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

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Abstract

Considerable research effort has focused on the forecasting of asset return volatility. Debate in this area centers around the performance of time series models, in particular GARCH, relative to implied volatility from observed option premiums. Existing literature suggests that the performance of any volatility forecast is sensitive to both the data and forecast horizon of interest. This paper rigorously examines the performance of several alternative volatility forecasts for fed cattle, feeder cattle, and corn cash price returns. Forecasts include time series, implied volatility, and composite specifications. The results provide considerable insight into the performance of these alternative volatility forecasting procedures over a range of relevant forecast horizons. The evidence suggests that composite methods be used when both time series and implied volatilities are available. Insight is also gained into the performance of procedures used for scaling one-period volatility forecasts to longer horizons. However, consistent with the existing volatility forecasting literature, this research confirms the difficulty in finding a "best" volatility forecasting method across alternative data sets and horizons.

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Introduction

Forecasting the volatility of asset price returns is a popular research topic among financial economists. Implied volatilities derived from options prices are often believed to provide the best prediction of future volatility since they are in essence forward looking, market based forecasts. However, the GARCH (1,1) specification is often found to be a good model of conditional asset return volatility. Hence, the literature contains numerous applications of GARCH models to financial data (Bollerslev, Chou and Kroner), as well as agricultural prices (Yang and Brorsen). Despite fitting the data well, the forecasting performance of GARCH models, especially relative to more simplistic time series models and implied volatility, continues to be debated (e.g. Brailsford and Faff; Figlewski; Jorion). In addition, forecasters are aware that composite forecasts can potentially enhance accuracy relative to individual forecasts (e.g. Clemen; Granger and Ramanathan; Park and Tomek). Despite this, there are only limited attempts at using composite forecasting techniques, such as the work of Kroner, Kneafsey, and Claessens, in developing forecasts for volatility.

More recently, researchers have criticized procedures, such as multiplying one-period volatility forecasts by the square root of the forecast horizon, in extrapolating one-period forecasts to longer horizons (Diebold et al.; Christoffersen, Diebold, and Schuermann; Christoffersen and Diebold). Overall, the literature suggests that no one particular method for forecasting the volatility of asset returns performs best over a wide array of data series and alternative forecast horizons. "The forecastibility of volatilities and the sensitivity of the forecasts to different techniques depend very much on the return series in question" (Jackson, Maude, and Perraudin, p. 79).

It is well known that cattle feeding is a risky business and that the variability of key market prices, in particular fed cattle, feeder cattle, and corn prices, greatly influence cattle feeding profitability (Schroeder et al.; Jones et al.). Jones et al. (p. 336) state "In order to manage the risks associated with profit and cost of gain fluctuations, cattle feeders may need to focus attention on different determinants at different time periods." In this context, a greater understanding of the accuracy of various volatility forecasting procedures for these key economic components of cattle feeding could be beneficial.

In light of the interest in the variability of key market prices important to cattle feeding, as well as controversy concerning volatility forecasting practices, the overall objective of this research is to assess the performance of alternative volatility forecasting techniques on fed cattle, feeder cattle, and corn cash price returns. Consistent with this objective, several volatility forecasting methods are tested including time series, implied volatility from options on futures contracts, and composite models over both short and long horizons. Testing the performance of a variety of forecasting procedures over various forecast 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 risk managers who rely on measures of volatility in assessing commodity price risk and for developing risk management strategies.[1]

Data

In examining the performance of alternative volatility forecasting procedures, return series of the relevant prices are needed. Specifically, return series are constructed from Wednesday cash prices of fed cattle, feeder cattle, and corn. These return series are the continuously compounded rate of return (percent change in price) defined as:

$$R_{t,i} = \ln(p_{t,i}) - \ln(p_{t-1,i}) \qquad (1)$$

where $R_{t,i}$ is the weekly return of commodity i, ln is the natural logarithm, $p_{t,i}$ is the price at time t of commodity i (current Wednesday price), and $p_{t-1,i}$ is the price of commodity i at time t-1 (previous Wednesday price). 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 sources for these cash data are the *Wall Street Journal* and the Technical Tools Inc. *Database of Securities and Futures Prices*. Fed cattle prices ($/cwt) reflect the Texas-Oklahoma direct market for 1,100 to 1,300 pound choice steers. Feeder cattle ($/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. However, due to the liquidity of these cash markets and their frequency of reporting, these data should be appropriate for examining the performance of alternative volatility forecasts.

Futures and options price data as well as interest rate data are also used in order to calculate implied volatilities, which are one of the many forecasts examined in this study. 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. Live cattle futures and options are traded for the months of February, April, June, August, October, and December, while feeder cattle futures and options are traded for the months of January, March, April, May, August, September, October, and November. Corn futures and options are traded on the Chicago Board of Trade for the months of March, May, July, September, and December. The source for 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 is also needed when calculating implied volatilities. The interest rate used is the daily 3-month T-bill rate for the particular day that an implied volatility estimate is needed. The source for this interest rate data is the Federal Reserve Bank of Chicago WWW site (http://www.frbchi.org/).

Methodology

Several volatility forecasting procedures are outlined as well as methods for evaluating the resulting forecasts on an out-of-sample basis. Emphasis is placed on developing various time series forecasts as well as implied volatility. Techniques for creating composite volatility forecasts which combine information from time series and implied volatility procedures are also delineated.

Time Series Forecasts

Time series models provide an estimate of the variance of the relevant return series based on historical return data which are then used to create volatility 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). Each of the time series models outlined are weekly models consistent with the periodicity of the fed cattle, feeder cattle, and corn price return series. 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]

First, a long-run historical average (HISTAVG) is developed such that:

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

where $\hat{s}_{t+1,i}$ 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] At each point that a forecast is made, HISTAVG uses all the data available to that point. This model is often considered a benchmark to more complex models, in particular GARCH (West and Cho). Because of this, HISTAVG is used as a benchmark forecast for this study. Historical moving averages (or moving windows) are very similar to long-run historical averages, however, they incorporate a fixed number of data observations, dropping old observations at each time 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 to the number of observations to use in creating these models. Because of this, three historical moving average models are used such that in equation (1) 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 $\hat{s}_{t,h,i} = \hat{s}_{t+1,i}\sqrt{h}$ (JP Morgan *Risk Metrics*).

<u>*Naive Forecast*</u>

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

$$\hat{s}_{t,h,i} = \sqrt{\sum_{j=0}^{h-1} R_{t-j,i}^2} \tag{3}$$

where $\hat{s}_{t,h,i}$ is the h-period forecast of volatility for commodity i and h is the desired forecast horizon. Therefore, when a forecast of volatility over h periods is needed, it is calculated as the square root of the sum of the actual squared returns from time t to h-1. Hence, the past squared returns used in the calculation of equation (3) match the desired forecast horizon. This forecast can also be thought of as using the realized h-period volatility as a forecast over the next h periods (see equation 12).

GARCH

Models of conditional volatility, in particular GARCH (Generalized Autoregressive Conditional Heteroskedasticity), 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 often more complex variants of GARCH. However, controversy exists as to whether any GARCH specification provides superior volatility forecasts to simpler time-series alternatives, especially in light of the difficulty in estimating GARCH models.

Due to the popularity of GARCH models, two different GARCH specifications are examined in this study. First, a standard GARCH (1,1) model (GARCH) is defined such that:

(4) $$\sigma_{t,i}^{2} = \alpha_0 + \alpha_1 R_{t-1,i}^{2} + \beta_1 \sigma_{t-1,i}^{2}$$

where $\sigma^2_{t,i}$ is the conditional variance at time t of commodity i, $\sigma^2_{t-1,i}$ is the 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. Therefore, at each week that a forecast is made, all data up to that point are used. This is done in order to produce 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:

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

where $\hat{\sigma}^2_{t+h,i}$ is the conditional variance forecast at time t+h for commodity i. Therefore, the above equation produces individual conditional variance forecasts at each point t+h that revert to the unconditional mean at a rate of $\left(\hat{\alpha}_1 + \hat{\beta}_1\right)$ (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 (5) is needed such that:

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

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

Risk Metrics (Exponentially Weighted Moving Average)

In response to the need for simplistic metrics for developing Value-at-Risk measures, JP Morgan, through their *Risk Metrics* documentation, advocates the use of an exponentially weighted moving average model of asset return volatility incorporating a fixed decay factor. This model, also known as the *Risk Metrics* 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, *Risk Metrics* forecasts are developed such that:

$$\hat{\sigma}_{t+1,i} = \sqrt{\lambda \hat{\sigma}^2_{t,i} + (1 - \lambda) R^2_{t,i}} \tag{7}$$

where $\hat{\sigma}_{t+1,i}$ is the one-week ahead volatility forecast for commodity i, $\hat{\sigma}^2_{t,i}$ is the t-period *Risk Metrics* forecast for commodity i, $R^2_{t,i}$ is the squared return innovation, and λ is a fixed decay factor. Through their research, JP Morgan's *Risk Metrics* suggests using λ=.97 for monthly data and λ=.94 for daily data, however, does not recommend a value of λ for weekly data. Because of this, both the λ=.97 (RM97) and λ=.94 (RM94) are used as well as a decay factor that is optimized over each of the three weekly return series (RMOPT). The optimized λ's used for RMOPT are estimated over the entire historical return series (January, 1984 to December, 1987) using maximum likelihood procedures such that the variance in the likelihood function is specified as in equation 7 (see Martin 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 *Risk Metrics* for daily and monthly data. As well, these optimized estimates provide insight into the degree of compatibility of *Risk Metrics* 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 8=.91 (fed cattle), 8=.99 (feeder cattle) and 8=.78 (corn). Similar to the historical averages, all *Risk Metrics* forecasts are inherently one-period forecasts. Therefore, volatility forecasts are extended to h-period horizons by multiplying the t+1 forecast by $\sqrt{h}$ such that $\hat{s}_{t,h,i} = \hat{s}_{t+1,i}\sqrt{h}$.

Implied Volatility

It is a widely held notion, especially among academics, that implied volatility forecasts derived from option premia are superior to any alternative volatility forecast since it is in essence the markets' forecast of volatility (Figlewski). Despite this belief, enough evidence exists to fuel a controversy over the predictive accuracy of implied volatility forecasts to those of time series specifications (Figlewski; Day and Lewis, 1992, 1993; Lamoureux and Lastrapes). Because of this, implied volatilities are also used in this study and their forecasting ability evaluated relative to the other forecasts of return volatility.

Several theoretical issues exist regarding the estimation of implied volatility (e.g., potential violation of pricing model assumptions) which 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. First, in the absence of exchange traded options contracts specifically written on cash commodities, 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. Second, 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 subsequently yield the largest vega (Mayhew).[6] As well, Jorion (p. 512) also notes that the averaging of implied volatilities from both puts and calls helps to reduce measurement error.

Therefore, in accordance with these observations, the implied volatilities used for this study 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 resulting implied volatilities are annualized estimates, they must first be converted to weekly estimates and then extended to the desired horizon such that:

(8) $$\hat{s}_{t,h,i} = IV_{t,i} \cdot \frac{\sqrt{h}}{\sqrt{52}}$$

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 hypothesis have been suggested in explaining 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; *Risk Metrics*) 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:

$$(9) \qquad s_{t,i} = a_0 + b_1 \hat{s}_{1,t,i} + b_2 \hat{s}_{2,t,i} + \cdots + b_k \hat{s}_{k,t,i} + e_{t,i}$$

where $F_{t,i}$ is realized volatility at time t for commodity i and $\hat{s}_{k,t,i}$ 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:

$$\hat{s}_{t+1,i} = \hat{a}_0 + \hat{b}_1 \hat{s}_{1,t+1,i} + \hat{b}_2 \hat{s}_{2,t+1,i} + \cdots + \hat{b}_k \hat{s}_{k,t+1,i} \quad (10)$$

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.

Long-Run Volatility Forecasts

The above forecasting methods, in particular the time series procedures, inherently produce one-period ahead (weekly) volatility forecasts which are then scaled or extrapolated to longer horizons. These scaling procedures, although commonly used in the literature as well as by practitioners, recently have been criticized. In particular, Christoffersen, Diebold, and Schuermann, and Diebold et al. state that scaling one-period volatility by $\sqrt{h}$ is theoretically valid only when one-period returns are distributed *i.i.d.*. Furthermore, these authors state that as the forecast horizon (h) approaches infinity, volatility fluctuations tend to disappear. Hence, scaling by $\sqrt{h}$ may increase volatility fluctuations, especially over long horizons. Diebold et al. (p. 7) state "if h-day (period) volatilities are of interest, it makes sense to use an h-day (period) model."

In response to this criticism, two methods are used specifically for forecasting long-horizon volatility and their performance is compared to the previously outlined procedures for developing h-period volatility forecasts in equations (2) through (10). The first method relies on implied volatility estimates from deferred options contracts in which the time to option expiration more closely matches the desired h-forecast horizon. Implied volatilities taken from the first and second deferred months relative to the nearby are called IV-1 and IV-2 respectively. The second method is a long-run matching model (LRMATCH) in which volatility forecasts are made from an h-period return series. These returns are generated as:

$$R(h)_{t,i} = \ln(p_{t,i} - p_{t-h,i}) \tag{11}$$

where $R(h)_{t,i}$ is the h-period return at time t of commodity i, $p_{t,i}$ is the price of commodity i at time t, and $p_{t-h,i}$ is the price of commodity i in period t-h. After the h-period returns are generated, the h-period volatility forecast is defined as in equation (2).

Estimation and Evaluation

The volatility forecasts are estimated and evaluated in a two-stage process. First, in order to estimate the regression composite forecasts, a large series of weekly (h=1) forecasts and corresponding realized volatility are needed. For all forecasts outlined in table 1, except the long-run volatility forecasts, 1-week (h=1) volatility forecasts are generated and updated for each week starting on January 1, 1987 through the end of October 1997, providing 564 forecasts and realized values of weekly volatility.[7] 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).

Second, since an objective of this research is also to evaluate volatility forecasts at horizons greater than one week (h>1), forecasts are also created and evaluated for the horizons of h=2, h=4, h=16, and h=20. These horizons correspond with characteristics of the cattle feeding industry (e.g., cattle usually on feed a maximum of 5 months) and provide a wide range of both short-term and long-term horizons to examine. However, special attention is given to creating and evaluating these forecasts such that the various forecast horizons are not overlapping. When forecast horizons overlap, autocorrelation of forecast errors is introduced.[8] Since the longest forecast horizon is h=20 (20 weeks), two non-overlapping forecast periods per year are established. Updated forecasts are examined at the beginning of April and at the beginning of October from 1987 to 1997. The month of October typically sees a large amount of placements of cattle into feedlots as well as being the predominate harvest month for corn. Similarly, April is a spring month when a large amount of calving takes place. On the first Wednesday before the first Friday of the months of April and October, forecasts of volatility are made for the h=1, through h=20 horizons. It is also on these days that the regression composite forecasts are also estimated.[9] To maintain recent information in the regression weights, the OLS regressions incorporate a maximum of 150 past observations of h=1 volatility forecasts and realizations.[10] Subsequently, these forecasts are compared with the volatility eventually realized over the desired horizon where realized (*ex post*) volatility is defined as:

(12)
$$s_{t,h,i} = \sqrt{\sum_{j=1}^{h} R_{t+j,i}^{2}}$$

where $F_{t,h,i}$ denotes the realized (total) volatility of commodity i at time t over the forecast horizon h and R^2_t is the squared return at time period t of commodity i (Brailsford and Faff). It is important to note that *ex-post* volatility is not directly observable and that the specification of realized volatility in equation (12) is a proxy for the true *ex-post* volatility (Anderson and Bollerslev). From 1987 to 1997 this procedure yields 11 non-overlapping forecast errors for the April forecast period and 10 for October resulting in 21 independent out-of-sample forecast errors for each of the horizons h=1 through h=20.

All volatility forecasts for each horizon are ranked based on a mean-squared error (MSE) framework. Although MSE evaluation is commonplace 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.

Because of this, a test for equality in forecast performance is conducted using methods recommended by Harvey, Leybourne, and Newbold (HLN test), which is a modified version of a test statistic put forth by Diebold and Mariano. 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:

$$S_1^* = \left[\frac{N + 1 - 2h + N^{-1}(h-1)}{N}\right]^{1/2} S_1 \qquad (13)$$

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:

(14) $$S_1 = \left[V\left(\bar{d}\right)\right]^{-\frac{1}{2}} \cdot \bar{d}$$

where $\bar{d}$ is the sample mean of the difference in squared errors and $V\left(\bar{d}\right)$ is the asymptotic variance of $\bar{d}$. The HLN statistic (S^*_1) is compared to a critical value from a Student's t-distribution with (N-1) degrees of freedom.[11]

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 also provide the MSE of each forecast relative to HISTAVG which is used as a benchmark forecast. Results of the HLN tests are also presented. HLN tests were conducted to determine equality in forecast performance among the top 10 forecasts at each horizon and the benchmark forecast HISTAVG. As well, the HLN test is 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, 400 unique forecasts are evaluated providing a rigorous examination of forecast performance.

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 10 across all horizons. Regression composite forecasts are among the top performers for the h=1 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 at least one simple composite was 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 individual forecasts, GARCH-t and GARCH also perform consistently well, ranking among the top 10 for h=1 through h=20. However, performance of the *Risk Metrics* forecasts across horizons, which are intended to be GARCH proxies, is relatively poor.

The NAIVE, LRMATCH, and COMP3-R forecasts performed poorly across horizons. Furthermore, the overall lackluster performance of IV-1, IV-2, and LRMATCH at longer horizons (e.g., h=4, h=16, and h=20) is contrary to claims made by Christoffersen, Diebold, and Schuermann, Diebold et al., and Figlewksi that long horizon volatility forecasts should be made with h-period models. One potential reason for this observation, at least in the case of the LRMATCH forecasts, is that when the respective weekly price series are converted to h-period returns, the number of historical return observations that can be used to develop LRMATCH forecasts at each of the April and October forecast dates decreases considerably as the desired horizon increases (e.g., h=16 and h=20). As well, the poor performance of IV-1 and IV-2 may be due to the nature of livestock futures and options contracts themselves. Live cattle options contracts for deferred months are thinly traded relative to the nearby option contract. This, as well as the lack of a theoretical linkage among nearby and deferred livestock futures contracts, likely contributes to the poor performance of IV-1 and IV-2 across horizons.

For the h=1, h=2, and h=4 horizons, all forecasts that rank in the top 10 provide at the very minimum approximately 17% MSE improvement over HISTAVG. However, this is not the case for the long horizons of h=16 and h=20. For the h=20 horizon most forecasts perform considerably worse than HISTAVG. When testing the difference between the top ranking forecast and all subsequent forecasts via the HLN test, there is no significant difference in forecast performance between the top ranking forecast and others that fall in the top 10 across all forecast horizons. Significant differences are often not realized until comparisons are made between the top forecast and those ranked considerably lower (e.g., the NAIVE forecast for h=16 and h=20).

Feeder Cattle Results

As with fed cattle, no one particular forecast dominates across horizons for feeder cattle (table 4). Composite forecasts perform well as a group over the h=1, h=2, and h=4 horizons. Regression composite forecasts rank high at short horizons (h=1 and h=2), but fall out of favor at longer horizons. Unlike fed cattle, however, most of the simple composite formulations also fall out of the top 10 at h=16 and h=20 except COMP2 at h=20 (ranked 10th) . Among individual forecasts, GARCH-t ranks among the top 10 across the h=1, h=2, and h=4 horizons while GARCH ranks in the top 10 at horizons h=4, h=16, and h=20. *Risk Metrics* forecasts perform well at the longer horizons of h=16 and h=20, but rank low at shorter horizons. The performance of implied volatilities across horizons is mixed with the long-run implied volatility forecast of IV-3 ranking 1st at h=4 and IV ranking 10th for h=1. At other horizons, the performance of the implied volatilities is less stellar. However, one of the most interesting findings is the gradual improvement of LRMATCH from the h=1 to h=20 horizons. Thus, for feeder cattle there is some evidence to support the use of LRMATCH for longer horizons.

For the h=1 horizon all of the top 10 forecasts have considerably smaller MSE's than HISTAVG with IV (ranked 10th) having the smallest relative improvement at approximately 12%. However, at longer horizons improvement of the top forecasts relative to HISTAVG is less, and in the case of h=20, H150 only provides minimal reduction in MSE in relation to HISTAVG (approximately 4%). In contrast to the fed cattle results, the size of the MSE's of the worst performing forecasts relative to HISTAVG at horizons h=16 and h=20 is considerably larger. The size of the MSE for COMP3-R at h=20 is about 5 times that of the MSE for HISTAVG. When testing equality in forecast performance using the HLN test between the top 10 forecasts and HISTAVG at each horizon, the top 5 ranking forecasts for h=1 are found to reject the null hypothesis of equal forecast accuracy. At h=16, only H150 is found to perform significantly better than HISTAVG based on MSE via the HLN test. However, this is the only pair among all forecast horizons h=2 to h=20. Except for the h=4 horizon, when testing equality of forecast performance between the top forecast and all subsequent forecasts, significant differences are found much earlier in the rankings than with the fed cattle results. This result coincides with the size of the MSE's for the lower ranking forecasts being considerably larger than those of the higher ranking forecasts, especially at h=16 and h=20. Thus, the size between the MSE's of the best and worst ranking forecasts likely contribute to the HLN tests rejecting the null hypothesis of equal forecast performance.

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). However, in general composite and IV forecasts perform consistently well across horizons. In particular, regression composites, especially those that incorporate dummy variables for option expiration month (e.g., COMP1-R-D) rank among the top forecasts for the short horizons of h=1 and h=2. 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, several simple composite forecasts (all but COMP5) 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. When testing the null hypothesis of equal forecast performance among the top 10 forecasts and HISTAVG, most of the HLN statistics are significant at the 5% or 10% levels for the h=1, h=2, and h=4 horizons. This is not the case, however, at the longer horizons of h=16 and h=20 barring IV-1 at h=20. Still, the top ranking forecasts at h=16 and h=20 yield sizeable reductions in MSE compared to the benchmark. In particular IV-1 provides at least a 20% reduction in MSE to that of HISTAVG for both h=16 and h=20, even though HISTAVG ranks 7^{th} and 8^{th} for h=16 and h=20 respectively. When testing equality in forecast performance with the top ranking forecast and all subsequent forecasts, statistically significant results are realized quickly, in particular at h=16 and h=20. In other words, it is not necessary to go far down the rankings to get statistically significant HLN test statistics.

Among the individual forecasts, implied volatilities clearly dominate. However, at h=16 and h=20, IV-1 and IV-2 have smaller MSE's than IV. Note again that IV-1 and IV-2 are specifically designed to better match longer forecast horizons. The strong performance of the implied volatility forecasts for corn over all the horizons, in particular when compared to the other individual forecasts, is consistent with the widely held belief among academics that implied volatility provides the best forecast of volatility. For h=1, h=2 and h=4, GARCH-t tends to follow the implied volatilities in the rankings. Overall, the three *Risk Metrics* forecasts perform poorly across horizons, in particular at h=1, h=2 and h=4. Despite this, several composites that contain a *Risk Metrics* forecast in their specification rank among the top forecasts. Similar to fed cattle, LRMATCH performs poorly, even at long horizons, despite being designed specifically to forecast long-horizon volatility. 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 evidence that volatility is best represented by some historical average forecast for long horizons. However, in the presence of long-horizon implied volatilities (e.g., IV-1 and IV-2), this may not be the case.

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 is informative and contributes to a better understanding of volatility forecasting. This study is especially unique since it concentrates on forecasting the volatility of key market variables important to cattle feeding. In this regard, the research provides forecasters 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. Furthermore, if 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 from this research 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, *Risk Metrics*, 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. Despite the poor performance of implied volatility for fed cattle and feeder cattle, these implied volatilities are useful in forming composite volatility forecasts for these cash returns. Given these results, it would seem imprudent for forecasters to ignore implied volatility from options on futures contracts even when forecasting the volatility of cash prices.

In light of the difficulty in developing accurate forecasts of volatility for long horizons, there is little if no difference between long-run forecasts created through scaling procedures versus those designed specifically to match the desired horizon (e.g., LRMATCH). However, the overall performance of long-run historical averages (e.g. HISTAVG) 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. At least for these data, it seems inefficient to develop complex forecasts of volatility for long horizons and that little improvement can be obtained over a simple long-run historical average or moving average forecast. However, in the case of corn at the 20-week horizon, implied volatility from the deferred options contract relative to the nearby provided statistically significant improvement in forecast accuracy relative to the long-run historical average. This result again shows that forecasting performance is data and horizon specific.

Thus, the findings from this univariate volatility forecasting exercise provide evidence for both specificity and flexibility in creating volatility forecasts. For example, regression composites tend to do better at short horizons, but their performance drops off drastically at longer horizons. In the case of regression composites, a forecaster sacrifices accuracy at longer horizons for improved accuracy at short horizons. On the other hand, tests of equality in forecast accuracy show that in many cases there is often no significant differences 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 lending caution to conclusions drawn 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.

Table 1. Volatility Forecast Key

Abbreviation	Forecast	Commodity
HISTAVG	Long-run historical average	all
NAIVE	Previous periods' 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	*Risk Metrics* with 8=.97	all
RM94	*Risk Metrics* with 8=.94	all
RMOPT	*Risk Metrics* using optimized 8	all
IV	Implied volatility taken from nearby options contract	all
IV-1	Implied volatility taken from distant option contract from nearby	all
IV-2	Implied volatility taken from next distant option contract from IV-1	all
IV-3	Implied volatility taken from next distant contract from IV-2	Feeder Cattle
LRMATCH	Volatility forecast developed from return data whose periodicity matches forecast horizon	all

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 contract 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

Table 3. MSE's of Fed Cattle Volatility Forecasts Using Both April and October Forecast Errors.[1]

	h=1			h=2			h=4		
Rank	**Forecast**	**MSE**	**REL** [2]	**Forecast**	**MSE**	**REL**	**Forecast**	**MSE**	**REL**
1	COMP1-R	0.0121	0.661 *	H100	0.0147	0.735 **	RM94	0.0208	0.562 *
2	COMP5-R	0.0123	0.670 *	GARCH-t	0.0153	0.768	RMOPT	0.0208	0.562 *
3	COMP2-R	0.0124	0.673 **	COMP4-R	0.0154	0.771	RM97	0.0220	0.594 *
4	GARCH-t	0.0125	0.679 *	COMP1	0.0154	0.772 **	COMP5	0.0234	0.632 *
5	COMP4-R	0.0125	0.682 **	GARCH	0.0159	0.795	GARCH	0.0234	0.632 *
6	COMP1	0.0137	0.745 *	COMP3	0.0160	0.803	GARCH-t	0.0236	0.638 *
7	GARCH	0.0137	0.747 *	COMP2	0.0161	0.808 *	COMP4	0.0237	0.641 *
8	COMP5	0.0142	0.775 **	COMP5	0.0163	0.816	H50	0.0238	0.643 *
9	RMOPT	0.0143	0.776	COMP4	0.0164	0.820	H100	0.0249	0.672 **
10	IV-2	0.0143	0.779	COMP5-R	0.0165	0.826	COMP5-R	0.0251	0.678
11	COMP4	0.0145	0.789	RM97	0.0167	0.836	COMP3	0.0252	0.681
12	RM94	0.0146	0.793	H50	0.0168	0.843	COMP1	0.0259	0.699
13	H50	0.0147	0.797	COMP1-R	0.0169	0.847	COMP1-R	0.0263	0.710
14	COMP2	0.0149	0.809	H150	0.0172	0.859	COMP4-R	0.0277	0.750
15	COMP3	0.0149	0.813	IV	0.0175	0.873	COMP2	0.0280	0.756
16	RM97	0.0150	0.817	COMP2-R	0.0178	0.891	H150	0.0318	0.859 ##
17	IV-1	0.0152	0.825	IV-1	0.0180	0.901	IV	0.0326	0.880
18	IV	0.0159	0.865 #	RM94	0.0183	0.915	COMP2-R	0.0327	0.883
19	H100	0.0164	0.891	RMOPT	0.0185	0.924	IV-1	0.0334	0.901
20	COMP3-R	0.0175	0.950	IV-2	0.0191	0.956	LRMATCH	0.0354	0.958 #
21	H150	0.0178	0.967	HISTAVG	0.0200	1.000 ##	HISTAVG	0.0370	1.000
22	LRMATCH	0.0184	1.000	COMP3-R	0.0207	1.037	NAÏVE	0.0370	1.001
23	HISTAVG	0.0184	1.000	LRMATCH	0.0220	1.100 #	IV-2	0.0384	1.038
24	NAÏVE	0.0194	1.054	NAÏVE	0.0276	1.380	COMP3-R	0.0447	1.207

[1] All MSE's are multiplied by 100.

[2] REL=MSE/HISTAVG

[*] Significantly different from the benchmark forecast (HISTAVG) at the 5% level.

[**] Significantly different from the benchmark forecast (HISTAVG) at the 10% level.

[#] Indicates first significant difference when comparing top ranking forecast with all subsequent forecasts at the 5% level.

[##] Indicates first significant difference when comparing top ranking forecast with all subsequent forecasts at the 10% level.

Table 3 (Continued). MSE's of Fed Cattle Volatility Forecasts Using Both April and October Forecast Errors.[1]

	h=16			h=20		
Rank	**Forecast**	**MSE**	**REL** [2]	**Forecast**	**MSE**	**REL**
1	H150	0.0849	0.844	H150	0.1089	0.926
2	COMP2	0.0904	0.898	COMP2	0.1120	0.952
3	COMP3	0.0915	0.909	HISTAVG	0.1176	1.000
4	RM97	0.0919	0.913	GARCH-t	0.1183	1.006
5	H100	0.0922	0.916	COMP3	0.1191	1.013
6	GARCH-t	0.0925	0.919	H100	0.1206	1.025
7	COMP4	0.0931	0.926	COMP1	0.1212	1.030
8	COMP1	0.0949	0.943	COMP4	0.1222	1.039
9	COMP5	0.0952	0.946	GARCH	0.1230	1.046
10	GARCH	0.0980	0.974	RM97	0.1239	1.054
11	HISTAVG	0.1006	1.000	COMP5	0.1246	1.059
12	H50	0.1008	1.002	H50	0.1333	1.134
13	RM94	0.1023	1.017	IV	0.1351	1.149
14	IV-1	0.1075	1.068	RM94	0.1390	1.182
15	IV	0.1077	1.070	IV-1	0.1391	1.183
16	RMOPT	0.1091	1.084	RMOPT	0.1471	1.251
17	LRMATCH	0.1137	1.130	IV-2	0.1576	1.340
18	IV-2	0.1221	1.213	COMP5-R	0.1647	1.400
19	COMP5-R	0.1246	1.239	COMP1-R	0.1711	1.455
20	COMP1-R	0.1293	1.285	COMP2-R	0.1786	1.519
21	COMP4-R	0.1363	1.355	COMP4-R	0.1788	1.521
22	COMP2-R	0.1373	1.365	NAÏVE	0.1841	1.566 ##
23	NAÏVE	0.1384	1.375 ##	LRMATCH	0.1860	1.582 #
24	COMP3-R	0.2055	2.042	COMP3-R	0.2658	2.260

[1]All MSE's are multiplied by 100.

[2] REL=MSE/HISTAVG

[*]Significantly different from the benchmark forecast (HISTAVG) at the 5% level.

[**]Significantly different from the benchmark forecast (HISTAVG) at the 10% level.

[#]Indicates first significant difference when comparing top ranking forecast with all subsequent forecasts at the 5% level.

[##]Indicates first significant difference when comparing top ranking forecast with all subsequent forecasts at the 10% level.

Table 4. MSE's of Feeder Cattle Volatility Forecasts Using Both April and October Forecast Errors.[1]

	h=1			h=2			h=4		
Rank	**Forecast**	**MSE**	**REL [2]**	**Forecast**	**MSE**	**REL**	**Forecast**	**MSE**	**REL**
1	NAÏVE	0.0126	0.640 **	COMP6-R	0.0262	0.839	IV-3	0.0250	0.880
2	COMP6	0.0132	0.674 *	COMP5-R	0.0279	0.894	COMP2	0.0254	0.894
3	COMP5-R	0.0139	0.707 **	COMP1-R	0.0281	0.899	IV-2	0.0255	0.897
4	COMP6-R	0.0143	0.727 **	COMP2-R	0.0291	0.933	COMP5	0.0262	0.922
5	GARCH-t	0.0156	0.794 *	COMP4-R	0.0292	0.935	IV-1	0.0264	0.929
6	COMP1	0.0157	0.802	GARCH-t	0.0293	0.938	GARCH-t	0.0267	0.940
7	COMP2-R	0.0158	0.804	COMP2	0.0296	0.948	COMP3	0.0268	0.946
8	COMP2	0.0163	0.830	COMP5	0.0307	0.985 ##	COMP4	0.0269	0.946
9	COMP5	0.0171	0.873	COMP1	0.0310	0.993 #	GARCH	0.0276	0.971
10	IV	0.0172	0.876	HISTAVG	0.0312	1.000	LRMATCH	0.0283	0.997
11	COMP4	0.0173	0.882	IV-3	0.0316	1.011	COMP1	0.0283	0.998
12	COMP3	0.0174	0.890	LRMATCH	0.0316	1.013	HISTAVG	0.0284	1.000
13	COMP1-R	0.0179	0.915	COMP3	0.0318	1.017	H150	0.0285	1.003
14	GARCH	0.0191	0.976 ##	COMP4	0.0321	1.030	RMOPT	0.0295	1.039
15	HISTAVG	0.0196	1.000	IV-2	0.0323	1.035	COMP6-R	0.0302	1.062
16	LRMATCH	0.0196	1.000	GARCH	0.0324	1.036	RM97	0.0310	1.091
17	IV-1	0.0196	1.002	H150	0.0324	1.038	RM94	0.0312	1.098
18	RMOPT	0.0201	1.027	RMOPT	0.0325	1.039	COMP1-R	0.0320	1.128
19	RM94	0.0206	1.050	H100	0.0334	1.069	H100	0.0327	1.151
20	IV-3	0.0207	1.054	IV-1	0.0338	1.082	COMP6	0.0331	1.166
21	IV-2	0.0208	1.060	RM97	0.0346	1.107	H50	0.0331	1.168
22	RM97	0.0208	1.063	IV	0.0352	1.128	COMP5-R	0.0334	1.177
23	H100	0.0210	1.069	RM94	0.0354	1.134	COMP2-R	0.0338	1.189
24	H150	0.0210	1.073	H50	0.0362	1.160	IV	0.0352	1.241 ##
25	COMP4-R	0.0220	1.122	COMP6	0.0363	1.164	COMP4-R	0.0371	1.306
26	H50	0.0221	1.129	COMP3-R	0.0388	1.242	COMP3-R	0.0504	1.775
27	COMP3-R	0.0252	1.286	NAÏVE	0.0594	1.904	NAÏVE	0.0514	1.812 #

[1]All MSE's are multiplied by 100.

[2]REL=MSE/HISTAVG

[*]Significantly different from the benchmark forecast (HISTAVG) at the 5% level.

[**]Significantly different from the benchmark forecast (HISTAVG) at the 10% level.

[#]Indicates first significant difference when comparing top ranking forecast with all subsequent forecasts at the 5% level.

[##]Indicates first significant difference when comparing top ranking forecast with all subsequent forecasts at the 10% level.

Table 4 (Continued). MSE's of Feeder Cattle Volatility Forecasts Using Both April and October Forecast Errors.[1]

	h=16				h=20			
Rank	**Forecast**	**MSE**	**REL [2]**		**Forecast**	**MSE**	**REL**	
1	RM97	0.0411	0.852		H150	0.0371	0.961	
2	H150	0.0419	0.870	**	HISTAVG	0.0386	1.000	
3	RM94	0.0427	0.886		GARCH	0.0388	1.007	
4	H50	0.0429	0.889		RMOPT	0.0390	1.011	
5	GARCH	0.0443	0.920		H50	0.0409	1.061	
6	RMOPT	0.0444	0.920		LRMATCH	0.0424	1.100	
7	HISTAVG	0.0482	1.000		RM97	0.0429	1.112	
8	NAÏVE	0.0489	1.015		H100	0.0485	1.258	##
9	H100	0.0505	1.047		RM94	0.0524	1.360	
10	LRMATCH	0.0539	1.119		COMP2	0.0715	1.853	#
11	COMP3	0.0635	1.317	##	COMP5	0.0750	1.944	
12	COMP2	0.0635	1.318		COMP3	0.0766	1.986	
13	COMP4	0.0640	1.327		NAÏVE	0.0806	2.090	
14	COMP5	0.0654	1.357		GARCH-t	0.0809	2.098	
15	GARCH-t	0.0705	1.463		COMP4	0.0809	2.098	
16	IV-2	0.0775	1.607		IV-2	0.0946	2.454	
17	IV-3	0.0785	1.629		IV-3	0.0989	2.566	
18	IV-1	0.0841	1.745		IV-1	0.1061	2.752	
19	COMP1	0.0890	1.847	#	COMP1	0.1102	2.858	
20	COMP1-R	0.1076	2.233		COMP1-R	0.1369	3.551	
21	COMP2-R	0.1081	2.242		COMP2-R	0.1387	3.595	
22	COMP6-R	0.1138	2.361		COMP6-R	0.1406	3.645	
23	IV	0.1359	2.820		COMP5-R	0.1683	4.365	
24	COMP5-R	0.1400	2.904		IV	0.1728	4.481	
25	COMP4-R	0.1482	3.073		COMP6	0.1904	4.937	
26	COMP6	0.1578	3.274		COMP4-R	0.1972	5.113	
27	COMP3-R	0.1710	3.548		COMP3-R	0.2040	5.291	

[1]All MSE's are multiplied by 100.

[2]REL=MSE/HISTAVG

*Significantly different from the benchmark forecast (HISTAVG) at the 5% level.

**Significantly different from the benchmark forecast (HISTAVG) at the 10% level.

#Indicates first significant difference when comparing top ranking forecast with all subsequent forecasts at the 5% level.

##Indicates first significant difference when comparing top ranking forecast with all subsequent forecasts at the 10% level.

Table 5. MSE's of Corn Volatility Forecasts Using Both April and October Forecast Errors.[1]

	h=1			h=2			h=4		
Rank	**Forecast**	**MSE**	**REL**[2]	**Forecast**	**MSE**	**REL**	**Forecast**	**MSE**	**REL**
1	COMP1-R-D	0.0266	0.570 **	COMP2-R-D	0.0187	0.314 *	COMP1	0.0268	0.324 *
2	IV	0.0267	0.572 *	COMP4-R-D	0.0229	0.383 *	COMP2-R-D	0.0317	0.384 *
3	COMP2-R-D	0.0270	0.578 **	COMP3-R-D	0.0233	0.391 *	COMP5	0.0330	0.399 *
4	IV-1	0.0284	0.607 *	COMP1-R-D	0.0235	0.394 *##	COMP2	0.0332	0.402 *
5	COMP5-R-D	0.0301	0.644	COMP2-R	0.0250	0.419 *	IV	0.0352	0.426 *
6	IV-2	0.0309	0.662	COMP5-R-D	0.0253	0.424 *	GARCH-t	0.0357	0.433 *
7	COMP1-R	0.0311	0.665	IV	0.0254	0.426 *	COMP1-R	0.0360	0.436 *
8	COMP4-R-D	0.0312	0.667	COMP1-R	0.0261	0.437 **	COMP4-R-D	0.0363	0.440 *
9	COMP5-R	0.0312	0.667	COMP5-R	0.0261	0.438 **	COMP5-R	0.0365	0.442 *
10	COMP2-R	0.0319	0.682	COMP1	0.0277	0.464 *	COMP1-R-D	0.0375	0.454 *
11	COMP3-R-D	0.0319	0.682	COMP3-R	0.0301	0.504	COMP3-R-D	0.0381	0.461
12	COMP1	0.0335	0.716	COMP4-R	0.0302	0.507	COMP4-R	0.0443	0.536 ##
13	COMP2	0.0348	0.746	IV-1	0.0320	0.537	COMP3-R	0.0464	0.561
14	COMP4-R	0.0356	0.762	COMP2	0.0323	0.541	IV-1	0.0469	0.567
15	COMP3-R	0.0360	0.770	COMP5	0.0352	0.590	COMP2-R	0.0490	0.593
16	COMP5	0.0391	0.837 ##	IV-2	0.0365	0.612 #	IV-2	0.0498	0.603 #
17	COMP3	0.0404	0.864	GARCH-t	0.0393	0.659	COMP3	0.0509	0.617
18	COMP4	0.0431	0.922 #	COMP3	0.0436	0.730	COMP5-R-D	0.0520	0.630
19	GARCH-t	0.0460	0.985	COMP4	0.0466	0.781	COMP4	0.0523	0.633
20	HISTAVG	0.0467	1.000	LRMATCH	0.0593	0.994	NAÏVE	0.0595	0.721
21	LRMATCH	0.0467	1.000	HISTAVG	0.0597	1.000	RMOPT	0.0683	0.826
22	H150	0.0544	1.164	RMOPT	0.0637	1.068	GARCH	0.0792	0.959
23	H100	0.0574	1.228	GARCH	0.0695	1.165	HISTAVG	0.0826	1.000
24	RM97	0.0597	1.277	H150	0.0714	1.197	RM94	0.0851	1.030
25	RMOPT	0.0609	1.302	RM97	0.0730	1.224	RM97	0.0894	1.082
26	H50	0.0626	1.340	RM94	0.0740	1.241	LRMATCH	0.0985	1.193
27	RM94	0.0628	1.344	H100	0.0763	1.279	H150	0.1003	1.214
28	GARCH	0.0633	1.354	H50	0.0819	1.374	H100	0.1059	1.282
29	NAÏVE	0.1034	2.213	NAÏVE	0.0903	1.513	H50	0.1065	1.289

[1]All MSE's are multiplied by 100.

[2]REL=MSE/HISTAVG

[*]Significantly different from the benchmark forecast (HISTAVG) at the 5% level.

[**]Significantly different from the benchmark forecast (HISTAVG) at the 10% level.

[#]Indicates first significant difference when comparing top ranking forecast with all subsequent forecasts at the 5% level.

[##]Indicates first significant difference when comparing top ranking forecast with all subsequent forecasts at the 10% level.

Table 5 (Continued). MSE's of Corn Volatility Forecasts Using Both April and October Forecast Errors.[1]

	h=16			h-20		
Rank	**Forecast**	**MSE**	**REL** [2]	**Forecast**	**MSE**	**REL**
1	IV-1	0.3743	0.792	IV-1	0.4438	0.739 *
2	IV-2	0.3891	0.823	IV-2	0.4632	0.772
3	IV	0.4191	0.887 ##	IV	0.5020	0.836 ##
4	COMP3	0.4517	0.956	COMP3	0.5500	0.916 #
5	COMP4	0.4639	0.982 #	COMP4	0.5682	0.946
6	H100	0.4666	0.988	H100	0.5795	0.965
7	HISTAVG	0.4725	1.000	COMP2	0.5855	0.975
8	COMP2	0.4804	1.017	HISTAVG	0.6003	1.000
9	H150	0.5138	1.087	H150	0.6407	1.067
10	COMP1	0.5572	1.179	COMP1	0.6692	1.115
11	H50	0.5695	1.205	COMP1-R-D	0.6959	1.159
12	RM97	0.5750	1.217	H50	0.7000	1.166
13	COMP5	0.5801	1.228	COMP2-R-D	0.7007	1.167
14	COMP2-R-D	0.5811	1.230	COMP5	0.7030	1.171
15	COMP1-R-D	0.5824	1.232	RM97	0.7113	1.185
16	COMP1-R	0.6057	1.282	COMP1-R	0.7222	1.203
17	COMP5-R-D	0.6555	1.387	COMP5-R-D	0.7857	1.309
18	COMP2-R	0.6661	1.410	COMP5-R	0.7989	1.331
19	COMP5-R	0.6663	1.410	COMP2-R	0.7996	1.332
20	RM94	0.6943	1.469	RM94	0.8561	1.426
21	COMP4-R-D	0.7099	1.502	COMP4-R-D	0.8569	1.427
22	GARCH-t	0.7242	1.533	GARCH-t	0.8638	1.439
23	COMP3-R-D	0.7462	1.579	COMP3-R-D	0.9013	1.501
24	COMP4-R	0.7525	1.593	COMP4-R	0.9074	1.511
25	GARCH	0.7583	1.605	COMP3-R	0.9580	1.596
26	COMP3-R	0.7915	1.675	GARCH	0.9815	1.635
27	LRMATCH	0.8542	1.808	LRMATCH	1.0363	1.726
28	RMOPT	0.8908	1.885	RMOPT	1.0912	1.818
29	NAÏVE	1.0668	2.258	NAÏVE	1.2449	2.074

[1]All MSE's are multiplied by 100.

[2] REL=MSE/HISTAVG

[*]Significantly different from the benchmark forecast (HISTAVG) at the 5% level.

[**]Significantly different from the benchmark forecast (HISTAVG) at the 10% level.

[#]Indicates first significant difference when comparing top ranking forecast with all subsequent forecasts at the 5% level.

[##]Indicates first significant difference when comparing top ranking forecast with all subsequent forecasts at the 10% level.

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Endnotes

[1]Volatility is often thought of as the annualized measure of the second moment of asset price returns (Duffie and Pan), however, it can be defined over any horizon. For this study, volatility specifically refers to the standard deviation of price returns over the specified horizon.

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

[3]It is common practice in the volatility forecasting literature to constrain the mean return of a series to zero when developing volatility forecasts. In addition, Figlewski provides empirical evidence showing that setting the mean of the return series to zero can provide more accurate volatility estimates. Thus, throughout the remainder of this research, the mean return is constrained to zero.

[4]GARCH forecasts using a moving sample size of 150 past return observations, similar to H150, were 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 $\alpha_1 + \beta_1 < 1$.

[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.

[7]The sample of h=1 forecasts ends in October 1997, coinciding with the last possible implied volatility estimate constructed using 1997 options prices.

[8]Specifically, Diebold and Mariano suggest that for optimal h-step forecasts that the forecast errors are h-1 dependent.

[9]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. For both the April and October forecast regressions, the May corn contract is the base, thus represented by the constant. This was done since it was observed that large jumps in the nearby implied volatility series related to changes in the options contract month existed. This observation was not found with the live cattle and feeder cattle option contracts.

[10]The early composite forecasts of 1987, 1988, and 1989 do not use 150 observations of h=1 volatility forecasts and realizations since at these forecast dates 150 past observations of forecasts and realizations do not exist. For the April forecast periods, N=13, 65, and 118 for 1987, 1988, and 1989 respectively. For the October forecast periods, N=39 (1987), 92 (1988) and 1989 (144).

[11]The HLN test is designed to be used to correct for autocorrelation in the series d_t that may result from overlapping forecast horizons. However, due to the development of the non-overlapping April and October forecasts, there is no reason to believe that the difference in forecast errors (d_t) is autocorrelated. Hence, the *h* term in the S^*_1 is 1 for all horizons (h=1 through h=20) and $V(\bar{d}) \approx N^{-1}[g_0]$ where γ_0 is the first autocovariance (variance) of $\bar{d}$ (Harvey, Leybourne, and Neubold, pp. 282-283).