The Forecasting Performance of Implied Volatility From Live Cattle Options Contracts: Implications for Agribusiness Risk Management

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ABSTRACT

This research examines the forecasting performance of implied volatility derived from nearby live cattle options contracts in predicting 1-week volatility of nearby live cattle futures prices. Forecast evaluation is conducted from the perspective of an agribusiness risk manager. The methodology employed avoids overlapping forecast horizons and focuses on forecast errors, minimizing interpretive issues. Results suggest that implied volatility is a biased and inefficient forecast of 1-week nearby live cattle futures price volatility. However, implied volatility encompasses all information provided by a time series alternative, and it has improved as a forecast over time. These findings provide insight to agribusiness risk managers on how to adjust for bias and inefficiency of implied volatility, and provide insight into their information content. [JEL/EconLit citations: Q130, Q140, G130.] © 2004 Wiley Periodicals, Inc.

1. INTRODUCTION

Risk managers need reliable and meaningful agricultural commodity price volatility forecasts. Furthermore, they need to understand how well these forecasts perform (Aaron, 2000). This is particularly true given the growing emphasis on market risk measurement and management in an increasingly industrialized agricultural sector (Boehlje & Lins, 1998). Many of the recent innovations in risk measurement and management, such as Value-at-Risk, require volatility forecasts as inputs (Manfredo & Leuthold, 2001). As well, in many agribusiness firms, commodity cash prices are often negotiated relative to nearby futures prices using a cost-plus formula. For instance, consider a meat-processing firm that prices its raw beef inputs using a cost-plus formula relative to nearby live cattle futures. Furthermore, assume that it manufactures a retail meat-based product sold at relatively stable shelf prices. Then, the volatility of the beef purchase price—and the firm's profit margin—is directly linked to the volatility of nearby live cattle futures prices. Given this, accurate and meaningful measures of commodity price volatility are

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necessary to make informed risk management decisions and to develop department- or firm-wide risk measures.

To further clarify the importance of volatility forecasting in agribusiness, consider the case of a food service firm, such as a restaurant chain, that formula prices steaks off of nearby live cattle futures prices. Clearly, this firm's input price risk is directly proportional to the volatility of live cattle futures. If the firm maintains an in-house hedging program, then financial managers need volatility forecasts to evaluate potential cash flow demands. If the firm does not forward price inputs, then they still need volatility forecasts to evaluate potential deviations in input costs and profit margins (Sanders & Manfredo, 2002). In either case, volatility forecasts play an important role in measuring and monitoring risk, whether it be cash flow risk or input price risk. If, say, the forecasts systematically underestimate volatility, the firm may experience a liquidity crisis due to hedging losses or an earnings disappointment due to cost overruns. Similarly, poor volatility forecasts may result in a misallocation of scarce capital within the firm. Therefore, it is crucial that risk managers and financial analysts have a thorough understanding of alternative volatility forecasts, their biases, forecasting performance, and costs.

While various forecasts of commodity price volatility can be developed, implied volatility derived from options on commodity futures prices are readily available given observed options premiums, underlying futures prices, short-term interest rates, and knowledge of an assumed options pricing model (e.g., Black's, 1976, option pricing model for options on futures contracts). Furthermore, there is a general belief by both academics and practitioners that implied volatility is the best forecast of market volatility. Given that implied volatility is a market-based forecast, it theoretically impounds all information provided by alternative forecasts (Figlewski, 1997). However, in a review of several studies examining the forecasting performance of implied volatility for financial markets (e.g., the S&P 100 options market), Figlewski notes that there is ample evidence contrary to this popular belief. In general, implied volatility for many options markets has been found to be a biased and inefficient forecast, and has often been found not to encompass information in time series alternatives (Figlewski, 1997; Canina & Figlewski, 1993). Several explanations have been given in the finance literature that may account for these findings, namely violations of Black and Scholes (1973) option pricing assumptions, transactions costs, and other market frictions (Figlewski, 1997; Christensen & Prabhala, 1998; Poteshman, 2000). While these explanations for the bias and inefficiency found in implied volatility are important from a theoretical and market efficiency perspective, they ultimately do not provide insight to risk managers, as in the case of the meat-processing firm or meat-merchandising firm that may use implied volatility for risk measurement and risk management purposes (Hayenga, Jiang, & Lence, 1996).

The overall objective of this study is to examine the forecasting performance of implied volatility, namely implied volatility derived from options on live cattle futures contracts. Specifically, we examine the performance of implied volatility in predicting 1-week volatility of nearby live cattle futures prices. Live cattle futures are the most liquid of the meat futures contracts traded (vis-à-vis lean hogs, feeder cattle, and frozen pork bellies), are used extensively for hedging cattle in feedlots, for managing risks of meat products by meat processors and merchandisers, and are commonly used in formula-driven pricing by food companies.

With this in mind, this research takes a practical risk management approach to the evaluation of implied volatility. Unlike the studies in the finance literature that attempt to answer or pose questions regarding options market efficiency through the evaluation of implied volatility, we focus on information that can be of use to risk managers who use implied volatility. For instance, if implied volatility is known to be a systematically biased forecast of short-run live cattle futures price variability, how would a risk manager adjust implied volatility so that it is a useful risk measure? Thus, we test for forecast optimality (i.e., bias and efficiency), information content, and also test to see if implied volatility as a forecast has improved over time. In regard to bias and efficiency, we seek to determine whether implied volatility is indeed biased, and, if so, how risk managers can make adjustments to the forecasts. Furthermore, if implied volatility is found not to encompass all information from a standard time-series alternative, then we will suggest ways to create an optimal composite forecast for volatility (Kroner, Kneafsey, & Claessens, 1994).

In addition to stressing information vital for risk managers, our methodology focuses on forecast errors and not the forecasts themselves, thus helping to alleviate interpretive problems with traditional rationality and encompassing tests that have been used previously in the volatility forecasting literature (Granger & Newbold, 1998). Furthermore, this study avoids the problem of overlapping forecast horizons by focusing only on short-run, 1-week-ahead forecasts. This procedure provides a large number of weekly forecasts and realized values over the sample period (1986 through 1999), allowing for a thorough analysis of forecast performance and improvement over time. Ultimately, this research provides a rigorous examination of the performance of implied volatility in forecasting nearby live cattle futures price volatility, provides useful information to agribusiness risk managers who use these forecasts, and circumvents some empirical problems that are typical of other studies examining the forecasting performance of implied volatility.

2. DATA SOURCES AND ESTIMATION OF IMPLIED AND REALIZED VOLATILITY

Historical futures and options data are used to calculate implied volatility, a time series alternative, and realized volatility. Chicago Mercantile Exchange historical live cattle options data (settlement prices) are from the Institute for Financial Markets (formally the Futures Industry Institute). Historical futures data come from the Technical Tools Inc. *Database of Securities and Futures Prices*. The source for the annualized 3-month Treasury bill rate, used in the estimation of implied volatility, is the United States Federal Reserve Bank of Chicago. These data span the time period from January 1986 through the end of November 1999, providing for 728 non-overlapping observations of weekly implied volatility forecasts, realized volatility, and forecasts generated by a time series alternative.

Specifically, we focus on the ability of implied volatility from live cattle futures options to forecast the realized volatility of nearby live cattle futures prices over the ensuing week. In doing this, we estimate a weekly (Wednesday-to-Wednesday) series of both implied volatility and realized volatility. Implied volatility is estimated with the Black model for options on futures contracts using the Financial CAD program. Implied volatility is derived from the nearby, at-the-money options contract (settlement price) on Wednesday during each week in the sample period. Live cattle options expire on the first Friday of the contract month. To avoid estimating implied volatility in the options delivery month, the nearby contract is defined to have at least 15 days to expiration. Using the nearby at-the-money options price minimizes the small upward bias in the volatility estimate caused by using a European option pricing model (i.e., the Black model) for American style options like options on live cattle futures contracts (Whaley, 1986; Shastri & Tandon, 1986). Furthermore, it has been found that implied volatilities taken from at- or near-the-money options tend to provide the most accurate volatility forecasts and tend to contain the most information regarding future volatility since they are usually the most liquid options trading (Beckers, 1981; Mayhew, 1995). This is particularly important given the known "volatility smile" that often arises as implied volatility is calculated from options that are either more in- or out-of-the money relative to the at-the-money contract. In creating this series of implied volatilities, we also average the implied volatility from both puts and calls, reducing estimation error (Jorion, 1995). More important than these theoretical and estimation issues, this method is consistent with how a risk manager is likely to compute implied volatility to forecast 1-week volatility. That is, they would likely derive implied volatility from the at-the-money, nearby options contracts (both puts and calls) on the day that the forecast is made.

To assess the performance of implied volatility in forecasting short-run live cattle futures volatility, a measure of realized 1-week volatility is needed. While the true realized volatility is not observable (Anderson & Bollerlsev, 1998), a proxy must be developed. The most common measure of realized volatility used in the volatility forecasting literature, one commonly used for risk measurement purposes (Jorion, 1997), defines realized volatility as the square root of the average of squared returns over a particular time horizon h such that:

$$ {}_t\sigma_{t+h} = \sqrt{\frac{1}{h}\sum_{j=1}^{h} R_{t+j}^2} \qquad (1) $$

where ${}_t\sigma_{t+h}$ is realized volatility and R_t is the continuously compounded return estimated as

$$ R_t = \ln(P_t) - \ln(P_{t-1}) \qquad (2) $$

where P_t and P_{t-1} are the futures prices observed in time period t and t-1, respectively.[1,2] Given that the realized variable of interest is 1-week volatility, equation 1 reduces to ${}_t\sigma_{t+1} = \sqrt{R_{t+1}^2}$. Thus, consistent with equations 1 and 2, as well as the methods for calculating implied volatility, realized volatility is calculated from weekly nearby live cattle futures prices. Rollover of the nearby futures follows that of the options rollover described previously. Careful attention is given to make sure that R_t in equation 2 is not generated between different contract months. In other words, if the implied volatility forecast at time t for time t+1 is derived from the (say) February options contract, and the following week (Wednesday) the options and futures contract roll to the April contract, the realized return from t to t+1 will be computed from the February futures contract consistent with the forecast made in time period t. Because implied volatility theoretically represents the *annualized* average volatility expected over the remaining life of the

[1]Consistent with the volatility forecasting literature, equation 1 assumes a zero mean (Figlewski, 1997).

[2]While other measures of realized volatility can be used, for instance the Parkinson's high/low method (Parkinson, 1980), the method used here is standard in the volatility forecasting and risk measurement literature, is relatively simple to calculate, is consistent with how a risk manager may view volatility, and allows for a comparison of implied volatility relative to a simple GARCH model.

option contract, actual volatility as defined by equation 1 is annualized to be consistent with implied volatility

$$ {}_t\sigma_{t+1} = \sqrt{R_{t+1}^2 \cdot 52}. \tag{3} $$

Thus, the measure used in equation 3 is a reasonable and commonly used proxy for realized volatility, which in the purest sense, is a non-observable variable.

To compare the forecasting performance of implied volatility vs. a time series alternative, a GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model is estimated using the nearby futures return series presented above. Specifically, the GARCH (1,1) is chosen as the alternative model because it is widely used to describe asset return series of both agricultural futures prices (Yang & Brorsen, 1993) and financial asset prices (Bollerslev, Chou, & Kroner, 1992). Furthermore, it is often used as the standard time series alternative to implied volatility in many volatility forecasting studies (Jorion, 1995; Lamoureux & Lastrapes, 1993; Figlewski, 1997). With standard ARCH models (Autoregressive Conditional Heteroskedasticity), the serial correlation found in financial asset return volatility is modeled as a distributed lag of past squared innovations (squared returns). GARCH is a more general form of an ARCH process. In this case, given that a one-week forecast is needed, the GARCH (1,1) forecast used here is a function of the current squared return, R_t^2, and current variance, σ_t^2 where:

$$ {}_t\sigma_{t+1} = \sqrt{\alpha_0 + \alpha_1 R_t^2 + \beta_1 \sigma_t^2} \tag{4} $$

and α_0, α_1, and β_1 are the maximum likelihood GARCH estimates. These parameters are generated using the BHHH (Berndt, Hall, Hall, & Hausman, 1974) algorithm in the S+GARCH software package. Initial estimation of the GARCH model requires nearby, weekly return data prior to the first observation of implied and realized volatility examined. Initial estimation of the GARCH model is taken from weekly nearby futures returns starting from the first week of January 1983 through the first week of January 1986. From this point on, with each week during the sample period from January 1986 to November 1999, the GARCH model is updated and the 1-week volatility forecast is made.[3]

Summary statistics, as well as common measures of forecast accuracy (mean square error, mean absolute error, and mean error) are presented in Table 1.[4] The means suggest that both implied volatility (IV) and GARCH are greater than the realized volatility. Furthermore, the standard deviation of the forecasts are almost half that of the realized volatility. This may be because neither IV or GARCH do a good job at forecasting extreme volatility associated with the tails of the return distribution, an important caveat for forecasters who are concerned with generating Value-at-Risk estimates. This is further emphasized by the minimum and maximum values of IV and GARCH relative to the minimum and maximum values of realized volatility. The forecast accuracy measures suggest that GARCH may have performed slightly better over the sample period. However,

[3]Given that the GARCH (1,1) is used only as a representative alternative volatility forecast to that of implied volatility, no attempt is made to optimize a GARCH specification. Furthermore, this research focuses on the forecasting performance of implied volatility, and is not intended to be a forecasting horserace between implied volatility and GARCH.

[4]Augmented Dickey Fuller and Phillips-Perron tests found no evidence of a unit root in either the nearby return series, realized volatility, or the forecast series examined.

TABLE 1. Summary Statistics and Forecast Accuracy Measures (Jan. 1986 to Nov. 1999)

	Mean	Stdev	Min	Max	MSE	MAE	ME
Implied volatility	0.14504	0.04282	0.07901	0.32599	0.00871	0.07695	−0.04545
GARCH(1,1)	0.13271	0.04074	0.07677	0.33529	0.00840	0.07341	−0.03311
Realized volatility	0.09960	0.08755	0.00000	0.65771			

Note. MSE = mean squared error; MAE = mean absolute error; ME = mean error.
There is no statistically significant difference in squared forecast errors at the 5% level (Harvey et al., 1997).
N = 728.

no statistically significant difference was found between the forecast errors of IV and GARCH at the 5% level using the test proposed by Harvey, Leybourne, & Newbold (1997).

3. FORECAST OPTIMALITY: TESTS AND RESULTS

Our procedure focuses on the performance of implied volatility derived from nearby, at-the-money options in forecasting 1-week live cattle futures price volatility. It is assumed that a risk manager uses implied volatility derived from Black's option pricing model as an input into the firm's risk management system.[5] This is not an unreasonable assumption given the popularity of Black-Scholes type models as well as available software (e.g., Financial CAD) used to estimate implied volatility. Thus, the tests presented below are joint tests of the live cattle option market's ability to forecast future volatility as well as the efficacy of the Black model. Because the Black model is used consistently throughout this exercise, it is difficult, if not impossible, to determine if any bias or inefficiency is caused by the market's ability (inability) to forecast future volatility, the Black model itself, the forecast horizon, the definition of realized volatility, or a combination of all these factors. Given this, it is again important to keep in mind the perspective of this report: to gain a better understanding of the performance of implied volatility in forecasting short-run volatility such that risk managers can make more informed risk measurement and management decisions. Thus, if implied volatility is found to be biased or inefficient in its ability to forecast short-run volatility of nearby live cattle futures prices, this information can provide clues as to the best way to adjust for these phenomena.

Most studies examining implied volatility, such as those summarized by Figlewski (1997), use the traditional regression test for forecast optimality. Using notation put forth by Figlewski (1997), implied volatility is unbiased and efficient if both $\alpha = 0$ *and* $\beta = 1$ in the following OLS regression:

$$\sigma_{realized,t} = \alpha + \beta\sigma_{IV,t} + \varepsilon_t \tag{5}$$

where $\sigma_{realized,t}$ is the realized volatility and $\sigma_{IV,t}$ is the implied volatility (IV) forecast. The null unbiased-forecast hypothesis suggests that the mean of the forecast error is zero and that $\sigma_{IV,t}$ is uncorrelated with the forecast error. Similarly, the information content of

[5]While various pricing models could be used by the market, it is likely a vast majority of option market participants use some variant of the Black model or other Black-Scholes type model (Figlewski, 1997).

TABLE 2. Test for Forecast Bias, $e_t = \gamma_1 + \mu_t$ (Jan. 1986 to Nov. 1999)

	Implied volatility	GARCH(1,1)
Estimated γ	−0.04545	−0.03311
(t-statistic)	(−15.01)*	(−10.45)*

*Significant at the 5% level (two-tailed, t-test).

implied volatility is typically examined in the context of the common encompassing regression where:

$$\sigma_{realized,t} = \alpha + \beta_1 \sigma_{IV,t} + \beta_2 \sigma_{alternative,t} + \varepsilon_t \tag{6}$$

and $\sigma_{alternative,t}$ is an alternative volatility forecast generated by a time series procedure (e.g., historical volatility or GARCH). The joint null hypothesis of no bias, efficiency, and that implied volatility encompasses all information provided by the alternative forecast is $\alpha = 0$, $\beta_1 = 1$, and $\beta_2 = 0$. However, given the potential interpretative and econometric problems associated with these traditional rationality and forecast encompassing tests, the tests used in this study focus on the forecast error series as suggested by Granger and Newbold (1998, p. 286), Holden and Peel (1990), Nordhaus (1987), and Harvey, Leybourne, and Newbold (1998). All tests are conducted for both implied volatility as well as the GARCH (1,1) alternative.

3.1 Test for Forecast Bias

A test for forecast bias consistent with that used by Pons (2000) is conducted. This test uses the following OLS regression:

$$e_t = (\sigma_t - \hat{\sigma}_t) = \gamma_1 + \mu_t \tag{7}$$

where e_t is the error produced by the difference between realized volatility (σ_t) and the volatility forecast ($\hat{\sigma}_t$). The null hypothesis (H_o) is that of an unbiased forecasts ($\gamma_1 = 0$). Given the definition of forecast errors (e_t) in equation 7, the alternative hypothesis (H_a) of ($\gamma_1 < 0$) suggests that forecasts systematically overestimate the realized volatility and ($\gamma_1 > 0$) suggests that forecasts systematically underestimate realized volatility. Results presented in Table 2 indicate a significant (5% level) systematic bias in IV forecasts over the sample period. This is consistent with the ME statistics shown earlier. Thus, on average over the sample period, IV overestimates realized 1-week volatility by about 4.5% on an annualized basis. Similarly, GARCH tends to overestimate 1-week volatility by about 3.3% on an annualized basis. Given this result, risk managers using IV to forecast 1-week volatility can improve their forecasts by subtracting a constant ($\gamma_1 = -0.04545$) from their IV forecast. For example, if a risk manager derives an implied volatility measure of 0.25 (25%), then she should subtract 0.04545 from this to yield a corrected forecast of 0.20455.[6] Figure 1 illustrates the IV forecast, the actual volatility, and the IV adjusted for the bias over the sample period. This result is important for the practicing

[6] All volatility measures, forecasts and actual, are presented on an annualized basis.

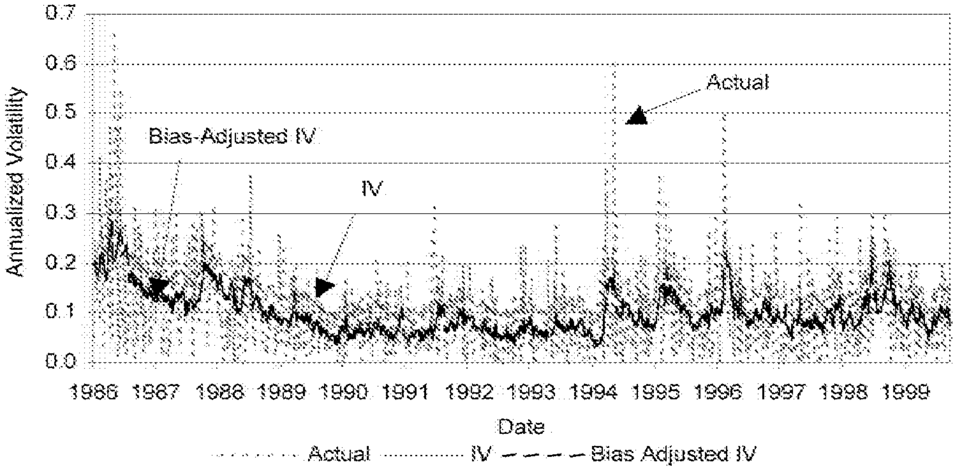

Figure 1 Live cattle volatility (Jan. 1986 to Nov. 1999).

risk manager. A consistent overestimation of volatility may lead to a misallocation of risk dollars within a firm. Given the maintained hypothesis, that the analysis is a joint test of the Black model, the methodology, and the market's ability to forecast volatility, it is not possible to isolate the exact source of this bias.

To put the bias in perspective, however, we estimate the average option premium using sample averages as Black model inputs along with the implied and actual volatility. A 90-day at-the-money call option would be priced at \$1.89 and \$1.27 per hundredweight using the average implied and actual volatility, respectively. Thus, an option writer received an average premium of \$0.62 per hundredweight over the sample period. This premium may partially reflect the transaction costs and returns earned by floor traders for providing market-making services. Or, as mentioned previously, it may reflect the aggregate violations of the Black model's assumptions. Regardless, this example illustrates the potential cost of overestimating volatility. Risk managers who use IV to forecast 1-week volatility should be aware of this bias and adjust their forecasts accordingly.[7]

3.2 Tests for Forecast Efficiency

Nordhaus shows that forecasts are weakly efficient if forecast errors (e_t) are orthogonal to all past information and past forecast errors. Thus, forecast efficiency (weak form) is tested using the following OLS regression framework:

$$e_t = \alpha_1 + \beta\hat{\sigma}_t + v_t \tag{8}$$

[7]This test for bias, as well as the subsequent efficiency, encompassing, and time improvement tests, are also estimated with a set of dummy variables (either intercept or slope shifting dummies where appropriate) representing the option contract months used when the implied volatility forecasts are made (February, April, June, August, or October). This was done to determine if the results of these tests are sensitive to any specific option contract month or months. In each case, a standard F-test failed to reject the null that the parameter estimates were zero at the 5% level (results not shown). So, there is no indication that the findings differ among contract months.

and

$$e_t = \alpha_2 + \rho e_{t-1} + \upsilon_t. \tag{9}$$

From here forward, equation 8 will be referred to as the test for Beta efficiency and equation 9 as the test for Rho efficiency. Thus, the condition for weak efficiency is that $\beta = 0$ and $\rho = 0$ in equations 8 and 9, respectively. Results of both the Beta and Rho efficiency tests are shown in Table 3. The statistically significant β for implied volatility suggests that IV is not an efficient forecast; therefore, it is not a minimum variance forecast. That is, IV does not efficiently incorporate all information regarding future volatility. Furthermore, the negative sign on β suggests that IV tends to produce forecasts that are too extreme such that large forecasts result in large errors. Given this, risk managers who use IV should scale down their forecast by $(1 + \beta)$, which translates into a scaling factor of 0.76936. For instance, if IV for one week hence is 0.25, then applying the scaling factor of 0.76936 would yield an adjusted forecast of 0.19234. The GARCH forecasts also show a propensity to be too extreme, requiring a scaling factor of 0.60711.

In the lower portion of Table 3, the results of the Rho efficiency test suggest that forecast errors for both IV and GARCH tend not to be repeated. That is, there is no time series pattern to the forecast errors. Thus, both GARCH and IV pass this condition for weak efficiency.

3.3 Test for Forecast Encompassing

Many academics perceive that implied volatility, being a market-based forecast, encompasses all information provided by alternative forecasts of volatility, namely time series forecasts like GARCH. In fact, much of the volatility forecasting literature focuses on testing the ability of implied volatility to encompass other forecasts (Figlewski, 1997). Forecast encompassing is tested using the following OLS regression framework (Harvey et al., 1998):

$$e_{1t} = \alpha_3 + \lambda(e_{1t} - e_{2t}) + \varepsilon_t \tag{10}$$

e_{1t} is the forecast error series of the preferred forecast (e.g., IV) and e_{2t} is the forecast error series of the competing forecast (e.g., GARCH). The null hypothesis of $\lambda = 0$ sug-

TABLE 3. Tests for Forecast Efficiency (Jan. 1986 to Nov. 1999)

	Implied volatility	GARCH(1,1)
$e_t = \alpha_1 + \beta\hat{\sigma}_t + \upsilon_t$		
Estimated β	−0.23064*	−0.39289*
(t-statistic)	(−2.126)[a]	(−3.379)[a]
$e_t = \alpha_2 + \rho e_{t-1} + \upsilon_t$		
Estimated ρ	−0.04398	−0.02309
(t-statistic)	(−1.186)	(−0.6222)

[a]White's covariance estimator.
*Significant at the 5% level (two-tailed t-test).

gests that the covariance between the preferred forecast error series (e_{1t}) and the difference between the preferred and competing series ($e_{1t} - e_{2t}$) is zero. If there is a failure to reject the null hypothesis, then the preferred forecast is said to encompass the competing forecast. In essence, the competing forecast contains no useful information beyond the preferred, and a composite forecast cannot be built that would yield a smaller squared error than the preferred forecast. In equation 10, the λ is the weight assigned to the competing model in forming an optimal composite forecast (Harvey et al., 1998). Estimation results are presented in Table 4 using both IV and GARCH as the preferred forecast.

The results indicate that IV does encompass all information provided by the GARCH forecasts. The estimated λ (−0.15827) is not statistically different from zero (5% level, two-tailed, t-test). Therefore, the weight assigned to the GARCH forecast in forming an optimal composite forecast is zero. This implies that the GARCH model provides no incremental information relative to IV in forecasting 1-week volatility. Reversing the preferred forecast to GARCH confirms these findings. In this case, the statistically significant λ (1.1583) suggests that a composite could be formed that would reduce squared error relative to the preferred forecast (GARCH). Note, in this case, the estimated λ is not statistically different from one, again indicating that the full weight in a composite forecast is allocated to the IV forecasts. These results are consistent with many other studies of implied volatility, that implied volatility encompasses information found in time series alternatives.

3.4 Test for Time Improvement

It is also of interest to know if the quality of forecasts are getting better or worse. It may be that the accuracy of IV as a forecast of market volatility has changed over time. This would not be surprising, given that options on futures were a relatively new phenomenon at the time of the live cattle options launch (circa 1986). Advances in computer technology, option pricing models, market liquidity, and statistical forecasting techniques may have improved the market's ability to forecast volatility.

We test for time improvement in IV as well as the competing GARCH forecasts by using a methodology similar to that of Bailey and Brorsen (1998). In this test, the absolute value of forecast errors are regressed against a time trend such that:

$$|e_t| = \theta_1 + \theta_2 Trend_t + v_t \tag{11}$$

and the null hypothesis is for no systematic improvement in the forecasts over time, $\theta_2 = 0$. Results presented in Table 5 show that there has been statistically significant improvement

TABLE 4. Test for Forecast Encompassing, $e_{1t} = \alpha_3 + \lambda(e_{1t} - e_{2t}) + \varepsilon_t$ (Jan. 1986 to Nov. 1999)

	Preferred forecast	
	Implied volatility	GARCH(1,1)
Estimated λ	−0.15827	1.15830*
(t-statistic)	(−0.8551)[a]	(6.257)[a]

[a]White's covariance estimator.
*Significant at the 5% level.

TABLE 5. Test for Time Improvement, $|\varepsilon_t| = \theta_1 + \theta_2 Trend_t + \upsilon_t$ (Jan. 1986 to Nov. 1999)

	Implied volatility	GARCH(1,1)
Estimated $\theta_2 \times 10^{10}$	−0.00277*	−0.00327*
(t-statistic)	(−2.452)[a]	(−2.756)[a]

[a]Newey-West covariance estimators.
*Significant at the 5% level.

in the ability of IV to forecast 1-week volatility over the sample period. The statistically significant negative coefficient illustrates that absolute forecast errors have systematically declined over time. Because the Black model is used consistently throughout, any biases and inefficiencies it creates are relatively constant through time. This would imply that the systematic reduction in absolute errors is possibly due to an improvement in the market's ability to forecast future volatility. Specifically, it suggests that the average implied volatility from nearby at-the-money puts and calls has improved as a forecast of 1-week volatility.

Interestingly, the GARCH forecast has also seen systematic improvement over time. This is potentially due to the addition of new data and the updating of the forecasting model's parameters after each week. However, the improvement of both IV and GARCH may also suggest that volatility has just become easier to forecast over time due to a systematic decrease in the underlying volatility. This possibility is tested by regressing weekly actual volatility against a time trend and testing if the slope coefficient is statistically different from zero. The results from this test (not presented) indicate that there has been a systematic decline in weekly live cattle futures price volatility over the sample period. While this may not fully explain the improved performance of the IV and GARCH forecasts documented in Table 5, it is certainly a plausible alternative explanation. In general, the above results indicate that the errors associated with IV- and GARCH-based volatility forecasts declined over the 1986–1999 interval. The improved performance may be a result of the market becoming a "better" forecaster with improved technology and methods. But, it is also consistent with an observed decline in the underlying market volatility over the sample period.

4. SUMMARY AND CONCLUSIONS

This research examines the performance of implied volatility from live cattle options contracts to forecast short-run volatility of live cattle futures. Specifically, we examine the ability of implied volatility, derived from the Black model for options on futures contracts, to forecast the nearby, 1-week volatility of live cattle futures prices. We approach this problem from a practical risk management perspective, that of a risk manager that uses live cattle futures prices to price beef inputs. Thus, our results are premised on the use of our defined procedure for estimating implied volatility in this framework (i.e., average of implied volatility from both puts and calls, of the nearby, at-the-money contract, using the Black model for options on futures prices) and make no attempts to address market efficiency issues. Ultimately, the true volatility implied through the options market is the result of diverse market opinions, and the aggregate of many pricing models used by traders in the live cattle options market. As well, the tests for forecast optimality used here (e.g., bias, efficiency, and forecast encompassing) are different from traditional tests used in the volatility forecasting literature as they focus on forecast errors, and thus are less prone to interpretive problems. In particular, the results of these tests provide information so that simple adjustments to implied volatility forecasts can be made by risk managers. Unlike many studies found in the volatility forecasting literature, we also avoid the overlapping data problem.

Similar to many studies that examine implied volatility in the finance literature (Figlewski, 1997), we find that implied volatility provides a biased and inefficient forecast, but encompasses the information of a time series alternative, GARCH (1,1). However, like implied volatility, GARCH is also found to be a biased and inefficient forecast of the 1-week volatility of live cattle futures prices. Our findings also show that the implied volatility forecasts, as defined in this study, have systematically improved over time (e.g., smaller absolute errors). Assuming any biases caused by filtering options prices through the Black model have remained constant over time, this suggests that the market has improved its ability to forecast short-run volatility or that other market frictions have declined over time. An alternative statistical explanation is that the decline in market volatility observed over the sample drives this result. It is important to remember that the results are dependent on the specific methodology employed in this research. Alternative forecast horizons, volatility measures, and option pricing models could generate different results. Nonetheless, the presented methodologies are commonly employed in the literature and practiced in industry, making the results widely applicable to a broad audience.

It is difficult, and unnecessary from a risk manager's perspective, to determine the causes of the bias and inefficiency found. However, it is important to stress how a risk manager can use the results to adjust implied volatility forecasts. For instance, our results suggest that the IV forecast is upward biased by 4.545% (Table 2) and too extreme by a factor of 0.23064 (Table 3). So, for example, an IV forecast of 25% (annualized) needs to be reduced by a constant 4.545% and scaled down by 5.766% (25×0.23064), resulting in a corrected forecast of 14.689%. Agribusiness firms need to know this adjustment to prevent an over- or under-commitment of capital based on various risk measurement procedures such as Value-at-Risk (Manfredo & Leuthold, 2001), which often form the foundation of company-wide risk management protocols advocated by the growing Enterprise Risk Management movement (Dickinson, 2001).

The results and methodology presented here are particularly important given the widespread use of implied volatility forecasts. As firms focus more on risk measurement and risk management (e.g., VaR and Enterprise Risk Management), risk managers need to embrace procedures for forecasting volatility of prices that are inexpensive, accurate, and meaningful from an information standpoint. This research suggests that implied volatility does indeed provide a low-cost forecast of live cattle futures price volatility that encompasses a time series forecasting approach, namely GARCH (1,1). However, it is important that the users of this approach understand that implied volatility is systematically biased and too extreme. Therefore, decision makers need to adjust the forecasts accordingly.

Options prices, futures prices, and short-term interest rate data are readily available, and the use of simple software (e.g., Financial CAD) to calculate implied volatilities is commonplace. Furthermore, many newswire and quote services (e.g., Bloomberg) now provide IV as part of their normal data feed. Thus, risk managers basically have a forward-looking, market-based forecast of future volatility at their fingertips. In many respects, using implied volatility is more efficient than using a time series model such as GARCH that requires large amounts of historical data to generate meaningful estimates, as well as expertise in estimating these models. This claim is even greater given the finding that the information from implied volatility from live cattle options is found to encompass the information provided by GARCH forecasts. Overall, a greater understanding of the performance of implied volatility to forecast 1-week volatility of live cattle futures prices allows risk managers using these forecasts to make more informed decisions about the variability of input costs, cash flow risks, and capital allocation. In particular, suggestions on how to adjust the implied volatility forecasts will prevent decision makers from systematically overestimating the volatility of nearby live cattle futures.

Future research might look for corroborating evidence of bias and inefficiency in other livestock or agricultural futures and options markets. Or, the out-of-sample forecasting performance of implied volatility, once corrections for bias and inefficiency are made, can be evaluated. Figlewski (1997) suggests that such corrections might not produce more accurate volatility forecasts since the biases themselves might vary over time. Given this statement, as well as the preponderance of evidence in the volatility forecasting literature, it is clear that volatility forecasting, in whatever framework examined, continues to be a daunting task.

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