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

by

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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 1-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.

Introduction and Literature Review

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 be best 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 (Brailsford and Faff; Figlewski; Jorion). In addition, forecasters are aware that composite forecasts can potentially enhance forecast accuracy relative to individual forecasts (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 1-period volatility forecasts by the square root of the forecast horizon, in extrapolating 1-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).

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It is well known that cattle feeding is a risky business and that the variability of key market prices (e.g., fed cattle, feeder cattle, and corn) 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, accurate forecasts of volatility of these key economic components of cattle feeding could be beneficial.

In light of this, as well as controversy concerning "best" 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. 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.

Data and Methods

All of the volatility forecasts presented are premised on the assumption of normality of price returns. 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 $R_{t,i} = \ln(p_{t,i}) - \ln(p_{t-1,i})$ 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 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.

These three cash data series are consistent with those published daily in the Wall Street Journal. Fed cattle prices ($/cwt) are for the Texas-Oklahoma direct market for 1100 to 1300 pound choice steers. Feeder cattle ($/cwt) are for the Oklahoma City terminal market and represent 650 to 700 pound feeder steers (Miles). Corn prices ($/bu) are for Central Illinois number 2 yellow corn. Each cattle feeding operation 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 and reliability of reporting, these data are assumed robust for examining the performance of alternative volatility forecasts.

Time Series Forecasts

Historical Averages[1]

A long-run historical average (HISTAVG) is developed such that:

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

where $\hat{\sigma}_{t+1,i}$ 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

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

commodity i, and the mean return of the series is constrained to be zero.[2] 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). 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. Three historical moving average models are used such that in equation (1) T=150 (H150), T=100 (H100), and T=50 (H50). HISTAVG, H150, H100, and H50 are all inherently weekly forecasts and are extended to horizons greater than one week by multiplying the forecast by the square root of the desired horizon such that $\hat{\sigma}_{t,h,i} = \hat{\sigma}_{t+1,i}\sqrt{h}$.

Naive Forecast

In addition to the above specifications, a simple naive model (NAIVE) is established and is defined similar to Brailsford and Faff such that:

$$(2)\ \hat{\sigma}_{t,h,i} = \sqrt{\sum_{j=0}^{h-1} R_{t-j,i}^2}$$

where $\hat{\sigma}_{t,h,i}$ is the h-period forecast of volatility for commodity i and h is the 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 match the desired forecast horizon. This forecast can also be thought of as using the realized h-period volatility as a forecast of over the next h periods.

GARCH

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

$$(3)\ \sigma_{t,i}^2 = \alpha_0 + \alpha_1 R_{t-1,i}^2 + \beta_1 \sigma_{t-1,i}^2$$

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 the maximum likelihood parameter estimates. Second, consistent with findings of Yang and Brorsen as well as the fact that financial returns are often leptokurtotic, a GARCH (1,1) ~ t model is also specified (GARCH-t). In order to produce meaningful GARCH forecasts that conform to the constraints that α_1 and β_1 are non-negative and that $\alpha_1 + \beta_1 < 1$, a growing sample size is used similar to that with HISTAVG. Therefore, for

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[2]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.

each desired forecast point, all available data are used to estimate GARCH parameters and forecasts.

The forecasting equation for developing multiperiod GARCH variance forecasts is:

$$(4)\quad \hat{\sigma}^2_{t+h,i} = \begin{cases} \alpha_0 + \alpha_1 R^2_{t,i} + \beta_1 \sigma^2_{t,i} & \text{if } h = 1 \\ \alpha_0 + \left(\alpha_1 + \beta_1\right) \hat{\sigma}^2_{t+h-1,i} & \text{if } h \geq 2 \end{cases}$$

where $\hat{\sigma}^2_{t+h,i}$ is the conditional variance forecast at time t+h for commodity i. Therefore, the above equation produces individual conditional variance forecasts at each point t+h that revert to the unconditional mean at a rate of $(\alpha_1 + \beta_1)$ (Campbell, Lo, and MacKinlay, p. 484). Subsequently, to obtain a GARCH volatility forecast over the h-week horizon, the square root of the summation of these forecasts created from equation (4) is needed such that:

$$(5)\quad \hat{\sigma}_{t,h,i} = \sqrt{\sum_{j=1}^{h} \hat{\sigma}^2_{t+j,i}} \qquad \text{(Kroner, Kneafsey, and Claessens).}$$

<u>*Risk Metrics (Exponentially Weighted Moving Average)*</u>

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 return volatility using 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:

$$(6)\quad \hat{\sigma}_{t+1,i} = \sqrt{\lambda\, \hat{\sigma}^2_{t,i} + (1-\lambda)\, R^2_{t,i}}$$

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. The fixed decay factors used are: λ=.97 (RM97), λ=.94 (RM94), and a factor that is optimized over each return series (RMOPT) via MLE techniques using the BHHH algorithm in the S-Plus package. 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. Volatility forecasts are extended to h-period horizons by multiplying the t+1 forecast by $\sqrt{h}$.

Implied Volatility

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. Implied volatilities are derived using the Black-1976 model for European options on futures contracts using the Financial CAD software. To reduce potential bias resulting from using a European pricing model for American options, implied volatilities are computed as the simple average of the implied volatility derived from nearby, at-the-money, call and put options (Mayhew; Jorion).

Since implied volatilities are annualized estimates, implied volatilities must first be converted to weekly estimates and then extended to the desired horizon such that:

$$(7)\quad \hat{IV}_{t+h,i} = IV_{(annual),t,i} \cdot \frac{\sqrt{h}}{\sqrt{52}}.$$

These implied volatility forecasts derived from nearby options prices are designated as (IV).

Composite Forecasts

Two techniques are used in creating composite forecasts. In the spirit of Kroner, Kneafsey, and Claessens, both procedures focus on combining forecasts of conditional volatility (e.g., GARCH; *Risk Metrics*) with implied volatility. First, a simple averaging technique is used where the composite forecast is merely the average of individual forecasts at any time period t. The second method uses weights generated by an OLS regression of past realized volatilities on respective volatility forecasts such that:

$$(8)\quad \sigma_{t,i} = \alpha_0 + \beta_1 \hat{\sigma}_{1,t,i} + \beta_2 \hat{\sigma}_{2,t,i} + \cdots + \beta_k \hat{\sigma}_{k,t,i}$$

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:

$$(9)\quad \hat{\sigma}_{t+1,i} = \hat{\alpha}_0 + \hat{\beta}_1 \hat{\sigma}_{1,t+1,i} + \hat{\beta}_2 \hat{\sigma}_{2,t+1,i} + \cdots + \hat{\beta}_k \hat{\sigma}_{k,t+1,i}\ .$$

Each of the composite forecasts developed (both simple average and regression composites) are one-week (h=1) forecasts. Composite volatility forecasts for h>1 horizons are created by taking the one-week composite forecast and multiplying it by $\sqrt{h}$. The composite forecasts examined are outlined in table 2.

Long-Run Volatility Forecasts

Christoffersen, Diebold, and Schuermann, and Diebold et al. state that scaling 1-period volatility by $\sqrt{h}$ is theoretically valid only when 1-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. 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, 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 (1) through (9). 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:

$$(10)\quad R(h)_{t,i} = \ln(P_{t,i} - P_{t-h,i})$$

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 (1).

Estimation and Evaluation

Forecasts with a horizon of 1 week (h=1) are generated for each week starting on January 1, 1987 through the end of October 1997, providing 564 forecasts and realized values of weekly volatility.[3] 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). All forecasts, except the regression composites and long-run models, are then updated at each time period. This is necessary since a large sample of h=1 volatility forecasts is needed for developing the regression composite forecasts.

Since an objective of this research is to evaluate volatility forecasts at horizons greater than one week (h>1), forecasts are developed and tested for horizons of h=2, h=4, h=16, and h=20 weeks in addition to h=1. 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 spectrum of both short-term and long-term horizons to examine.

Special attention is given to evaluating these volatility forecasts such that the various forecast horizons are not overlapping. 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. Therefore, 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. Subsequently, these forecasts are compared with the volatility eventually realized (equation 11) over the horizon of interest. 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.

Realized (*ex post*) volatility is defined as:

$$(11)\quad \sigma_{t,h,i} = \sqrt{\sum_{j=1}^{h} R^2_{t+j,i}}$$

where $\sigma_{t,h,i}$ 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).

All volatility forecasts are ranked based on a mean-squared error framework. Although MSE evaluation is commonplace, researchers have found differences in MSE (or RMSE) from competing volatility forecasts to be quite subtle, and thus difficult to distinguish, or choose, a "best" forecast among several competing methodologies (Brailsford and Faff; West and Cho). In such cases, differences between MSE's may be due to chance.

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

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:

$$(12)\quad S_1^* = \left[\frac{N + 1 - 2h + N^{-1}(h-1)}{N}\right]^{1/2} S_1$$

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:

$$(13)\quad S_1 = \left[V(\bar{d})\right]^{-\frac{1}{2}} \cdot \bar{d}$$

where $\bar{d}$ is the sample mean of the difference in squared errors and $V(\bar{d})$ 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.[4]

Empirical Results

Tables 3 through 5 present the MSE rankings for fed cattle, feeder cattle, and corn volatility forecasts. 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. 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 and all subsequent forecasts for a particular horizon.

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

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[4]The HLN test is designed to be used to correct for autocorrelation in the series d_t. 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 are autocorrelated. Hence, the *h* term in the S^*_1 statistic becomes 1 for all h-horizons and $V(\bar{d}) \approx N^{-1}[\gamma_0]$ where γ_0 is the first autocovariance (variance) of $\bar{d}$ (Harvey, Leybourne, and Neubold, pp. 282-283).

composites may be more robust across a wide spectrum of forecast horizons than regression composites. 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. 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 barring 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 statistically different from HISTAVG. At h=16, H150 is statistically different from HISTAVG; however, this is the only pair among all forecast horizons h=2 to h=20. Overall, 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.

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, 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, despite the latter's ranking in the top 10. 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 long 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 assess the performance of alternative volatility forecasts for 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, this 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. 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 suggests 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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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 λ=.97	all
RM94	*Risk Metrics* with λ=.94	all
RMOPT	*Risk Metrics* using optimized λ	all
IV	Implied volatility taken from nearby options contract	all
	Implied volatility taken from distant option contract from nearby	all
	Implied volatility taken from next distant option contract from IV-1	all
	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	
COMP4-R-DV	Composite of RM94 and IV using regression weights and dummy variables representing the option contract month	
COMP5-R-DV	Composite of RMOPT and IV using regression weights and dummy variables representing the option contract month	

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

h=1

Rank	Forecast	MSE	REL
1	COMP1-R	0.0121	0.661 *
2	COMP5-R	0.0123	0.670 *
3	COMP2-R	0.0124	0.673 **
4	GARCH-t	0.0125	0.679 *
5	COMP4-R	0.0125	0.682 **
6	COMP1	0.0137	0.745 *
7	GARCH	0.0137	0.747 *
8	COMP5	0.0142	0.775 **
9	RMOPT	0.0143	0.776
10	IV-2	0.0143	0.779
:	:	:	:
18	IV	0.0159	0.865 #
:	:	:	:
20	COMP3-R	0.0175	0.950
21	H150	0.0178	0.967
22	LRMATCH	0.0184	1.000
23	HISTAVG	0.0184	1.000
24	NAÏVE	0.0194	1.054

h=2

Rank	Forecast	MSE	REL
1	H100	0.0147	0.735 **
2	GARCH-t	0.0153	0.768
3	COMP4-R	0.0154	0.771
4	COMP1	0.0154	0.772 **
5	GARCH	0.0159	0.795
6	COMP3	0.0160	0.803
7	COMP2	0.0161	0.808 *
8	COMP5	0.0163	0.816
9	COMP4	0.0164	0.820
10	COMP5-R	0.0165	0.826
:	:	:	:
:	:	:	:
.	:	:	:
20	IV-2	0.0191	0.956
21	HISTAVG	0.0200	1.000 ##
22	COMP3-R	0.0207	1.037
23	LRMATCH	0.0220	1.100 #
24	NAÏVE	0.0276	1.380

h=4

Rank	Forecast	MSE	REL
1	RM94	0.0208	0.562 *
2	RMOPT	0.0208	0.562 *
3	RM97	0.0220	0.594 *
4	COMP5	0.0234	0.632 *
5	GARCH	0.0234	0.632 *
6	GARCH-t	0.0236	0.638 *
7	COMP4	0.0237	0.641 *
8	H50	0.0238	0.643 *
9	H100	0.0249	0.672 **
10	COMP5-R	0.0251	0.678
:	:	:	:
16	H150	0.0318	0.859 ##
:	:	:	:
20	LRMATCH	0.0354	0.958 #
21	HISTAVG	0.0370	1.000
22	NAÏVE	0.0370	1.001
23	IV-2	0.0384	1.038
24	COMP3-R	0.0447	1.207

h=16

Rank	Forecast	MSE	REL
1	H150	0.0849	0.844
2	COMP2	0.0904	0.898
3	COMP3	0.0915	0.909
4	RM97	0.0919	0.913
5	H100	0.0922	0.916
6	GARCH-t	0.0925	0.919
7	COMP4	0.0931	0.926
8	COMP1	0.0949	0.943
9	COMP5	0.0952	0.946
10	GARCH	0.0980	0.974
:	:	:	:
:	:	:	:
20	COMP1-R	0.1293	1.285
21	COMP4-R	0.1363	1.355
22	COMP2-R	0.1373	1.365
23	NAÏVE	0.1384	1.375 ##
24	COMP3-R	0.2055	2.042

h=20

Rank	Forecast	MSE	REL
1	H150	0.1089	0.926
2	COMP2	0.1120	0.952
3	HISTAVG	0.1176	1.000
4	GARCH-t	0.1183	1.006
5	COMP3	0.1191	1.013
6	H100	0.1206	1.025
7	COMP1	0.1212	1.030
8	COMP4	0.1222	1.039
9	GARCH	0.1230	1.046
10	RM97	0.1239	1.054
:	:	:	:
:	:	:	:
20	COMP2-R	0.1786	1.519
21	COMP4-R	0.1788	1.521
22	NAÏVE	0.1841	1.566 ##
23	LRMATCH	0.1860	1.582 #
24	COMP3-R	0.2658	2.260

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

[*] 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.

REL = MSE/HISTAVG

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

h=1

Rank	Forecast	MSE	REL
1	NAÏVE	0.0126	0.640 **
2	COMP6	0.0132	0.674 *
3	COMP5-R	0.0139	0.707 **
4	COMP6-R	0.0143	0.727 **
5	GARCH-t	0.0156	0.794 *
6	COMP1	0.0157	0.802
7	COMP2-R	0.0158	0.804
8	COMP2	0.0163	0.830
9	COMP5	0.0171	0.873
10	IV	0.0172	0.876
		:	:
14	GARCH	0.0196	0.976 ##
:	:		
23	H100	0.0210	1.069
24	H150	0.0210	1.073
25	COMP4-R	0.0220	1.122
26	H50	0.0221	1.129
27	COMP3-R	0.0252	1.286

h=2

Rank	Forecast	MSE	REL
1	COMP6-R	0.0262	0.839
2	COMP5-R	0.0279	0.894
3	COMP1-R	0.0281	0.899
4	COMP2-R	0.0291	0.933
5	COMP4-R	0.0292	0.935
6	GARCH-t	0.0293	0.938
7	COMP2	0.0296	0.948
8	COMP5	0.0307	0.985 ##
9	COMP1	0.0310	0.993 #
10	HISTAVG	0.0312	1.000
:	:	:	:
:	:	:	:
:	:	:	:
23	RM94	0.0354	1.134
24	H50	0.0362	1.160
25	COMP6	0.0363	1.164
26	COMP3-R	0.0388	1.242
27	NAÏVE	0.0594	1.904

h=4

Rank	Forecast	MSE	REL
1	IV-3	0.0250	0.880
2	COMP2	0.0254	0.894
3	IV-2	0.0255	0.897
4	COMP5	0.0262	0.922
5	IV-1	0.0264	0.929
6	GARCH-t	0.0267	0.940
7	COMP3	0.0268	0.946
8	COMP4	0.0269	0.946
9	GARCH	0.0276	0.971
10	LRMATCH	0.0283	0.997
:	:	:	:
:	:	:	:
:	:	:	:
23	COMP2-R	0.0338	1.189
24	IV	0.0352	1.241 ##
25	COMP4-R	0.0371	1.306
26	COMP3-R	0.0504	1.775
27	NAÏVE	0.0514	1.812 #

h=16

Rank	Forecast	MSE	REL
1	RM97	0.0411	0.852
2	H150	0.0419	0.870 **
3	RM94	0.0427	0.886
4	H50	0.0429	0.889
5	GARCH	0.0443	0.920
6	RMOPT	0.0444	0.920
7	HISTAVG	0.0482	1.000
8	NAÏVE	0.0489	1.015
9	H100	0.0505	1.047
10	LRMATCH	0.0539	1.119
11	COMP3	0.0635	1.317 ##
:	:	:	:
19	COMP1	0.0890	1.847 #
:	:	:	:
23	IV	0.1359	2.820
24	COMP5-R	0.1400	2.904
25	COMP4-R	0.1482	3.073
26	COMP6	0.1578	3.274
27	COMP3-R	0.1710	3.548

h=20

Rank	Forecast	MSE	REL
1	H150	0.0371	0.961
2	HISTAVG	0.0386	1.000
3	GARCH	0.0388	1.007
4	RMOPT	0.0390	1.011
5	H50	0.0409	1.061
6	LRMATCH	0.0424	1.100
7	RM97	0.0429	1.112
8	H100	0.0485	1.258 ##
9	RM94	0.0524	1.360
10	COMP2	0.0715	1.853 #
:	:	:	:
:	:	:	:
:	:	:	:
:	:	:	:
23	COMP5-R	0.1683	4.365
24	IV	0.1728	4.481
25	COMP6	0.1904	4.937
26	COMP4-R	0.1972	5.113
27	COMP3-R	0.2040	5.291

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

*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.

REL = MSE/HISTAVG

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**	**Rank**	**Forecast**	**MSE**	**REL**	**Rank**	**Forecast**	**MSE**	**REL**
	COMP1-R-D	0.0266	0.570 **	1	COMP2-R-D	0.0187	0.314 *	1	COMP1	0.0268	0.324 *
2	IV	0.0267	0.572 *	2	COMP4-R-D	0.0229	0.383 *	2	COMP2-R-D	0.0317	0.384 *
3	COMP2-R-D	0.0270	0.578 **	3	COMP3-R-D	0.0233	0.391 *	3	COMP5	0.0330	0.399 *
4	IV-1	0.0284	0.607 *	4	COMP1-R-D	0.0235	0.394 *##	4	COMP2	0.0332	0.402 *
5	COMP5-R-D	0.0301	0.644	5	COMP2-R	0.0250	0.419 *	5	IV	0.0352	0.426 *
6	IV-2	0.0309	0.662	6	COMP5-R-D	0.0253	0.424 *	6	GARCH-t	0.0357	0.433 *
7	COMP1-R	0.0311	0.665	7	IV	0.0254	0.426 *	7	COMP1-R	0.0360	0.436 *
8	COMP4-R-D	0.0312	0.667	8	COMP1-R	0.0261	0.437 **	8	COMP4-R-D	0.0363	0.440 *
9	COMP5-R	0.0312	0.667	9	COMP5-R	0.0261	0.438 **	9	COMP5-R	0.0365	0.442 *
10	COMP2-R	0.0319	0.682	10	COMP1	0.0277	0.464 *	10	COMP1-R-D	0.0375	0.454 *
	:	:	:		:	:	:	:	:	:	:
16	COMP5	0.0391	0.837	16	IV-2	0.0365	0.612 #	12	COMP4-R	0.0443	0.536 ##
	:	:	:					:	:	:	:
18	COMP4	0.0431	0.922 #					16	IV-2	0.0498	0.603 #
	:	:	:			:	:	:	:	:	:
25	RMOPT	0.0609	1.302	25	RM97	0.0730	1.224	25	RM97	0.0894	1.082
26	H50	0.0626	1.340	26	RM94	0.0740	1.241	26	LRMATCH	0.0985	1.193
27	RM94	0.0628	1.344	27	H100	0.0763	1.279	27	H150	0.1003	1.214
28	GARCH	0.0633	1.354	28	H50	0.0819	1.374	28	H100	0.1059	1.282
29	NAÏVE	0.1034	2.213	29	NAÏVE	0.0903	1.513	29	H50	0.1065	1.289

	h=16				h-20		
Rank	**Forecast**	**MSE**	**REL**	**Rank**	**Forecast**	**MSE**	**REL**
1	IV-1	0.3743	0.792	1	IV-1	0.4438	0.739 *
2	IV-2	0.3891	0.823	2	IV-2	0.4632	0.772
3	IV	0.4191	0.887 ##	3	IV	0.5020	0.836 ##
4	COMP3	0.4517	0.956	4	COMP3	0.5500	0.916 #
5	COMP4	0.4639	0.982 #	5	COMP4	0.5682	0.946
6	H100	0.4666	0.988	6	H100	0.5795	0.965
7	HISTAVG	0.4725	1.000	7	COMP2	0.5855	0.975
8	COMP2	0.4804	1.017	8	HISTAVG	0.6003	1.000
9	H150	0.5138	1.087	9	H150	0.6407	1.067
10	COMP1	0.5572	1.179	10	COMP1	0.6692	1.115
	:	:	:				
	:	:	:		:	:	:
25	GARCH	0.7583	1.605	25	COMP3-R	0.9580	1.596
26	COMP3-R	0.7915	1.675	26	GARCH	0.9815	1.635
27	LRMATCH	0.8542	1.808	27	LRMATCH	1.0363	1.726
28	RMOPT	0.8908	1.885	28	RMOPT	1.0912	1.818
29	NAÏVE	1.0668	2.258	29	NAÏVE	1.2449	2.074

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

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

[illegible]tly different fr[illegible] [illegible]STAVG) at the

#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.

REL = MSE/HISTAVG