARCH	1.003	GARCH-t	1.046##	COMP4	1.346
13	H150	0.994	H100	1.006	RM94	1.048	NAÏVE	1.568#
14	HISTAVG	1.000	RM94	1.025	COMP1	1.072#	GARCH-t	1.698
15	H100	1.004	IV	1.041	IV	1.258	COMP1	1.736
16	RM97	1.006	COMP6-R	1.105	COMP2-R	1.336	IV	2.471
17	GARCH	1.008	COMP2-R	1.124	COMP6-R	1.359	COMP2-R	2.704
18	H50	1.008	COMP1-R	1.133	COMP1-R	1.393	COMP6-R	2.747
19	RM94	1.026	COMP5-R	1.158	COMP5-R	1.435	COMP1-R	2.901
20	COMP4-R	1.041	COMP4-R	1.252	COMP4-R	1.589	COMP5-R	3.084
21	COMP3-R	1.056	COMP3-R	1.274	COMP3-R	1.624	COMP4-R	3.559
22	COMP6	1.117	COMP6	1.357	COMP6	1.664	COMP3-R	3.692
23	NAÏVE	1.762	NAÏVE	1.749	NAÏVE	1.751	COMP6	3.948

[a] $h = 1$, $h = 2$, $h = 4$, and $h = 20$ represent 1-week, 2-week, 4-week, and 20-week forecast horizons, respectively.
[b] REL = MSE/HISTAVG.
[c] MSE of HISTAVG for $h = 1$ is 0.0227; $h = 2$ is 0.0275; $h = 4$ is 0.0324; $h = 20$ is 0.0493.
[d] * Indicates MSE is significantly different from the benchmark forecast (HISTAVG) at the 5% level.
[e] ** Indicates MSE is significantly different from the benchmark forecast (HISTAVG) at the 10% level.
[f] # Indicates the first MSE that is significantly different from the top ranking forecast at the 5% level.
[g] ## Indicates the first MSE that is significantly different from the top ranking forecast at the 10% level.

Table 5. MSE Rankings of Corn Volatility Forecasts

Rank	$h = 1$[a] Forecast	$N = 542$ REL[b,c]	$h = 2$ Forecast	$N = 542$ REL	$h = 4$ Forecast	$N = 542$ REL	$h = 20$ Forecast	$N = 542$ REL
1	COMP1	0.611*[d]	COMP1	0.537*	COMP1	0.531*	IV	0.683*
2	COMP2-R	0.628*	IV	0.591*	IV	0.566*	COMP2	0.765
3	COMP1-R	0.633*	COMP2-R	0.593*	COMP2	0.596*#	COMP3	0.781**[e]
4	COMP5-R	0.638*	COMP1-R	0.598*	COMP2-R	0.626*	COMP5	0.802
5	GARCH-t	0.643*	COMP4-R	0.599*##	GARCH-t	0.641*	COMP4	0.840
6	COMP2-R-DV	0.644*	COMP5-R	0.601*	COMP4	0.647*	COMP1	0.860
7	COMP4-R	0.650*	COMP4-R-DV	0.602*	COMP1-R	0.654*	H100	0.989
8	COMP1-R-DV	0.651*	GARCH-t	0.604*#	COMP4-R	0.656*	HISTAVG	1.000#
9	COMP3-R-DV	0.656*	COMP3-R-DV	0.604*	COMP5-R	0.662*	COMP2-R-DV	1.052
10	COMP4-R-DV	0.658*	COMP3-R	0.608*	COMP2-R-DV	0.663*	H150	1.056
11	COMP5-R-DV	0.659*	COMP2	0.617*	COMP5	0.664*	COMP2-R	1.088
12	COMP3-R	0.659*##[g]	COMP1-R-DV	0.617*	COMP4-R-DV	0.666*	RM97	1.104
13	IV	0.674*#[f]	COMP2-R-DV	0.629*	COMP3-R	0.668*	H50	1.136
14	COMP2	0.685*	COMP5-R-DV	0.640*	COMP3-R-DV	0.671*	GARCH-t	1.137
15	COMP4	0.724*	COMP4	0.657*	COMP3	0.674*	COMP1-R-DV	1.181
16	COMP5	0.742*	COMP5	0.678*	COMP1-R-DV	0.680*	COMP1-R	1.190
17	RMOPT	0.745*	COMP3	0.690*	COMP5-R-DV	0.711*	RM94	1.244
18	COMP3	0.752*	RMOPT	0.702*	RMOPT	0.756	COMP5-R	1.252
19	GARCH	0.760*	GARCH	0.719*	NAÏVE	0.779	COMP4-R	1.274
20	RM94	0.872*	NAÏVE	0.814*	GARCH	0.801	COMP4-R-DV	1.278
21	RM97	0.919*	RM94	0.852*	RM94	0.888	COMP3-R-DV	1.295
22	H100	0.981	RM97	0.907	RM97	0.927	COMP5-R-DV	1.300
23	H50	0.991	H100	0.988	H100	1.000	COMP3-R	1.304
24	H150	0.992	HISTAVG	1.000	HISTAVG	1.000	RMOPT	1.476
25	NAÏVE	0.999	H50	1.001	H150	1.021	NAÏVE	1.579
26	HISTAVG	1.000	H150	1.007	H50	1.028	GARCH	2.253

[a] $h = 1$, $h = 2$, $h = 4$, and $h = 20$ represent 1-week, 2-week, 4-week, and 20-week forecast horizons, respectively.
[b] REL = MSE/HISTAVG.
[c] MSE of HISTAVG for $h = 1$ is 0.0699; $h = 2$ is 0.1057; $h = 4$ is 0.1718; $h = 20$ is 0.5654.
[d] * Indicates MSE is significantly different from the benchmark forecast (HISTAVG) at the 5% level.
[e] ** Indicates MSE is significantly different from the benchmark forecast (HISTAVG) at the 10% level.
[f] # Indicates the first MSE that is significantly different from the top ranking forecast at the 5% level.
[g] ## Indicates the first MSE that is significantly different from the top ranking forecast at the 10% level.

Fed Cattle Results

No one particular forecast of fed cattle cash return volatility dominates across horizons (Table 3). However, several composite forecasts rank among the top forecasts across all horizons. Regression composite forecasts are among the top performers for the $h = 1$ and $h = 2$ horizon, but fall out of favor as the forecast horizon increases. In fact, regression composites are among the worst performing forecasts for the $h = 16$ and $h = 20$ horizons. This observation is most likely explained by the fact that regression weights are optimized over the $h = 1$ forecasts and corresponding realized volatilities and then extended to longer horizons. This, along with noting that several of the simple composites were among the top 10 forecasts at each horizon, suggests that simple composites may be more robust across a wide spectrum of forecast horizons than regression composites for fed cattle. Among the individual forecasts, GARCH-t ranks among the top 10 across all horizons. However, performance of the *RiskMetrics*™ forecasts across horizons, which are intended to be GARCH proxies, is relatively poor except at the longer horizons of $h = 16$ and $h = 20$. While the historical average forecasts (H50, H100, H150, and HISTAVG) ranked near the bottom for $h = 1$ through $h = 4$, they were ranked considerably higher for the longer horizons of $h = 16$ and $h = 20$. NAIVE performed poorly across horizons, consistently ranking at the bottom.

For the $h = 1$, $h = 2$, and $h = 4$ horizons, all forecasts that rank in the top 10 provide at the very minimum approximately 14 percent MSE improvement over HISTAVG. The results of the HLN tests suggest that for $h = 1$, $h = 2$, and $h = 4$, the difference between MSE's of HISTAVG and higher ranking forecasts are statistically significant in many, if not most, cases (Table 3). However, this is not true for the long horizons of $h = 16$ and $h = 20$, where no forecasts are found to provide statistically significant improvement over HISTAVG at either the 5-percent or 10-percent level. Furthermore, the MSE's of most forecasts ranked among the top 10 are not significantly different from that of the top ranked forecast at the 5-percent level.

Feeder Cattle Results

As with fed cattle, no one particular forecast dominates across horizons for feeder cattle (Table 4). Simple composite forecasts perform well as a group over the $h = 1$, $h = 2$, and $h = 4$ horizons. While three regression composite forecasts ranked among the top 10 for $h = 1$, they performed poorly at all other horizons. Unlike fed cattle, however, most of the simple composite formulations fall out of the top 10 at long horizons except COMP5 and COMP2 at $h = 16$ and $h = 20$ (ranked 9th and 10th respectively for both horizons). Among individual forecasts, GARCH-t ranks among the top 10 across the $h = 1$ and $h = 2$ horizons, while GARCH ranks in the top 10 at horizons $h = 4$, $h = 16$, and $h = 20$. *RiskMetrics*™ forecasts perform well at the longer horizons of $h = 16$ and $h = 20$, but performance is more varied at shorter horizons. Similar to fed cattle, the performance of the historical average forecasts (H50, H100, H150, and HISTAVG) greatly improves as the forecast horizon increases. In fact, H150 is the top ranking forecast at $h = 20$.

For the $h = 1$ horizon, the top ranking forecast (COMP1) provides approximately 11-percent MSE improvement over HISTAVG, but COMP2-R which ranks 10th only provides about 2-percent improvement. In fact for all horizons, the top forecasts provide much less improvement in MSE relative to HISTAVG than is seen for fed cattle. When testing equality in forecast performance using the HLN test between the benchmark HISTAVG and forecasts that rank higher, the seven top-ranking forecasts for $h = 1$ and the top four forecasts for $h = 2$ are found to reject the null hypothesis of equal forecast accuracy. No forecasts are significantly different than HISTAVG at $h = 4$, $h = 16$, or $h = 20$. When testing equality of forecast performance between the top forecast and all others, significant differences are not found until the 5th ranked forecast for $h = 1$ and $h = 2$, and are found much further down the rankings for $h = 4$, $h = 16$, and $h = 20$.

Corn Results

Not unlike the findings for fed cattle and feeder cattle, no one particular forecast for corn is found to dominate across all horizons (Table 5).[12] In general, however, composite forecasts (in particular COMP1) and IV forecasts perform consistently well across horizons. Similar to fed cattle, regression composites do reasonably well with many ranking within the top 10 at the shorter horizons of $h = 1$, $h = 2$, and $h = 4$. Except at $h = 1$, only slight differences exist between the performance of regression composites that incorporate dummy variables for option expiration months versus those that do not. As is found with fed cattle and feeder cattle, regression composites tend to fall in the rankings, often among the lowest ranking forecasts, as the forecast horizon increases. However, at $h = 16$ and $h = 20$, all of the simple composites remain in the top 10. As was discussed with fed cattle, it may be that simple composites are more robust to a wide range of forecast horizons relative to regression composite specifications. All of the forecasts that rank among the top 10 for the $h = 1$, $h = 2$ and $h = 4$ horizons are found to provide ample MSE improvement relative to the benchmark forecast HISTAVG, in some cases almost 50 percent improvement. When testing the null hypothesis of equal forecast performance among HISTAVG and forecasts with smaller MSE's, a considerable number of forecasts are significant at the 5-percent level for the $h = 1$, $h = 2$, and $h = 4$ horizons. This is not the case, however, at the longer horizons, with only IV and COMP3 yielding statistically significant HLN statistics (5 percent and 10 percent respectively). Still, the top-ranking forecasts at $h = 16$ and $h = 20$ yield sizeable reductions in MSE compared to the benchmark. For instance, COMP1 which is ranked 6th for $h = 20$ provides a 14-percent reduction in MSE relative to HISTAVG which ranks 8th. When testing equality in forecast performance with the top-ranking forecast and all subsequent forecasts, statistically significant results are realized quickly at $h = 4$ and $h = 16$, but occur further down the rankings for $h = 1$ and $h = 20$.

Among the individual forecasts, IV performs near or at the top for $h = 2$, $h = 4$, $h = 16$, and $h = 20$. The strong performance of the implied volatility forecasts for corn over these horizons, in particular when compared to the other individual forecasts, is consistent with the belief that implied volatility provides the best forecast of volatility. GARCH-t falls within the top 10 forecasts for $h = 1$, $h = 2$, and $h = 4$ horizons, but loses favor at $h = 16$ and $h = 20$. Overall, the three *RiskMetrics*™ forecasts perform poorly across horizons, in particular at $h = 1$, $h = 2$ and $h = 4$. Despite this, several composites that contain a *RiskMetrics*™ forecast in their specification rank among the top forecasts. As with fed cattle, those forecasts that are constructed as a simple average of past squared returns (e.g., HISTAVG, H150) perform considerably better as the forecast horizon increases, providing more evidence that volatility may be best represented by some historical average forecast for long horizons.

Summary and Conclusions

This research assesses the performance of alternative volatility forecasts for cash price returns of fed cattle, feeder cattle, and corn at various forecast horizons. Although unable to identify one superior volatility forecast across these commodities and alternative horizons, this rigorous and comprehensive volatility forecasting exercise contributes to a better understanding of volatility forecasting. In particular, this research provides economists, livestock risk managers, and extension educators with practical insight regarding the forecasting of fed cattle, feeder cattle, and corn cash return variability. Most importantly, this research confirms that the performance of different volatility forecasts is both data and horizon specific, a common finding in the volatility forecasting literature. However, the results highly suggest that composite forecasting techniques

[12] Some of the regression composites for corn, in particular COMP2-R and COMP2-R-DV, yielded some very small negative volatility forecasts, especially during 1988. In these cases, the forecasts were set to zero.

provide improved volatility forecasts for most if not all of the horizons and prices examined here. When both time series forecasts and implied volatilities are available, it seems prudent to combine the information from these two forecasts in an attempt to provide improved forecast accuracy. The findings here also suggest that combining forecasts need not be difficult and that simple composite methods provide forecast performance equal to that of regression composites for these data.

Insight is also gained into the forecasting performance of individual forecasts, specifically time series and implied volatility. For instance, similar to the findings of Yang and Brorsen, GARCH (1,1) ~ *t* fits the data examined well and provides some improved accuracy over other individual forecasts at short horizons. Except for a few instances, *RiskMetrics*™, which is designed to be a proxy to GARCH models, does not provide the overall accuracy of a GARCH (1,1) ~ *t*. Furthermore, implied volatilities derived from options on corn futures contracts appear to provide useful forecasts for corn cash return volatility, while they do not perform well for fed cattle and feeder cattle. Despite the relatively weak performance of implied volatility for fed cattle and feeder cattle, these implied volatilities are useful in forming composite volatility forecasts. Given these results, it would seem imprudent for forecasters to ignore implied volatility from options on futures contracts when forecasting the volatility of cash prices, especially since they are readily available.

At least for these data, it seems inefficient to develop complex forecasts of volatility (e.g. GARCH) for long horizons and appears that little improvement can be obtained over a simple long-run historical average or moving average forecast. Additionally, the strong overall performance of historical averages (e.g. HISTAVG, H150, H100) at 16- and 20-week horizons supports claims by authors such as Figlewski who suggest that volatility reverts to an average volatility at long horizons. Forecasting performance is clearly data and horizon specific.

Thus, the findings from this univariate volatility forecasting exercise provide evidence for both specificity and flexibility in creating volatility forecasts. Tests of equality in forecast accuracy show that in many cases there is often no significant difference between alternative forecasts, especially among the top performing forecasts for a particular commodity and horizon. In one respect these tests confirm the difficulty in assigning superiority to any one given forecast for any horizon, therefore suggesting caution in drawing conclusions from mean-squared error rankings. On the other hand, these tests also suggest that forecasters can be flexible in what forecasts they incorporate since many competing forecasts may provide similar forecast accuracy for a particular horizon.

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