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Intermediate Volatility Forecasts Using Implied Forward Volatility: The Performance of Selected Agricultural Commodity Options

Thorsten M. Egelkraut and Philip Garcia

Options with different maturities can be used to generate an implied forward volatility, a volatility forecast for non-overlapping future time intervals. Using five commodities with varying characteristics, we find that the implied forward volatility dominates forecasts based on historical volatility information, but that the predictive accuracy is affected by the commodity's characteristics. Unbiased and efficient corn and soybeans market forecasts are attributable to the well-established volatility during crucial growing periods. For soybean meal, wheat, and hogs, volatility is less predictable and investors appear to demand a risk premium for bearing volatility risk.

Key words: agricultural commodity, efficiency, forecasts, implied forward volatility, options

Introduction

Options markets are markets in future volatility—each option implies a particular volatility forecast. This forecast, obtained from the observed premium by inverting a theoretical pricing model, is referred to as the implied volatility and is commonly interpreted as the expected average volatility until expiration. The implied volatility, however, is not the only information about future volatility contained in option premiums. The premiums also hold information about the implied forward volatility. The implied forward volatility is generated from two options with consecutive maturities, and represents the expected average volatility for the non-overlapping future time interval between their expiration dates. Figure 1 illustrates this concept for a pair of options maturing at T_1 and T_2, $T_1 < T_2$. At t_0, implied volatilities for two different intervals can be recovered: $\sigma_{IV(t_0,T_1)}$ and $\sigma_{IV(t_0,T_2)}$. In addition, the option premiums also contain the implied forward volatility, $\sigma_{IFV(T_1,T_2)}$, over the interval T_1 to T_2.

Options are generally considered to provide the most accurate predictions of future volatility because investors have the ability to incorporate all publicly available information into prices. A large empirical literature has examined this hypothesis for volatility forecasts over nearby time horizons using options with short maturities (for an overview,

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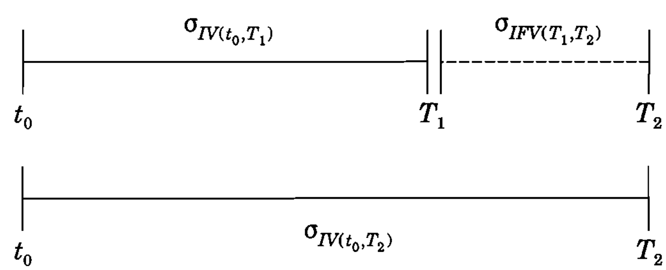

Figure 1. Conceptual model of the volatilities $\sigma_{IV(t_0,T_1)}$ and $\sigma_{IV(t_0,T_2)}$ implied by two options maturing at T_1 and T_2 and the implied forward volatility $\sigma_{IFV(T_1,T_2)}$ between these expiration dates (i.e., for the interval T_1 to T_2)

see Poon and Granger, 2003). In contrast, volatility forecasts for more distant horizons have received almost no attention. The lack of research is somewhat surprising since the relevant risk management horizons can vary by the nature of the firms' decisions. While a one-day trading horizon may be appropriate for many risk managers, significant components of industry exist that require intermediate and longer-term volatility estimates for effective hedging decisions. McNew (1996), Locke (1999), and Falloon (1999), for example, all argue that relevant risk management horizons extend beyond the daily market makers' framework, and can reach up to 12 months for corporate risk management systems and up to 10 years for pension funds. Clearly, there is no one relevant horizon for all decision makers. Christoffersen and Diebold (2000) reaffirm the notion that very short horizons may be appropriate for certain contexts while longer time frames are more suitable for others.

This paper evaluates the implied forward volatility as a forecast of subsequent realized volatility for intermediate future time intervals. Specifically, we investigate the predictive performance of implied forward volatility for several important agricultural commodities with different degrees of seasonality in price and production behavior. The choice of these commodities permits us to assess the forecast accuracy of the implied forward volatility in a more comprehensive manner, as the nature of production affecting these markets is known. Moreover, by focusing on just one sector/commodity type, we minimize the impact of external factors on the analysis.

The implied forward volatility constitutes an unconventional method to recover volatility forecasts for more distant time intervals from the options market. Our assessment extends previous research on predicting volatility in several important dimensions. First, the limited ability of the traditional time-series models to provide accurate volatility forecasts beyond the short term requires exploring alternative forecasting methods (Tomek, 1997; Christoffersen and Diebold, 2000; Poon and Granger, 2003). Second, the possibility of using the information contained in options with multiple maturities simultaneously to generate an implied forward volatility has been largely ignored. Yet, Egelkraut, Garcia, and Sherrick (forthcoming) report that the implied forward volatility performs well in predicting the volatility of corn futures prices over various time horizons. Finally, volatility forecasts are typically evaluated relative to their immediate historical volatility as an alternative forecast. For commodities, however, this approach may favor the options-based forecasts because it does not adequately account for the potential of commodity-specific patterns in the resolution of uncertainty. Therefore, we assess the predictive performance of the implied forward volatility against three alternative predictors of volatility: (*a*) a traditional historical volatility, (*b*) a volatility realized during the same time intervals in the three previous years, and (*c*) a composite forecast that incorporates both recent information and seasonal effects.

Review of Literature

The financial literature has proposed a wide range of statistical forecasting techniques to predict an asset's future volatility. Spurred by the introduction of ARCH and GARCH models (Engle, 1982; Bollerslev, 1986), the number of studies on the subject has exploded over the past decade. Most empirical studies, primarily in financial markets, tend to confirm that these models provide powerful predictions of short-term volatility (Anderson and Bollerslev, 1998; Poon and Granger, 2003). However, for long-term volatility predictions, ARCH and GARCH models are less appropriate, as their forecasts revert to the unconditional mean. For example, Day and Lewis (1993) report little explanatory power of GARCH and E-GARCH models in predicting long-term volatility of crude oil futures. Similarly, Holt and Moschini (1992) find that ARCH and GARCH models provide poor forecasts of long-term variances in real hog prices. For financial markets, Christoffersen and Diebold (2000) argue convincingly that if the forecast horizon extends beyond 10 to 20 days, ARCH- and GARCH-based volatility forecasts may be of little value.

Volatility forecasts based on options premiums take a different approach. In an efficient options market, the implied volatility is the best available volatility forecast because options premiums impound all information of past volatility as well as expectations about future volatility.[1] If the options-based volatility forecast is obtained using an options pricing model that is linear in volatility, and if there is no premium for bearing volatility risk, the implied volatility equals the expected average volatility until expiration (Hull and White, 1987). Under this assumption, the difference between two implied volatilities from options maturing in T_1 and T_2, $T_1 < T_2$, reflects the average volatility that market participants expect to prevail during the non-overlapping time interval T_1 to T_2 (figure 1). The expected average volatility for the non-overlapping time interval is the implied forward volatility. Since options trade with various maturities, implied forward volatilities can be obtained for various time horizons. Decomposing the expected average volatilities implied in options with different maturities therefore represents a novel approach for obtaining volatility forecasts for intermediate and distant time intervals, where ARCH- and GARCH-type models have displayed poor predictive power.

The forecasting performance of the implied forward volatility was examined by Gwilym and Buckle (1997) for one- and two-month maturity American options on the FTSE 100 index from June 1993 to September 1995. Comparing the implied forward volatility between the two expiration dates with the realized volatility, the implied forward volatility was found to consistently overstate realized volatility as evaluated by mean absolute and mean squared errors, and to forecast poorly.

[1] As reported by Poon and Granger (2003), the results from 44 out of 53 studies evaluated support the notion that market forecasts contain the most information.

Egelkraut, Garcia, and Sherrick (forthcoming) report contrasting results for the forward volatilities implied in corn futures options. Using a substantially larger data set, they examine the market's ability to predict the level of future volatility for intermediate time intervals and to forecast the direction and magnitude of future volatility changes for distant time intervals. Their results indicate that the implied forward volatility predicts future volatility well. For intermediate time intervals, the implied forward volatility provides unbiased forecasts and captures a larger portion of the systematic variability in the realized volatility than forecasts based on historical volatilities. The authors attribute the difference between the informational content of FTSE 100 index options and corn options to the characteristics of the underlying assets. In contrast to the FTSE 100 index, the volatility of corn futures prices displays strong annual seasonality which is reflected in the implied forward volatilities.

Methods

Implied Forward Volatility

An option's present value is its expected future payoff at maturity discounted at the risk-free rate. Hence, the current premiums of European call and put futures options, V_c and V_p, can be written as:

(1) $$V_c(x) = b(T) \int_0^{\infty} \max(0, F_T - x)\, dG(F_T)$$

and

(2) $$V_p(x) = b(T) \int_0^{\infty} \max(0, x - F_T)\, dG(F_T),$$

where $b(T)$ is the discount factor, x is the option's strike price, T is the time to expiration, F_T is the price of the underlying futures at maturity, and $G(F_T)$ is the risk-neutral valuation measure, i.e., the futures' cumulative distribution function. If $G(F_T)$ is lognormal, these relationships represent Black's (1976) standard formula for European futures options. Estimates of the implied volatility can then be obtained by inverting this pricing model and solving for the standard deviation.

At any moment, there are commonly several implied volatilities for a given maturity because options trade with different strike prices and as calls and puts. Multiple weighing schemes have been developed to attain a single best implied volatility from the various estimates, but differences in the resulting composite implied volatilities are small. Scott and Tucker (1989) argue that as long as greater weight is placed on at-the-money options, the choice of the weighting scheme is secondary. Because at-the-money options are approximately linear in volatility, and hence most sensitive to changes, all implied volatilities used in this study are obtained from options nearest to being at-the-money. Moreover, these options are the most actively traded, and therefore least impacted by noise resulting from wide bid-ask spreads and nonsynchronous trading. Possible measurement errors are further reduced by averaging the volatility estimates of the nearest-to-the-money call and put.

Black's (1976) model has been repeatedly questioned. In fact, the formula's underlying assumptions do not hold for most financial markets. Commodity futures, for example, may have return distributions that are not lognormal, and their associated options can typically be exercised any time before expiration rather than only at maturity. If the options are American type rather than European, Black's implied volatility is upward biased because it does not implicitly embed a premium for the right of early exercise in the options price. However, because this error is small for at-the-money options, the European pricing formula serves as a good approximation (Ramaswamy and Sundaresan, 1985; Barone-Adesi and Whaley, 1987).

There is also some empirical evidence that the distribution of the logarithmic futures returns is not normal but skewed and has leptokurtic tails. The thick-tailed and sometimes nonsymmetric return distribution is frequently attributed to be a result of a stochastic volatility process requiring a stochastic volatility model. Despite their less restrictive nature, stochastic volatility models reveal only small biases of Black's formula, which essentially disappear when at-the-money options are used (Hull and White, 1987; Heston, 1993; Heynen, Kemna, and Vorst, 1994). On the whole, the bias introduced by Black's formula has been shown to be at most marginal for at- or near-the-money options. When used appropriately, the model provides reasonably accurate estimates of the implied volatilities.

Denoting $\sigma_{IV(t_0,T_1)}$ and $\sigma_{IV(t_0,T_2)}$ as the implied volatility estimates expressed in annual terms for the time intervals t_0 and T_1 and t_0 to T_2, and denoting $D_{(t_0,T_1)}$ and $D_{(t_0,T_2)}$ as the number of trading days between t_0 and T_1 as well as between t_0 and T_2, the implied forward volatility (IFV) between the two expiration dates is defined as:

$$(3)\qquad \sigma_{IFV(T_1,T_2)} = \sqrt{\frac{D_{(t_0,T_2)} \times \sigma^2_{IV(t_0,T_2)} - D_{(t_0,T_1)} \times \sigma^2_{IV(t_0,T_1)}}{D_{(T_1,T_2)}}}, \quad T_2 > T_1,$$

where $D_{(T_1,T_2)}$ refers to the number of trading days between T_1 and T_2. The implied forward volatility $\sigma_{IFV(T_1,T_2)}$ represents the market's expectation of the average volatility that will prevail during this future interval (figure 1).

This ex ante volatility forecast can be compared to the ex post return volatility for the corresponding interval. The realized volatility is based on the futures contract, F, underlying the call and put with the longer time to maturity, and is calculated on daily log returns around an assumed mean of zero. Two reasons warrant this approach. First, in an efficient futures market, no arbitrage requires that the mean return from holding futures contracts is zero. Second, as Figlewski (1997) cautions, when dealing with sample periods containing relatively few observations (as is the case in this study), noisy price movements can result in deviations from the true mean and make its estimate very inaccurate. Expressed in annual terms, the realized volatility during the interval T_1 and T_2 is obtained as:

$$(4)\qquad \sigma_{REAL(T_1,T_2)} = \sqrt{\frac{\sum_{t=1}^{D_{(T_1,T_2)}} \left(\ln(F_t) - \ln(F_{t-1})\right)^2}{D_{(T_1,T_2)}} \times 252}\ .$$

Alternative Volatility Forecasts

The predictive performance of the implied forward volatility is evaluated with respect to alternative predictors of future volatility in order to assess whether market participants incorporate new information into their volatility forecasts. Three alternative forecasts are considered:[2]

- An immediate historical volatility (IHV) defined as the realized volatility during the period immediately preceding the date of the forecast, where the period is equal to the length of the forecasted interval (e.g., Szakmary et al., 2003);
- A historical three-year moving average of realized volatility (identified here as moving average historical volatility, MAHV) for the same period as the forward interval; and
- A composite historical volatility (CHV) defined as a rolling out-of-sample forecast generated by regressing realized volatility on a historical three-year moving average of the realized volatilities for the same period as the forward interval and the realized volatility for the period immediately preceding the forecast date, where the period is equal to the length of the forecasted interval.[3]

The immediate historical volatility is the conventional alternative forecast used in most research. Despite its popularity, this approach is not always the most appropriate. When volatility contains seasonal components, as is the case for many agricultural commodities, the immediate historical volatility may provide poor predictions of subsequent realized volatility. To remedy this situation, we offer two additional forecast alternatives: a three-year moving average historical volatility, and a composite forecast that combines the immediate historical volatility and the three-year moving average historical volatility. A three-year average is chosen because it has been shown to be an effective forecast horizon for agricultural commodities (Behrman, 1968; Garcia and Sanders, 1996) as it reduces the impact of nonsystematic deviations and yet remains rather flexible in adjusting to structural changes in the underlying commodity market.

Forecast Evaluation

To characterize the series and provide a structure for interpreting the statistical findings, the realized and forecasted volatilities are examined for seasonality in a framework that permits nonstationary. Seasonal deterministic effects in volatility are incorporated in equation (5) (Enders, 2004, p. 196):

$$\Delta\sigma_{i,t} = \alpha_{i,0} + \sum_{j=1}^{n_i-1} \alpha_{i,j} D_{i,j} + \gamma_i \sigma_{i,t-1} + \sum_{k=2}^{p_i} \beta_{i,k} \Delta\sigma_{i,t-k+1} + \varepsilon_t . \tag{5}$$

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[2] ARCH and GARCH models were estimated in the analysis using high (daily) and low (monthly) frequency data. These models have been found to be successful predictors of short-term volatility when estimated using high frequency (e.g., daily) data, but to have little if any predictive power one month or more into the future, as the forecasts revert to the unconditional mean. Averaging data over longer time periods or sampling at lower frequency (e.g., monthly) reduces the number of observations and ARCH effect dramatically, making estimation problematic and forecasts unreliable. Our findings confirm these concerns and support Day and Lewis (1993), Holt and Moschini (1992), and Christoffersen and Diebold (2000) who report difficulties in forecasting long-term volatility with these models.

[3] We also considered a one-year lagged historical volatility as an alternative forecast, but because the results do not improve on those reported here, they are not presented.

Here, $\sigma_{i,t}$ is the realized or forecasted (IFV, IHV, MAHV, CHV) volatility for the series i for each commodity in period t; n_i is the number of forward intervals per year; $D_{i,j}$ are centered seasonal dummy variables; and the lag length p_i is determined by minimizing the Schwarz Bayesian Criterion (SBC) (Enders, 2004, p. 196). Deterministic seasonality was selected to characterize the data rather than the framework proposed by Hylleberg et al. (1990) because of the limited number of observations in each interval and the low power of stochastic seasonality tests. While nonstationarity tests also have limited power due to the small number of observations, we investigate the unit-root hypothesis. Using the critical values reported by Fuller (1976), the unit-root hypothesis ($\gamma_i = 0$) is rejected when the t-statistic is significant.

Consistent with the literature (e.g., Christensen and Prabhala, 1998; Szakmary et al., 2003), the predictive ability of the implied forward volatility is assessed using three criteria: (*a*) forecast unbiasedness, (*b*) superior predictive power, and (*c*) informational efficiency relative to alternative forecasts. Each criterion is stated as a testable hypothesis and then explained.

- H_1: *The implied forward volatility is an unbiased forecast of future realized volatility.*

For each commodity, unbiasedness of the implied forward volatility is examined using the following:

$$\sigma_{REAL,t} = \alpha_0 + \alpha_{IFV}\sigma_{IFV,t} + \varepsilon_t, \tag{6}$$

where σ_{REAL} and σ_{IFV} are the annualized realized and implied forward volatilities for period t. A significant coefficient α_{IFV} indicates that the implied forward volatility contains information about future realized volatility, and a significant constant term α_0 indicates an average level of stochastic volatility which the market is unable to predict. An unbiased forecast is characterized by $\alpha_0 = 0$ and $\alpha_{IFV} = 1$, which can be tested using a standard F-test. Moreover, if the residuals ε_t are white noise and independent, the implied forward volatility is efficient.

- H_2: *The implied forward volatility has more predictive power than alternative forecasts of future realized volatility.*

For each commodity, the predictive power of the implied forward volatility relative to the alternative forecasts is evaluated by comparing the results from equation (6) to those obtained using

$$\sigma_{REAL,t} = \alpha_0 + \alpha_{AF}\sigma_{AF,t} + \varepsilon_t, \tag{7}$$

where σ_{AF} is the annualized alternative forecast volatility (IHV, MAHV, or CHV). Greater predictive power will be reflected in α_0 closer to zero, α_{IFV} closer to one, and a larger adjusted R^2 for the implied forward volatility in equation (6) than for the alternative forecasts in equation (7).

For each commodity, differences in accuracy of the volatility forecasts are also evaluated based on relative forecast errors using mean absolute percentage errors (MAPEs) and mean squared percentage errors (MSPEs):

(8) $$MAPE = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{\left(\sigma_{FORECAST,t} - \sigma_{REAL,t}\right)}{\sigma_{REAL,t}} \times 100\right|$$

and

(9) $$MSPE = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{\left(\sigma_{FORECAST,t} - \sigma_{REAL,t}\right)}{\sigma_{REAL,t}} \times 100\right)^2,$$

where $\sigma_{FORECAST}$ is the annualized volatility of a forecast (IFV, IHV, MAHV, or CHV), and where T, the total number of forward intervals, depends on the commodity examined. These error measures are then compared for different forecasts using the modified Diebold-Mariano (MDM) test proposed by Harvey, Leybourne, and Newbold (1997). The procedure involves specifying a cost-of-error function, $g(e)$, of the forecast errors e and testing pairwise the null hypothesis of equality of expected forecast performance. The test statistic, which Harvey, Leybourne, and Newbold indicate should be compared with the critical values from the Student's t distribution with $(T - 1)$ degrees of freedom, is computed for one-step-ahead forecasts as:

(10) $$MDM = \sqrt{\frac{T-1}{\frac{1}{T}\sum_{t=1}^{T}\left(d_t - \bar{d}\right)^2}}\;\bar{d},$$

where $d_t = g(e_{t,1}) - g(e_{t,2})$, $\bar{d}$ is the average difference across all years, and the null hypothesis is $E(d_t) = 0$. For example, when testing for significant differences of the MAPEs of two forecasts, $g(e_{t,1}) = |e_{t,1}|$ is the absolute percentage forecast error of method 1, $g(e_{t,2}) = |e_{t,2}|$ is the absolute percentage forecast error of method 2, and $d_t = |e_{t,1}| - |e_{t,2}|$ is the difference between the respective absolute percentage forecast errors at time t.

Harvey, Leybourne, and Newbold (1998) demonstrate that the size of the MDM test is insensitive to contemporaneous correlation between the forecast errors, and that its power declines only marginally with departures from normality. They argue that these characteristics are important since researchers attempting to differentiate between forecasts are often faced with correlated forecasts which possess occasional large errors. Other advantages of the MDM test include its applicability to multiple-step-ahead forecast horizons, its nonreliance on an assumption of forecast unbiasedness, and its applicability to cost-of-error functions other than the conventional quadratic loss. Harvey, Leybourne, and Newbold (1997) assert that the MDM test constitutes the "best available" method for determining the significance of observed differences in competing forecasts.

- H_3: *The implied forward volatility is informationally efficient, and no alternative forecast of future realized volatility contains additional information that is not already incorporated in the implied forward volatility.*

This hypothesis is assessed by including the implied forward volatility and a particular alternative forecast of future realized volatility in equation (11):

(11) $$\sigma_{REAL,t} = \alpha_0 + \alpha_{IFV}\sigma_{IFV,t} + \alpha_{AF}\sigma_{AF,t} + \varepsilon_t.$$

Informational efficiency requires that $\alpha_0 = 0$, $\alpha_{IFV} = 1$, and $\alpha_{AF} = 0$, which can be tested by a standard F-test, and that the residuals ε_t be independent and distributed as white noise. A nonsignificant coefficient α_{AF} means the information provided by the alternative forecast is already contained in the implied forward volatility. If the coefficient α_{AF} is significant, then the alternative forecast does provide additional information about future volatility not contained in the implied forward volatility. Since market participants can incorporate all publicly available information about past prices into their volatility forecasts, the latter case implies the options market is inefficient and signals potentially profitable arbitrage opportunities.

Data and Construction of Volatility Intervals

Daily closing prices of futures and standard futures options on five agricultural commodities—corn, soybeans, soybean meal, wheat, and hogs (all American exercise)—were obtained from the Chicago Board of Trade and the Chicago Mercantile Exchange. The futures data extend from November 8, 1978, to February 28, 2002, and the options data from January 2, 1992, to December 31, 2001, providing 10 complete years of options observations. Since the contract months traded are different for each commodity, the length and number of forward intervals that can be generated from the options first and second in maturity vary (table 1). The forward intervals are either one, two, or three months long, resulting in a total of 50 intervals for corn and wheat, 70 for soybeans and hogs, and 80 for soybean meal. For example, the October-December 2000 soybean forward interval extends over two months and is determined by the expiration of the NOV 2000 and JAN 2001 soybean futures options on October 20, 2000, and December 15, 2000. All intervals are essentially fixed across years because the futures options always mature at approximately the same point in time. The expiration dates vary only by a few days from year to year.

The data are first filtered to exclude uninformative options observations. Such observations include: (*a*) options that are listed but did not actually trade, i.e., zero volume observations; (*b*) options violating monotonic strike-price patterns; and (*c*) options with prices less than three times their minimum tick size. The first criterion is used because options prices with no associated trades are simply price quotes and not the result of a (negotiation) process in which market participants agree on their value and form a common volatility expectation. The second criterion removes options that are inconsistent with monotonic strike prices. Call premiums must decrease with increasing strike price, and put premiums must increase with increasing strike price. The third criterion avoids possible distortions of the implied volatility calculation introduced by the discrete nature of options prices.

All forward volatilities are derived from options that traded one month before the beginning of every interval, i.e., one month before the expiration of the options with the shorter maturity. For the previous October-December 2000 soybean forward interval example, the implied forward volatility is generated from the option prices observed on September 22, 2000. Because the forward intervals are one, two, or three months long, the approach assures non-overlapping observations.

The computation occurs in two steps. First, the volatility estimates for each of the two option maturities that enter equation (3) are computed as the arithmetic average of Black's (1976) implied volatilities for the nearest-to-the-money call and the nearest-to-

Table 1. Contracts, Forward Intervals, and Average Trading Volume of Near-to-the-Money (NTM) Calls and Puts, 1992–2001

			Number of Forward Intervals				Average Trading Volume of NTM Calls and Puts for All Forward Intervals	
Exchange	Commodity	Contract Months [a,b]	One-Month	Two-Month	Three-Month	Total	Start Date	End Date
CBOT	Corn	Z, H, K, N, U		30	20	50	677	467
	Soybeans	U, X, F, H, K, N, Q	20	50		70	803	335
	Soybean Meal	V, Z, F, H, K, N, Q, U	40	40		80	140	67
	Wheat	N, U, Z, H, K		30	20	50	328	179
CME	Hogs [c]	G, J, M, N, Q, V, Z [d]	20	50		70	21	15

[a] In addition to the standard contract months, a small number of serial options traded during the data period. These options were not included in the analysis because their irregular occurrence forbids the construction of independent alternative forecasts across years.

[b] Contract months are defined as follows: F = January, G = February, H = March, J = April, K = May, M = June, N = July, Q = August, U = September, V = October, X = November, and Z = December.

[c] The December 1996 contract was the last live hog futures traded, and the February 1997 contract was the first lean hog futures traded. This change in contract specification is of no consequence for this study because it focuses on volatility and not price levels.

[d] May options were introduced by the CME only in 2001. Since the data period ends before the first contract (May 2002) expires, these options are not part of the analysis.

Table 2. Mean Annual Realized Volatility, and Mean, Standard Deviation, Skewness, Kurtosis, Minimum, and Maximum of the Realized Volatilities for Forward Intervals, 1992–2001

		Interval Volatility						
Commodity	Annual Volatility Mean	Mean	Standard Deviation	Coefficient of Variation	Skewness	Kurtosis	Minimum	Maximum
Corn	18.628	19.238	6.431	0.33	0.782	0.503	8.561	36.883
Soybeans	18.135	19.111	7.253	0.38	1.421	3.164	7.725	48.603
Soybean Meal	19.493	19.837	7.282	0.37	1.104	2.581	8.401	48.737
Wheat	21.395	21.796	4.710	0.22	1.280	2.383	14.333	38.552
Hogs	21.627	21.470	7.944	0.37	2.308	7.226	11.417	56.803

the-money put. The three-month T-bill rate obtained from the Federal Reserve Board is used as the risk-free rate in all volatility calculations. On September 22, 2000, the NOV 2000 soybean futures closed at \$4.960, and the JAN 2001 soybean futures closed at \$5.065. The nearest-to-the-money NOV 2000 soybean call and put with a strike of 500 each closed at \$0.130 and \$0.170, and the nearest-to-the-money JAN 2001 call and put with a strike of 500 each closed at \$0.255 and \$0.190. The average annual implied volatility of the NOV 2000 call (= 26.763%) and put (= 26.797%) options is $\sigma_{IV(0,20)}$ = 26.780% with 20 trading days to expiration, and the average annual implied volatility of the JAN 2001 call (= 23.131%) and put (= 23.036%) options is $\sigma_{IV(0,59)}$ = 23.084% with 59 trading days to expiration. Next, the resulting volatility estimates are used to recover the implied forward volatility for the interval between the expiration dates of the two option pairs [equation (3)]. The implied forward volatility on September 22, 2000, for the above interval is $\sigma_{IFV(20,59)}$ = 20.937%. The volume of options used to obtain the implied forward intervals varies across commodities, with corn and soybeans being the most and hogs the least actively traded (table 1).

The realized volatilities for the corresponding time intervals, as well as the alternative volatility forecasts, are computed using equation (4). Futures prices from 1978–1992 are used to begin generating the three-year moving average forecast (MAHV) and the rolling composite forecast (CHV), which is based on a fixed sample size of 12 years to estimate the most recent parameters. Finally, all volatility measures are expressed in annual terms to allow for comparisons across intervals and years. Table 2 presents for all commodities the mean annual realized volatility and the summary statistics of the realized volatilities during all forward intervals contained in 1992–2001. Although the mean volatilities are comparable, significant differences in price behavior across commodities exist, as reflected by the variability in the higher-order moments.

Analysis and Results

Using equation (5), we examine the stationarity and seasonality of the volatility series. For brevity, only the findings for the realized volatilities are presented in tabular form (table 3) for each commodity, but the other results are discussed in the narrative.[4] We find that the realized volatilities and the implied forward volatilities are stationary for virtually all commodities except wheat, where both the realized and implied forward volatilities show modest and similar evidence of nonstationarity at the 10% level. The immediate historical volatilities are also all stationary, but evidence of nonstationarity appears for all the three-year moving average forecasts and for the corn and wheat composite forecasts. While the findings for the three-year moving average and the corn and wheat composite forecasts do not necessarily imply nonstationarity due to the small number of observations and the limited power of the tests, they are suggestive that the patterns in these forecasts are less likely to be consistent with the pattern of the realized and the implied forward volatilities. In terms of the seasonality, based on the magnitude of the coefficients (α_1–α_7) and the significance of the seasonal dummy variables in the realized volatility equations, the effects are most pronounced in corn, followed by soybeans, soybean meal, wheat, and hogs (table 3).

[4] The full set of results is available from the authors on request.

Table 3. Seasonality and Stationarity of the Realized Volatility, 1992–2001

	Seasonal Effects[a]									
Commodity	α_0 (p-Value)	Interval α_1 (p-Value)	Interval α_2 (p-Value)	Interval α_3 (p-Value)	Interval α_4 (p-Value)	Interval α_5 (p-Value)	Interval α_6 (p-Value)	Interval α_7 (p-Value)	γ[b]	Number of Lags[c]
Corn		Feb/Apr	Apr/Jun	Jun/Aug	Aug/Nov				-0.465	1
	0.092	0.061	0.105	0.147	0.011					
	(0.010)	(0.023)	(0.001)	(0.000)	(0.712)					
Soybeans		Feb/Apr	Apr/Jun	Jun/Jul	Jul/Aug	Aug/Oct	Oct/Dec		-0.676	0
	0.134	0.019	0.048	0.126	0.035	0.011	-0.008			
	(0.000)	(0.464)	(0.072)	(0.000)	(0.270)	(0.708)	(0.765)			
Soybean Meal		Feb/Apr	Apr/Jun	Jun/Jul	Jul/Aug	Aug/Sep	Sep/Nov	Nov/Dec	-0.567	0
	0.119	0.013	0.033	0.099	-0.029	0.024	-0.003	-0.024		
	(0.000)	(0.632)	(0.239)	(0.002)	(0.355)	(0.384)	(0.919)	(0.388)		
Wheat		Feb/Apr	Apr/Jun	Jun/Aug	Aug/Nov				-0.303*	3
	0.069	0.041	0.046	0.076	0.031					
	(0.116)	(0.048)	(0.043)	(0.001)	(0.150)					
Hogs		Feb/Apr	Apr/Jun	Jun/Jul	Jul/Aug	Aug/Oct	Oct/Dec		-0.338	0
	0.075	0.008	-0.003	0.033	-0.012	0.031	0.044			
	(0.002)	(0.784)	(0.912)	(0.271)	(0.674)	(0.300)	(0.140)			

[a] For each commodity, the regression results are obtained by estimating $\Delta\sigma_t = \alpha_0 + \sum_{j=1}^{n_i-1} \alpha_j D_j + \gamma\sigma_{t-1} + \sum_{k=2}^{p_i} \beta_k \Delta\sigma_{t-k+1} + \varepsilon_t$.

[b] The unit-root hypothesis is H_0: $\gamma = 0$. An asterisk indicates that nonstationarity is not rejected using the Dickey-Fuller τ_μ statistic at the 10% level.

[c] The optimal lag length is identified by minimizing the Schwarz Bayesian Criterion (SBC).

Table 4. Implied Forward Volatility's (IFV) Predictive Performance of the Realized Volatility, 1992–2001

	Regression[a,b]			F-Test	Errors[c]
Commodity	α_0 (p-Value)	α_1 (p-Value)	Adjusted R^2	$\alpha_0 = 0$ and $\alpha_1 = 1$ p-Value	MAPE MSPE
Corn	0.038 (0.092)	0.841 (0.000)	0.507	0.146	18.173 4.819
Soybeans	0.071 (0.031)	0.670 (0.002)	0.225	0.002	25.008 12.340
Soybean Meal	0.098 (0.001)	0.603 (0.001)	0.181	0.000	28.025 14.489
Wheat	0.131 (0.001)	0.468 (0.021)	0.088	0.000	16.802 4.480
Hogs	0.095 (0.001)	0.667 (0.001)	0.181	0.000	22.185 7.568

[a] For each commodity, the results are obtained by estimating $\sigma_{REAL,t} = \alpha_0 + \alpha_{IFV}\sigma_{IFV,t} + \varepsilon_t$.
[b] If needed, the estimates are adjusted for heteroskedasticity using the Newey-West procedure.
[c] MAPE and MSPE are the mean absolute and mean squared percentage errors.

The results from examining H_1–H_3 are reported in tables 4–7, and are discussed below.

■ H_1: *Informational Content and Unbiasedness of the Implied Forward Volatility*

The results from estimating equation (6) are displayed in table 4. All slope coefficients are positive and significant, indicating that the implied forward volatility contains information about future realized volatility for each commodity. The α_{IFV} estimates are smaller than one, ranging from 0.468 for wheat to 0.841 for corn. Moreover, the constant terms are significant for soybeans, soybean meal, wheat, and hogs, resulting in rejection of the joint hypothesis $\alpha_0 = 0$ and $\alpha_{IFV} = 1$. For those commodities, small values of the implied forward volatility tend to over-predict and large values tend to under-predict future realized volatility. In contrast, α_0 is not significant ($p = 0.092$) for corn, and the unbiasedness hypothesis cannot be rejected ($p = 0.146$). Further, in light of the absence of autocorrelation in the residuals, the corn market is efficient.

■ H_2: *Relative Predictive Power*

Corn, Soybeans, Soybean Meal, and Wheat. As expected, the immediate historical volatility does not capture the systematic volatility changes associated with crop production, and hence provides the least accurate predictions for corn, soybeans, soybean meal, and wheat. The small adjusted R^2s and nonsignificant α_{IHV} estimates in equation (7) reflect little informational content (table 5). Relative to the implied forward volatility (table 4), the immediate historical volatility possesses larger constant terms, smaller slope coefficients, and greater MAPEs and MSPEs, all indicating lower predictive power. Using the MDM test, the MAPEs and the MSPEs of each forecast are compared more formally. The error function $g(e)$ is specified as the absolute and the squared percentage forecast error, and tests for statistical significance in the differences of the MAPEs and

Table 5. Immediate Historical Volatility's (IHV) Predictive Performance of the Realized Volatility, and Test of Forecast Encompassing by the Implied Forward Volatility (IFV), 1992–2001

	Regression[a,b]				MDM[c]	Errors[d]
Commodity	α_0 (p-Value)	α_{IFV} (p-Value)	α_{IHV} (p-Value)	Adjusted R^2	MAPE p-Value MSPE p-Value	MAPE MSPE
Corn	0.167		0.143	-0.002	0.003	33.693
	(0.000)		(0.351)		0.000	21.766
	0.038	0.840	0.004	0.497		
	(0.175)	(0.000)	(0.970)			
Soybeans	0.205		-0.074	-0.011	0.001	36.913
	(0.000)		(0.604)		0.030	25.157
	0.105	0.791	-0.303	0.274		
	(0.003)	(0.000)	(0.025)			
Soybean Meal	0.159		0.193	0.038	0.009	38.299
	(0.000)		(0.057)		0.029	29.949
	0.094	0.577	0.039	0.172		
	(0.002)	(0.003)	(0.675)			
Wheat	0.193		0.128	-0.001	0.015	21.981
	(0.000)		(0.153)		0.005	6.966
	0.132	0.509	-0.048	0.071		
	(0.001)	(0.035)	(0.751)			
Hogs	0.105		0.613	0.185	0.135	24.614
	(0.005)		(0.009)		0.149	8.971
	0.079	0.385	0.369	0.207		
	(0.026)	(0.029)	(0.165)			

[a] For each commodity, the first regression results are obtained by estimating $\sigma_{REAL,t} = \alpha_0 + \alpha_{IHV}\sigma_{IHV,t} + \varepsilon_t$, and the second regression results are obtained by estimating $\sigma_{REAL,t} = \alpha_0 + \alpha_{IFV}\sigma_{IFV,t} + \alpha_{IHV}\sigma_{IHV,t} + \varepsilon_t$.
[b] If needed, the estimates are adjusted for heteroskedasticity using the Newey-West procedure.
[c] The modified Diebold-Mariano (MDM) statistic tests the significance in the differences of the mean absolute percentage errors (and the mean squared percentage errors) between the implied forward volatility and the immediate historical volatility (IHV). The null hypothesis is that the difference in the mean absolute percentage errors (and mean squared percentage errors) between the forecasts is zero.
[d] MAPE and MSPE are the mean absolute and mean squared percentage errors.

the MSPEs between the immediate historical volatility and the implied forward volatility. The p-values displayed in table 5 show that for both specifications of the error function, these differences are significant.

In contrast to the immediate historical volatility, the three-year moving average historical volatility and the composite forecast do incorporate the volatility patterns associated with crop production. As a result, they possess greater predictive power than the immediate historical volatility (tables 6 and 7). The composite forecast generally outperforms the three-year moving average historical volatility because it incorporates recent available information as well as seasonal effects. Despite this improvement in accuracy, the implied forward volatility continues to dominate the alternative forecasts for corn, soybeans, and soybean meal. The adjusted R^2s in equation (6) (table 4) remain larger and the MAPEs and MSPEs smaller than those reported for the three-year moving average historical volatility (table 6) and the composite forecast (table 7). Yet, the differences between the error measures become less significant when evaluated with the MDM test. For wheat, the implied forward volatility provides somewhat less

Table 6. Moving Average Historical Volatility's (MAHV) Predictive Performance of the Realized Volatility, and Test of Forecast Encompassing by the Implied Forward Volatility (IFV), 1992–2001

	Regression [a,b]				MDM [c]	Errors [d]
Commodity	α_0 (*p*-Value)	α_{IFV} (*p*-Value)	α_{MAHV} (*p*-Value)	Adjusted R^2	MAPE *p*-Value MSPE *p*-Value	MAPE MSPE
Corn	0.047		0.784	0.428	0.225	20.782
	(0.060)		(0.000)		0.065	6.218
	0.028	0.619	0.277	0.517		
	(0.295)	(0.000)	(0.125)			
Soybeans	0.087		0.544	0.171	0.325	27.495
	(0.010)		(0.005)		0.017	16.694
	0.062	0.519	0.186	0.223		
	(0.106)	(0.035)	(0.395)			
Soybean Meal	0.121		0.395	0.082	0.203	31.967
	(0.000)		(0.020)		0.001	22.928
	0.089	0.543	0.097	0.174		
	(0.011)	(0.006)	(0.602)			
Wheat	0.129		0.420	0.087	0.453	15.345
	(0.000)		(0.005)		0.449	3.875
	0.112	0.285	0.249	0.090		
	(0.009)	(0.280)	(0.296)			
Hogs	0.215		-0.003	-0.015	0.058	28.023
	(0.000)		(0.987)		0.040	14.284
	0.134	0.735	-0.250	0.189		
	(0.001)	(0.001)	(0.301)			

[a] For each commodity, the first regression results are obtained by estimating $\sigma_{REAL,t} = \alpha_0 + \alpha_{MAHV}\sigma_{MAHV,t} + \varepsilon_t$, and the second regression results are obtained by estimating $\sigma_{REAL,t} = \alpha_0 + \alpha_{IFV}\sigma_{IFV,t} + \alpha_{MAHV}\sigma_{MAHV,t} + \varepsilon_t$.
[b] If needed, the estimates are adjusted for heteroskedasticity using the Newey-West procedure.
[c] The modified Diebold-Mariano (MDM) statistic tests the significance in the differences of the mean absolute percentage errors (and the mean squared percentage errors) between the implied forward volatility and the three-year moving average of realized volatilities (MAHV). The null hypothesis is that the difference in the mean absolute percentage errors (and mean squared percentage errors) between the forecasts is zero.
[d] MAPE and MSPE are the mean absolute and mean squared percentage errors.

accurate predictions than the three-year moving average historical volatility (tables 6 and 4) and the composite forecast (tables 7 and 4), as indicated by comparable coefficient estimates and adjusted R^2s (adjusted $R^2_{IFV} = 0.088$ and adjusted $R^2_{CHV} = 0.088$) but greater error measures ($MAPE_{IFV} = 16.802 > MAPE_{CHV} = 13.915$; $MSPE_{IFV} = 4.480 > MSPE_{CHV} = 3.222$).

Hogs. The difference between the implied forward volatility and the immediate historical volatility is less pronounced in hogs (table 5). Both forecasts predict about equally well (adjusted $R^2_{IFV} = 0.181$ and $R^2_{IHV} = 0.185$). Though the implied forward volatility has a slightly larger slope coefficient and a smaller constant term than the immediate historical volatility as well as smaller forecast errors ($MAPE_{IFV} = 22.185 < MAPE_{IHV} = 24.614$; $MSPE_{IFV} = 7.568 < MSPE_{IHV} = 8.971$), the differences in these error measures are not significant ($p_{MAPE} = 0.135$ and $p_{MSPE} = 0.149$). Since hog production is largely weather independent,[5] systematic periods of greater and smaller volatility characteristic

[5] The shift away from traditional farm-based hog production began in the 1970s, and proceeded at a rapid pace. Today, almost all hogs are raised in confined operations with large, factory-like dimensions (Rhodes, 1995).

Table 7. Composite Historical Volatility's (CHV) Predictive Performance of the Realized Volatility, and Test of Forecast Encompassing by the Implied Forward Volatility (IFV), 1992–2001

	Regression[a,b]				MDM[c]	Errors[d]
Commodity	α_0 (p-Value)	α_{IFV} (p-Value)	α_{CHV} (p-Value)	Adjusted R^2	MAPE p-Value MSPE p-Value	MAPE MSPE
Corn	0.024		0.919	0.406	0.699	19.167
	(0.429)		(0.000)		0.007	6.515
	0.019	0.648	0.296	0.514		
	(0.525)	(0.000)	(0.179)			
Soybeans	0.094		0.513	0.107	0.496	26.576
	(0.031)		(0.034)		0.107	16.042
	0.076	0.724	-0.076	0.214		
	(0.080)	(0.006)	(0.791)			
Soybean Meal	0.102		0.488	0.108	0.754	28.896
	(0.005)		(0.010)		0.149	19.456
	0.085	0.515	0.136	0.176		
	(0.017)	(0.012)	(0.503)			
Wheat	0.119		0.479	0.088	0.053	13.915
	(0.007)		(0.021)		0.018	3.222
	0.114	0.262	0.265	0.081		
	(0.010)	(0.426)	(0.431)			
Hogs	0.104		0.575	0.080	0.667	23.013
	(0.002)		(0.004)		0.487	8.484
	0.088	0.631	0.070	0.170		
	(0.019)	(0.002)	(0.723)			

[a] For each commodity, the first regression results are obtained by estimating $\sigma_{REAL,t} = \alpha_0 + \alpha_{CHV}\sigma_{CHV,t} + \varepsilon_t$, and the second regression results are obtained by estimating $\sigma_{REAL,t} = \alpha_0 + \alpha_{IFV}\sigma_{IFV,t} + \alpha_{CHV}\sigma_{CHV,t} + \varepsilon_t$.
[b] If needed, the estimates are adjusted for heteroskedasticity using the Newey-West procedure.
[c] The modified Diebold-Mariano (MDM) statistic tests the significance in the differences of the mean absolute percentage errors (and the mean squared percentage errors) between the implied forward volatility and a composite forecast (CHV) based on IHV and MAHV. The null hypothesis is that the difference in the mean absolute percentage errors (and mean squared percentage errors) between the forecasts is zero.
[d] MAPE and MSPE are the mean absolute and mean squared percentage errors.

for corn, soybeans, soybean meal, and wheat are not present in hogs. As a result, neither the three-year moving average historical volatility nor the composite forecast possess more predictive ability than the immediate historical volatility or the implied forward volatility forecasts (tables 4–7).[6]

■ H_3: *Informational Efficiency Relative to Alternative Forecasts*

The informational efficiency of the implied forward volatility is also examined by incorporating the implied forward volatility and each of the alternative forecasts into one regression [equation (11)]. Similar to results under H_1, only the implied forward volatility from the corn options is found to provide evidence of informational efficiency (joint F-test for $\alpha_0 = 0$, $\alpha_{IFV} = 1$, $\alpha_{AF} = 0$; IHV $p = 0.283$, MAHV $p = 0.021$, and CHV $p = 0.029$; all other commodities and forecasts $p < 0.010$). With the exception of soybeans

[6] The quality of the hog forecasts may have also been affected by the limited trading volume in its options market.

($\alpha_{IHV} = -0.303$, $p = 0.025$), none of the slope coefficients for the alternative forecasts are significant. However, the lack of significant coefficients and negative sign may be symptomatic of the moderately higher degree of correlation between the IFV and some of the alternative forecasts (e.g., highest correlation—corn: $\rho_{IFV,MAHV} = 0.81$; soybeans: $\rho_{IFV,CHV} = 0.76$; soybean meal: $\rho_{IFV,CHV} = 0.67$; wheat: $\rho_{IFV,CHV} = 0.79$; and hogs: $\rho_{IFV,IHV} = 0.70$). The corresponding adjusted R^2s reported in tables 5–7 change only marginally relative to those from equation (6) in table 4, but provide modest evidence that the alternative forecasts do offer some additional information.

Further Analysis

To assess the robustness of the findings, we follow Christensen and Prabhala (1998) and employ an instrumental variable approach. The instrumental variable approach can be useful in the presence of measurement error in the implied forward volatilities which could result in biased coefficients and inappropriate statistical inference. Focusing on the best alternative forecast for each commodity and using lagged implied forward volatility and the respective alternative forecast as instruments, the instrumental variable results do not alter the basic character of our findings; our quantitative tests and qualitative conclusions from examining hypotheses H_1–H_3 remain. Only for soybeans does a change emerge. The unbiasedness hypothesis (using lagged implied forward volatility as the instrument), and the efficiency hypothesis can no longer be rejected ($p = 0.342$; $p = 0.366$), indicating the presence of some measurement error and supporting the efficiency of the soybean market.

Interpretation and Discussion of Differences

The varying degree of forecast accuracy across commodities reflects different levels of difficulty in correctly anticipating when and how much uncertainty will be resolved over time. The finance literature frequently models volatility as a stochastic process around a long-run mean (Heynen, Kemna, and Vorst, 1994; Poon and Granger, 2003). For commodities, however, the volatility process can contain seasonal components depending on the characteristics of the specific commodity. Seasonality in agricultural commodities has been previously reported by Roll (1984), Anderson (1985), and Kenyon et al. (1985). In our study, the realized volatility of corn displays strong seasonality as displayed in table 3 and depicted in figure 2, whereas for hogs such seasonality is virtually nonexistent. Within these two seasonal extremes, the strongest evidence of seasonal volatility exists in soybeans, followed by soybean meal and wheat (figures not presented).

The periods of higher and lower corn futures volatility follow the growing and non-growing cycle of the crop. This cycle is particularly pronounced in corn because the plants grow according to an internal clock and cannot generate new growth to compensate for stress during key growth periods. Intervals that contain these short, but critical, periods are therefore characterized by greater volatility than periods where weather has a less profound impact on crop development and future yields. Because the critical periods repeat annually, traders know the approximate times of higher risk and uncertainty, and subsequently incorporate the expected greater price volatility into the options premiums. Furthermore, the growing region for corn is geographically limited,

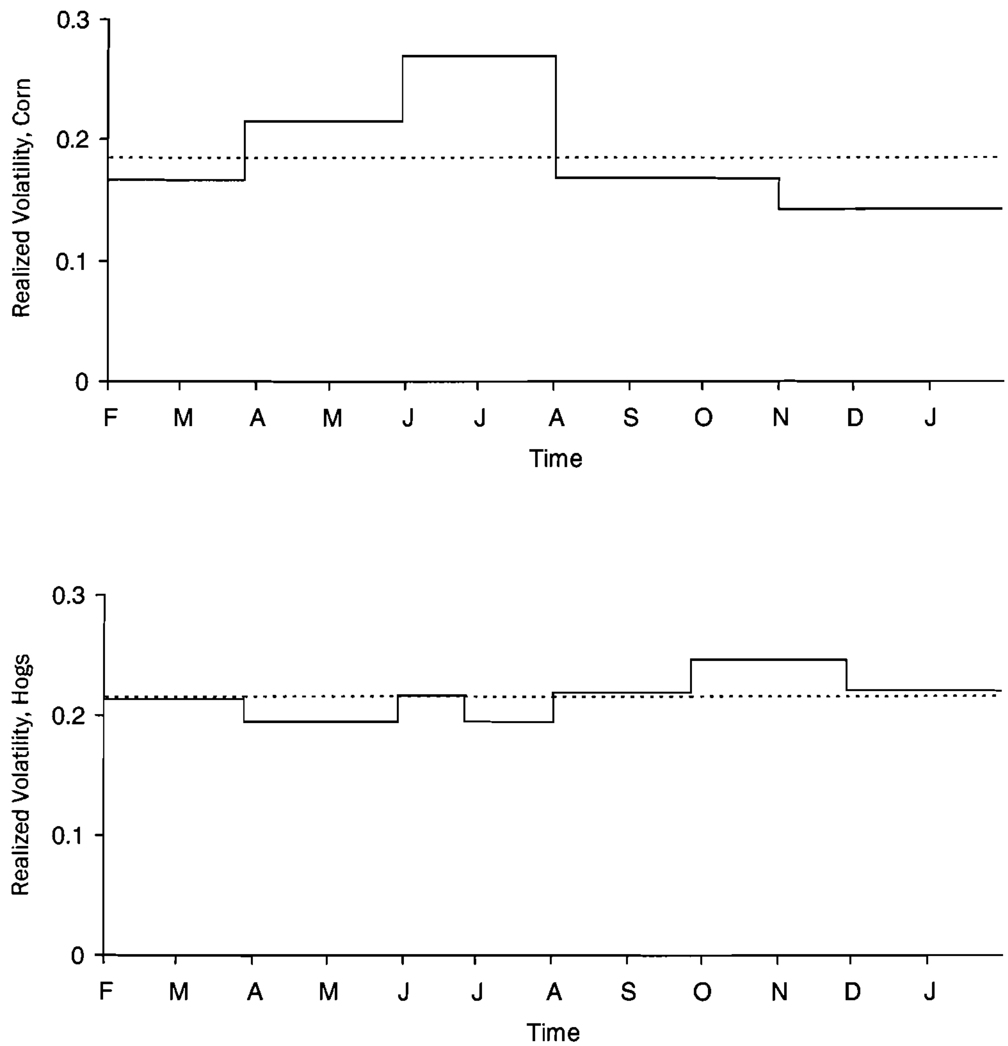

Figure 2. Average annual (dashed) and interval (solid) realized volatilities in the corn and hog futures markets, 1992–2001

making it less likely that adverse weather conditions in one area are compensated through favorable environmental factors in another. This combination of the crop's particular temporal and spatial characteristics leads to a concentration of uncertainty resolution over narrow time periods, resulting in more accurate volatility forecasts.

In contrast to corn, soybeans can make up for lost growth during stress periods and are also geographically less concentrated. Unfavorable growing conditions during a particular time or in a certain region therefore have a smaller impact on future yields. As a consequence, soybean price uncertainty is resolved over a wider time window, making it more difficult for market participants to anticipate intervals of greater volatility. The volatility of soybean meal follows that of soybeans but the pattern is even less pronounced, and thus more difficult to predict, because meal is only one of several products produced from soybeans and its volatility is impacted by additional supply and demand conditions.

Compared to corn and soybeans, wheat production extends over the largest area in North America. In addition to this spatial element, a temporal dimension exists—deliverable grades for the underlying futures contract include spring and winter wheat—that further reduces the weight of adverse environmental factors. Likewise, timing and geographic location have little influence on price volatility in hogs because production has largely moved toward confined operations (Rhodes, 1995). Moreover, the hog options market provides fewer volatility forecasts, as reflected in reduced trading volume (table 1)—a sign of lower informational content in the market. Because there is little or no concentration of uncertainty resolution, volatility is less predictable, and differences in the forecast accuracy between the implied forward volatility and the composite forecast and the immediate historical volatility for wheat and hogs become less pronounced. Hence, the results in tables 4–7 are rather consistent with the notion that the predictive performance of the implied forward volatility is influenced by the relative importance of the commodity's temporal and spatial characteristics which lead to different uncertainty resolution over time.

Summary and Conclusion

This paper has evaluated the implied forward volatility recovered from options with multiple maturities as a prediction of future realized volatility for intermediate time intervals that extend beyond the effective forecast horizon of traditional ARCH and GARCH models. Our results are therefore particularly important for decision makers in agricultural and financial industries who require intermediate and longer-term volatility estimates for effective hedging and pricing decisions. Using data for five agricultural commodities (corn, soybeans, soybean meal, wheat, and hogs), the implied forward volatility is derived for one-, two-, and three-month intervals. In addition, three alternative volatility forecasts are generated from futures prices: an immediate historical volatility, a three-year moving average historical volatility, and a composite forecast that incorporates both recent information and seasonal effects.

The results indicate that the corn and soybeans implied forward volatilities provide unbiased and reasonably efficient forecasts of subsequent realized volatility in futures prices. Soybean meal, wheat, and hogs provide information about realized volatility, but are biased such that small values of the implied forward volatility tend to over-predict and large values tend to under-predict future realized volatility. For corn, soybeans, soybean meal, and hogs, the options-based forecasts provide either equal or better predictions of future realized volatility than the best alternative forecast based on past volatility information. For wheat, the implied forward volatility dominates the immediate historical volatility; yet the evidence for the three-year moving average and the composite forecasts is mixed. Inclusion of historical information as alterative forecasts changes these findings only marginally, but gives modest evidence that the alternative forecasts do provide information. Finally, the relative accuracy of the implied forward volatility across commodities is influenced by the importance of each commodity's temporal and spatial characteristics, which affects uncertainty resolution over time. The implied forward volatility displays greater predictive power for commodities where the resolution of uncertainty is concentrated in narrow time periods and spatial production areas.

While market-based volatility forecasts appear to provide substantial information, the unbiasedness hypothesis is rejected for soybean meal, wheat, and hogs, and there is some evidence that alternative historical forecasts provide modest information. Biases have also been reported for the traditional implied volatilities of options on financial and nonfinancial assets (e.g., Jorion, 1995; Szakmary et al., 2003) as well as for the implied forward volatilities of FTSE 100 index options (Gwilym and Buckle, 1997). The unbiased nature of the corn and soybean market forecasts and their degree of relative efficiency may be attributable to the well-established volatility patterns in the realized futures prices. When volatility becomes less predictable, investors may demand a risk premium for bearing volatility risk, which could explain the findings in the soybean meal, wheat, and hog markets.

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