The Information Content of Implied Volatility from Options on Agricultural Futures Contracts

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Abstract

Agricultural risk managers need forecasts of price volatility that are accurate and meaningful. This is especially true given the greater emphasis on firm level risk measurement and management (e.g., Value-at-Risk and Enterprise Risk Management). Implied volatility is known to provide a readily available, market based forecast of volatility. Because of this, it is often considered to be the "best" available (e.g., optimal) volatility forecast. However, many studies have provided evidence contrary to this claim for many markets (Figlewski). This research examines the forecasting performance of implied volatility derived from the Black-1976 option pricing model in predicting 1-week volatility of nearby live cattle futures prices. Unlike many studies of implied volatility, this research takes a practical approach to evaluating implied volatility, namely from the perspective of an agribusiness risk manager who uses implied volatility in risk management applications, and thus needs to understand its forecasting performance. This research also uses a methodology that avoids overlapping forecast horizons. As well, the methodology focuses on forecast errors that can reduce interpretive issues that can arise from traditional forecast evaluation procedures. Results suggest that implied volatility derived from nearby options contracts on live cattle futures is a biased and inefficient forecast of 1-week nearby futures price volatility, but encompasses all information provided by a time series forecast (i.e., GARCH). As well, our results suggest that implied volatility has improved as a forecast of 1-week volatility over time. These results provide practical information to risk managers on the bias, efficiency, and information content of implied volatility from live cattle options markets, and provide practical suggestions on how to adjust the bias and inefficiency that is found in this forecasting framework.

Introduction

Agribusiness risk managers need reliable and meaningful forecasts of volatility for agricultural commodity prices. This is particularly true given the use of risk management systems that are built around risk measures such as Value-at-Risk. As well, in many agribusiness firms, cash prices are often negotiated relative to nearby futures prices. For instance, a purchasing and/or risk manager might price beef purchases using a cost-plus formula relative to nearby live cattle futures contracts. Thus, the volatility of this beef purchase is directly linked to the volatility of nearby live cattle futures prices. A purchasing or risk manager needs an accurate and meaningful measure for volatility of live cattle futures in order to make informed risk management decisions (e.g., hedging strategies) as well as develop firm or department wide risk measures (e.g., VaR measures).

While various forecasts of volatility can be developed, implied volatility of live cattle futures prices are readily available given observed options prices, underlying futures prices, short-term interest rates, and knowledge of an assumed options pricing model (e.g., Black's option pricing model for options on futures contracts). Furthermore, there is a general belief by both academics and practitioners alike that implied volatility is the most appropriate forecast for volatility since it is a market based forecast, thus theoretically impounding all information that could be provided by alternative forecasts such as historical volatility and GARCH (Figlewski). However, several studies, in particular studies examining the forecasting performance of implied volatility for financial markets, like the S&P 100 options market, have found results contrary to this belief

(Figlewksi). 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; Canina and Figlewski). Several explanations have been given in the literature that may account for these findings, namely violations of Black Scholes option pricing assumptions, transactions costs, and other market frictions (Figlewski; Christensen and Prabhala; Poteshman). 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 a purchasing and/or risk manager that might use implied volatility in a practical risk measurement and management setting.

The objective of this study is to examine the forecasting performance of implied volatility derived from options on live cattle futures contracts in predicting short-run 1-week volatility of nearby live cattle futures prices. Unlike many studies presented in the finance literature, we approach the forecasting performance of implied volatility from a practical risk management perspective. We test for forecast optimality (i.e., bias and efficiency), information content, and also test to see if implied volatility has improved in its forecasting ability over time. In regards to bias and efficiency, if implied volatility is found to be biased, we use this information to illustrate how risk managers can make adjustments to their forecasts. Furthermore, if implied volatility is found not to encompass all information from a standard time-series alternative, then these results will suggest ways in which a composite forecast that considers both implied volatility and a time series forecast (Kroner, Kneafsey, and Claessens; Manfredo, Leuthold, and Irwin). Our methodology focuses on forecast errors and not the forecasts themselves, thus helping to alleviate interpretive problems with traditional rationality and encompassing tests used extensively in the volatility forecasting literature (Granger and Newbold). Furthermore, this study avoids the problem of overlapping forecast horizons by focusing on short-run, 1-week ahead forecasts only. This procedure ensures a large number of weekly forecasts and realized values over the sample period (1986 through 1999), providing for a thorough analysis of forecast performance and improvement over time.

Data Sources and Estimation of Implied and Realized Volatility

In calculating implied volatility, a time series alternative, and in defining realized volatility, both historical futures and options data are used. The source of Chicago Mercantile Exchange historical live cattle options data (settlement price) is 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. Given the following procedures described below, this provides for 728 non-overlapping observations of weekly (Wednesday) nearby, at-the-money implied volatility forecasts, realized volatility, and forecasts using a time series alternative.

Specifically, we focus on the forecasting ability of implied volatility from live cattle options to forecast the volatility of nearby live cattle prices expected over 1-week. In doing this, we estimate a weekly (Wednesday) series of both implied volatility and realized volatility. Implied volatility is estimated using 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 the Wednesday of each week in the sample period. Since live cattle options expire on the first

Friday of the contract month, and to avoid estimating implied volatility in the options delivery month, the nearby contract is defined to have at least 15 days (approximately 2 weeks) 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; Shastri and Tandon). 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 contract trading (Beckers; Mayhew). In addition, in creating this series of implied volatilities, we average the implied volatility from both nearby, at-the-money puts and calls, aiding in reducing estimation error (Jorion). More importantly than these theoretical and estimation issues, this method is consistent with how a risk manager is likely to use implied volatility to forecast 1-week volatility. That is, they would likely derive implied volatility from the at-the-money, nearby options contracts (either puts and calls) on the day that the forecast is made.

To assess the performance of implied volatility derived from live cattle options, a measure of realized 1-week volatility is needed. While the true realized volatility is not observable (Anderson and Bollerlsev), a proxy must be developed. The most common measure of realized volatility used in the volatility forecasting literature defines realized volatility as square root of the average of squared returns over a particular time horizon *h* such that:

$$ {}_{t}\sigma_{t+h} = \sqrt{\frac{1}{h}\sum_{j=1}^{h} R_{t+j}^{2}} \qquad (3) $$

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

$$ R_t = \ln(P_t) - \ln(P_{t-1}) \qquad (4) $$

where P_t and P_{t-1} are the futures prices observed in time period t and t-1 respectively.[1] Given that the realized variable of interest is 1-week volatility, equation 3 reduces to ${}_{t}\sigma_{t+1} = R_{t+1}$. Thus consistent with equations 3 and 4, 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 above. Careful attention is given to make sure that R_t in equation 4 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 options contract consistent with the forecast made in time period t. Since implied volatility theoretically represents the *annualized* average volatility expected over the life of the option contract, actual volatility as defined by equations 3 and 4 is annualized to be consistent with implied volatility

$$ {}_{t}\sigma_{t+1} = R_{t+1} * \sqrt{52}\ . \qquad (5) $$

[1] Consistent with the volatility forecasting literature, equation 3 assumes a zero mean (Figlewksi).

To compare the forecasting performance of implied volatility versus a time series alternative, a simple GARCH (1,1) model is estimated using the nearby futures return series presented above. The GARCH (1,1) is chosen as the alternative model since it is widely used to describe asset return series of both agricultural futures prices (Yang and Brorsen) and other financial asset prices (Bollerslev, Chou, and Kroner). 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 a GARCH forecast of 1-week volatility is made.[2]

Summary statistics, as well as common measures of forecast accuracy (mean square error, mean absolute error, and mean error) are presented in Table 1. Also, a plot of both IV and realized volatility is shown in Figure 1. The mean of both implied volatility (IV) and GARCH suggest that both are greater than the mean realized volatility. Furthermore, the standard deviation of the forecasts are almost half that of the realized volatility This may be the case because neither IV or GARCH do a good job at forecasting extreme returns that may occur in the tails of the return distribution, an important caveat for forecasters that are concerned with generating Value-at-Risk estimates. This is further emphasized given 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, it may be that the differences in forecast accuracy, as measured by MSE, MAE, and ME are not significantly different (Harvey, Leybourne, and Newbold; Manfredo, Leuthold, and Irwin). Most interesting of these summary performance measures, however, is the mean error (ME). The ME for both IV and GARCH are negative, with the ME being slightly larger (more negative) for IV. Based on ME alone, it appears that both IV and GARCH are biased forecasts of 1-week volatility on an annualized basis, but that question is best answered by formal tests for forecast optimality.

Forecast Optimality: Tests and Results

Our procedure focuses on the performance of implied volatility derived from nearby, at-the-money options on live cattle futures in forecasting 1-week volatility. Given the risk management perspective of this research, as well as the use of the Black options pricing model to derive implied volatility, the maintained hypothesis is that a risk manager using implied volatility to forecast 1-week volatility of live cattle futures prices uses the Black model to derive their forecasts.[3] 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 become joint tests of the live cattle options market's ability to forecast future

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[2] 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.

[3] 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).

volatility as well as the efficacy of the Black model. However, since 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, or both. Furthermore, results are contingent on the definition of realized volatility presented in equations 3 through 4. Again, it is important to remember the risk management framework presented throughout this paper – to gain a greater understanding of the forecasting performance of implied volatility in forecasting short-run volatility. If IV is found to be biased and/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 this.

Given the potential interpretative problems associated with traditional rationality and forecast encompassing tests, the following tests focus on the forecast error series as suggested by Granger and Newbold (p. 286), Holden and Peel, Nordhaus, and Harvey, Leybourne, and Newbold (1998). All tests are conducted for both implied volatility as well as the GARCH (1,1) alternative.

Test for Forecast Bias

A test for forecast bias is conducted consistent with that of Pons. This test uses the following OLS regression:

$$e_t = \left({}_t\sigma_{t+1} - {}_t\hat{\sigma}_{t+1}\right) = \gamma_1 + \mu_t \tag{6}$$

where e_t is the error produced by the difference between realized volatility (${}_t\sigma_{t+1}$) and the volatility forecast (${}_t\hat{\sigma}_{t+1}$). The null hypothesis (Ho) is that of an unbiased forecasts ($\gamma_1 = 0$). Given the definition of forecast errors (e_t) in equation 6, the alternative hypothesis (Ha) of ($\gamma_1 < 0$) suggests that forecasts systematically over estimate the realized volatility and ($\gamma_1 > 0$) suggest that forecasts systematically underestimate realized volatility. Results presented in Table 2 show that there is a significant (5% level) systematic bias of IV found over the sample period. This is consistent with the ME statistics shown earlier. Thus, on average over the sample period, IV has overestimated 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 – slightly less than IV. Given this result, risk managers using IV to forecast 1-week volatility could improve their forecasts by subtracting a constant ($\gamma_1 = -0.04545$) from their IV forecast.[4]

Given that IV is calculated from the nearby options contract at any given week, it may be possible that the bias illustrated was caused by IV being derived from a specific contract month. To test for this possibility, equation 6 was estimated with dummy variables representing the options contract month used when the implied volatility forecast was made (either February, April, June, August, or October). None of the coefficients on these dummy variables were statistically significant at either the 5% or 10% level, suggesting that the bias found was not influenced by the options contract month used. As well, given the maintained hypothesis that these tests are a joint test of the Black model and the market's ability to forecast volatility, it is difficult if not impossible to determine the

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[4] It is important to remember that since IV is a forecast of annualized volatility, and realized volatility takes weekly returns and annualizes them consistent with IV, that all results assume annualization. Thus, the suggested adjustments for bias must be made on IV in its original annualized state.

source of this bias. Despite this, risk managers who use IV to forecast 1-week volatility should be aware of this bias and adjust their forecasts accordingly.

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:

$$e_t = \alpha_1 + \beta_t \hat{\sigma}_{t+1} + \upsilon_t \qquad (7)$$

and

$$e_t = \alpha_2 + \rho e_{t-1} + \upsilon_t \quad . \qquad (8)$$

From here forward, equation 7 will be referred to as the test for Beta efficiency and equation 8 as the test for Rho efficiency. Thus the condition for weak efficiency is that $\beta = 0$ and $\rho = 0$ in equations 7 and 8 respectively. Results of both the Beta and Rho efficiency tests are shown in Table 3. The statistically significant β for implied volatility suggest that IV is not an efficient forecast of future 1-week volatility. IV is not a minimum variance forecast, thus, it is not efficiently incorporating all information regarding future volatility when the forecast is made. Furthermore the negative sign on β, suggests that IV tends to produce forecasts that are too extreme. Given this, risk managers who use IV should scale down their forecast by $(1+\beta)$, which translates into a scaling factor of 0.76936. Results of the Rho efficiency tests, however, suggest that forecast errors for both IV and GARCH tend not to be repeated, thus IV passes this condition for weak efficiency.

As with the bias test, dummy variables representing the contract month from which IV is taken are incorporated in both equations 7 and 8 in order to determine if efficiency is influenced by options contract month. Put another way, are there options contract months which more (less) efficiently incorporate information about future volatility? In doing this, both intercept shifters and slope shifters reflecting the various contract months are used. For the Beta efficiency test, no significant options contract month effect was found. However, for the Rho efficiency test, results show that forecast errors are likely to be repeated for some options contract months (Table 4). Both intercept and slope shifting dummy variables are significant for the February and October contract months. The coefficient (ρ) on the slope shifter for both February and October is negative, suggesting that overestimates of 1-week volatility are followed by underestimates. These findings are difficult to interpret, however, they could suggest that options traders tend to have a more difficult time incorporating information in their forecasts, and/or suggest that the market tends to over adjust their expectations, leading to systematic over and underestimates of actual volatility. It is important to note that this inefficiency is not found with the GARCH models, which inherently incorporate serial correlation.

Test for Forecast Encompassing

Given that implied volatility is a market based forecast, it is the perception of many academics that implied volatility 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. Forecast encompassing is tested using the following OLS regression framework:

$$e_{1t} = \alpha_3 + \lambda(e_{1t} - e_{2t}) + \varepsilon_t \qquad (9)$$

where 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 $\lambda=0$ suggests 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 forecast and a composite forecast can not be built that would yield a smaller squared error than the preferred forecast (Harvey, Leybourne, Newbold, 1998). In Table 5, results are presented using both IV and GARCH as the preferred forecast.

The results indicate that IV does encompass all information of the GARCH model. The statistically insignificant λ=-.1583 suggests that the GARCH model provides no incremental information relative to IV in forecasting 1-week volatility, and that a composite forecast could not be created that would reduce squared error. Reversing the preferred forecast to GARCH confirms these findings. In fact the statistically significant λ=1.1583 suggests that a composite could be formed that would see reduced squared error relative to the preferred forecast (GARCH). Similar to the bias and efficiency tests, both intercept and slope dummy variables were included for option contract months to determine if the encompassing relationship is different depending on the option contract month that IV is derived from, however, none of the dummy variables were found to be significant. Overall, these results are consistent with many other studies of implied volatility – that implied volatility encompasses information found in time series alternatives.

Test for Time Improvement

It may be the case that IV has gotten better or worse as a forecast of 1-week volatility over time. This would be expected, given that options trading was a relatively new phenomenon at the time of the live cattle options launch (circa 1986). Today, live cattle options are the most liquid traded options of the entire livestock complex (i.e., live cattle, feeder cattle, and lean hog options). Furthermore, computer technology as well as the understanding of Black Scholes pricing has likely improved the market's ability to forecast future volatility over time.

We test for time improvement in IV as well as the competing forecast GARCH using methodology similar to that used by Bailey and Brorsen and Sanders and Manfredo in testing for improvement over time in USDA meat production forecasts. In this test, the absolute value of forecast errors are regressed against a time trend such that:

$$|e_t| = \theta_1 + \theta_2 Trend_t + \upsilon_t \qquad (10)$$

and the null hypothesis of no systematic improvement in the forecasts over time is $\theta_2 = 0$. Results presented in Table 6 shows that there has been statistically significant improvement 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. Since the Black model is used consistently throughout, and that any biases and inefficiencies caused by the use of the Black model are constant through time, this systematic reduction in absolute errors is assumed to be due to an improvement in the market's ability to forecast future volatility. More appropriately, however, it suggests that the particular IV forecast generated here (average implied volatility from both puts and calls of the nearby, at-the-money option) has improved as a forecast of 1-week volatility over time. The GARCH forecast has also seen systematic improvement over time, but this is likely due to the addition of new data after each week passes and updating of the forecasts commensurate with this.

To complement the findings from the time improvement test presented in equation 10 above, a Chow test was performed breaking the data at the start of 1993. The null hypothesis of no change in parameter estimates between the two samples was rejected at the 5% level by the F-statistic generated by the Chow test. Furthermore, to identify the potential observation where instability of parameter estimates might have begun, the CUSUM recursive residuals test is also performed. Consistent with the results for the Chow test, the CUSUM test shows evidence of parameter instability occurring during the summer (July) of 1992. Interestingly, similar findings were found when the CUSUM test was conducted for GARCH, in fact, evidence of parameter instability was initially found during the latter months of 1992. Overall, these two tests for structural change in equation 10 provide greater evidence as to the possibility that IV has improved over time, however, it is difficult if not impossible to identify what factors have caused this improvement.

As with the bias, efficiency, and encompassing tests, both intercept and slope shifting dummy variables are included in equation 10 to determine if absolute errors have gotten systematically smaller or larger over time for particular option contract months. While the signs on the dummy variables and the size of the coefficients, in particular the slope shifting dummy variables, suggest that there is improvement (or worsening performance) in some contract months relative to others, none of the coefficients were significant at the 5% level. In fact, only the intercept shifter for August was found to be significant at the 10% level.

Summary and Conclusions

This research thoroughly 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 consistent with the definition of volatility commonly used in the volatility forecasting literature. Furthermore, we approach this problem from a practical risk management perspective – that of a risk or purchasing manager that uses live cattle futures prices to price their 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. As well, the tests for forecast optimality proposed (e.g., bias, efficiency, and forecast encompassing) are different than traditional tests used in the volatility forecasting literature as they focus on forecast errors and thus are less prone to interpretive problems. Unlike many studies found in the volatility forecasting literature, we avoid the overlapping data problem, and are also sensitive to the influence that the option contract month might have on the forecasting performance of implied volatility.

Similar to the bulk of the studies examining implied volatility in the finance literature (Figlewski), we find that implied volatility provides a biased and inefficient forecast, but encompasses the information of a time series alternative, GARCH (1,1). We also find that forecast errors tend to be repeated for certain option contract months, but this is not the case with GARCH which considers serial correlation in its forecast. 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). Given this, and assuming any biases caused by filtering options prices through the Black model have remained constant over time, suggest that the market has improved its ability to forecast short-run volatility, or that other market frictions (e.g., consideration of stochastic volatility, etc.) have reduced over time.

From the results of the forecast optimality tests, we make recommendations on how a risk manager might adjust for bias and inefficiency found in implied volatility. This is particularly important given the availability of implied volatility forecasts. As firms focus more on risk measurement and risk management throughout the firm (e.g., VaR; Enterprise Risk Management) risk managers need to embrace procedures for forecasting volatility of prices that are inexpensive, accurate, and meaningful from an information standpoint. 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 also commonplace. 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 made even greater given that implied volatility from live cattle options are found to encompass GARCH forecasts. Overall, a greater understanding of the forecasting performance of implied volatility to forecast 1-week volatility of live cattle futures prices will allow risk managers to make more informed decisions about their use of this forecast, as well as provide suggestions on how to adjust the forecast. Given this, future research might examine the out-of-sample performance of implied volatility once corrections are made. However, despite this insight on how to correct implied volatility from live cattle options prices, Figlewski suggest that such corrections still might not produce more accurate volatility forecasts since the biases themselves might vary over time. Given this statement, it is clear that volatility forecasting, in whatever framework examined, continues to be a daunting task.

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Table 1. Summary Statistics and Forecast Accuracy Measures (Jan. 1986 – 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			
N=728							

Note: MSE is mean squared error, MAE is mean absolute error, and ME is mean error

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

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

*Significant at the 5% level.

Table 3. Tests for Forecast Efficiency (Jan. 1986 – Nov. 1999)

	Implied Volatility	GARCH(1,1)
$e_t = \alpha_1 + \beta_t \hat{\sigma}_{t+1} + \upsilon_t$		
Estimated β	-0.23064	-0.39289
(t-statistic)	(-2.126)*#	(-3.379)*#
$e_t = \alpha_2 + \rho e_{t-1} + \upsilon_t$		
Estimated ρ	-0.04398	-0.02309
(t-statistic)	(-1.186)	(-0.6222)

*Significant at the 5% level.
#White's covariance estimator

Table 4. Test for Rho Efficiency with Intercept and Slope Shifters for Option Contract Month (Jan.1986 – Nov 1999)

Variable#	Coefficient	t-statistic
ρ	-0.05748	-1.1820
DV_G	0.05535	2.3180*
DV_J	0.03400	1.2660
DV_M	0.04324	1.5350
DV_Q	0.00216	0.0476
DV_V	0.06834	2.1020*
DV_G*e_{t-1}	-0.39981	-2.4020*
DV_J*e_{t-1}	-0.27514	-1.4530
DV_M*e_{t-1}	-0.29607	-1.4200
DV_Q*e_{t-1}	-0.02306	-0.0694
DV_V*e_{t-1}	-0.50174	-2.1800*
α_2 €	-0.04573	-7.4070*

*Significant at the 5% level.

G=February, J=April, M=June, Q=August, V=October, DV_i is dummy variable for option contract month i.

Table 5. Test for Forecast Encompassing, $e_{1t} = \alpha_3 + \lambda(e_{1t} - e_{2t}) + \varepsilon_t$, **(Jan. 1986 – Nov. 1999)**

	Preferred Forecast	
	Implied Volatility	GARCH(1,1)
Estimated λ	-0.15827	1.15830
(t-statistic)	(-0.8551) #	(6.257)*#

*Significant at the 5% level.
#White's covariance estimator.

Table 6. Test for Time Improvement, $|e_t| = \theta_1 + \theta_2 Trend_t + \upsilon_t$, **(Jan. 1986 – Nov. 1999)**

	Implied Volatility	GARCH(1,1)
Estimated θ_2 [%]	-0.00277	-0.00327
(t-statistic)	(-2.452)*[#]	(-2.756)*[#]

*Significant at the 5% level.

[#]Newey-West covariance estimators

[%] θ_2 * 100

Figure 1. Implied Volatility and Realized 1-Week Volatility (Jan. 1986 – Nov. 1999)