Determinants of Endogenous Price Risk in Corn and Wheat Futures Markets

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This analysis evaluates determinants of price variability in U.S. corn and wheat futures markets. The analysis is conducted in two segments. In the first segment, conditional heteroscedasticity models of price variability are estimated and used to examine the extent to which market conditions influence price variability. The second component of the analysis uses nonstructural vector autoregressive models to evaluate factors related to implied volatilities calculated from options premia. Our results indicate that corn and wheat price variability is significantly related to the ratio of use to stocks, futures market activity, and growing conditions. In addition, important seasonal and autoregressive effects are revealed. Our results provide an intuitive interpretation for GARCH and ARCH effects, which are often demonstrated for futures price data. © 2000 John Wiley & Sons, Inc. Jrl Fut Mark 20:753–774, 2000.

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INTRODUCTION

Comprehension of the factors affecting price variability for U.S. agricultural commodities is an issue of considerable importance to agricultural policy makers, producers, commodity traders, and researchers. Price variability is pertinent to markets in several dimensions. Interseason variability involves long-run price changes that occur from one year to the next. This variability is often influenced by policy changes as well as long-run movements in supply and demand variables. In contrast, intraseason variability pertains to price movements within the growing season. Prices typically fluctuate across the growing season as new information regarding expected production and demand variables reaches the market. Different factors are likely to be associated with intraseason and interseason variability.

This analysis focuses on the determinants of intraseason (weekly) price variability in U.S. corn and wheat futures markets. In addition to evaluating determinants of time-varying variances, we evaluate autoregressive relationships in price variance terms. Our work is distinguished from the large body of existing research on this topic in three ways. First, our analysis permits variance terms to vary on a weekly basis and estimates variance terms jointly with conditional means of prices. Second, our analysis is forward looking in its consideration of market factors and their effect on price variability. We use United States Department of Agriculture (USDA) forecasts of market variables and a measure of crop conditions during the growing season—an important indicator of expected yields and thus production in the future. Finally, our analysis considers the interpretation of the autoregressive effects typically shown in analyses of time-varying variances. In particular, conditional heteroscedasticity models imply that such autoregressive effects reflect autocorrelation in new information, such as growing conditions, which arrives to the market gradually (i.e., in an autocorrelated fashion).

Previous research as well as anecdotal evidence have demonstrated that price variability is time-varying. A simple examination of options data demonstrates this point. Figure 1 illustrates implied volatilities calculated from December corn and September wheat option contracts.[1] The implied volatilities display strong seasonality, each exhibiting higher levels of variation during the summer months. Increased levels of variability may reflect the uncertain weather conditions that have characterized the preceding year. Very large spikes in volatility are apparent in 1988, a period corresponding to widespread drought and crop losses.

[1]Implied volatilities are obtained by applying the standard Black-Scholes options pricing formula to observed options premia.

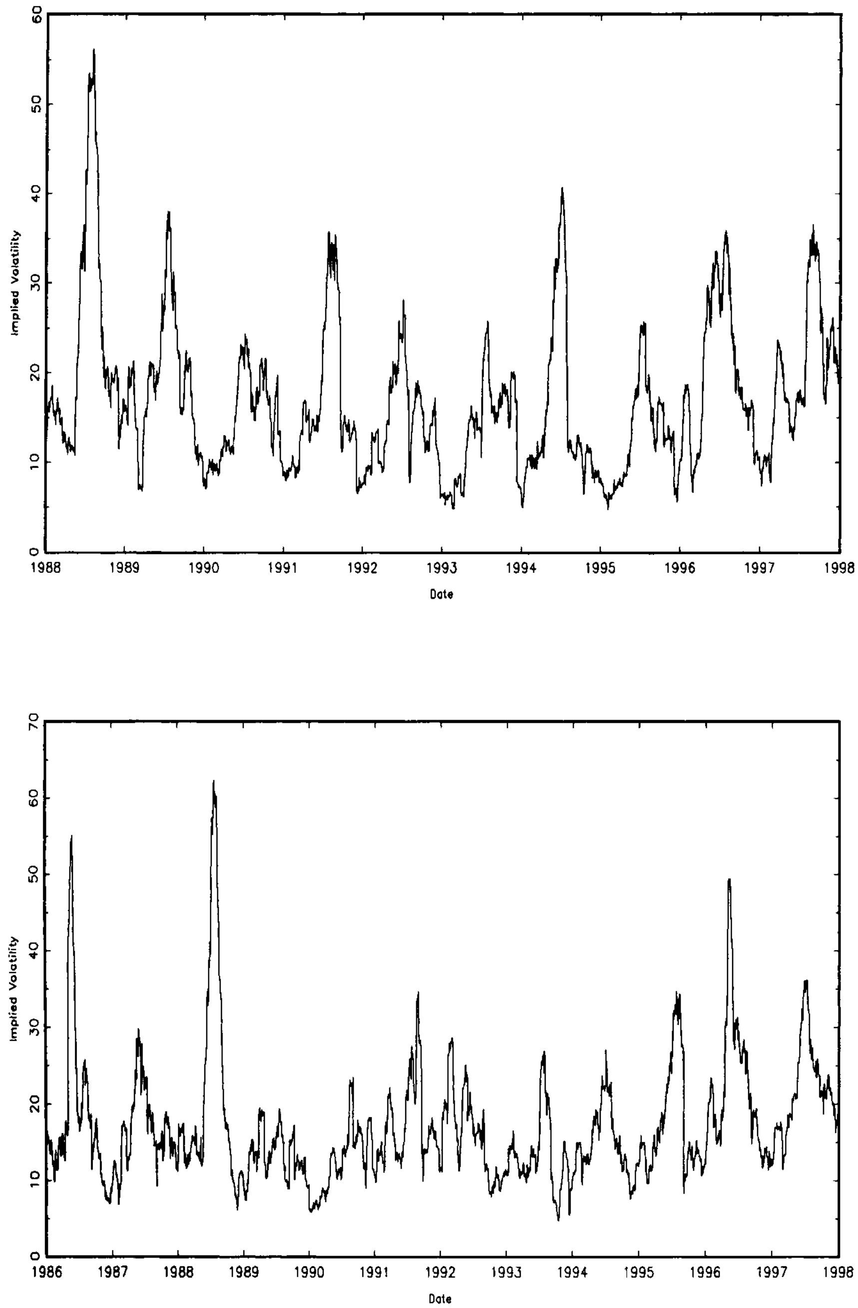

FIGURE 1
Implied volatility from (**A**) December corn options contract, and (**B**) September wheat options contract.

The objective of this article is to evaluate factors hypothesized to be conceptually relevant to the variability of prices, on the basis of empirical observation. Our empirical analysis investigates the variability of weekly corn and wheat futures prices. The empirical analysis proceeds in two distinct directions. The first uses conditional heteroscedasticity models to investigate deterministic factors related to futures price variability as well as autoregressive conditional heteroscedasticity (ARCH) and generalized autoregressive heteroscedasticity (GARCH) relationships. A second component of the analysis considers nonstructural dynamic models of observed option market volatilities. This discussion proceeds according to the following plan. The next section reviews recent literature that has evaluated determinants of price variability. The third section develops an econometric framework for evaluating determinants of price variability and discusses the empirical setting of our analysis. The fourth section presents the empirical results for conditional heteroscedasticity models of futures price variability. The fourth section also presents results of the nonstructural dynamic vector autoregressive (VAR) analysis of implied volatilities. The final section contains a brief review of the analysis and offers some concluding remarks.

PREVIOUS RESEARCH

An extensive literature has evaluated determinants of price variability for agricultural commodities. Many studies have been directed at an evaluation of the time to maturity or "Samuelson" effect. Samuelson (1965) argued that, because futures prices will incorporate more and more information as a contract nears expiration, the variability of futures prices should increase as time to maturity decreases. In light of the significant seasonality apparent in the variance of agricultural product prices (Fig. 1), it may be difficult, if not impossible, to distinguish time-to-maturity effects from patterns of seasonality when a single futures contract is examined.[2] In fact, Anderson (1985) found that the primary factor influencing the variability of futures prices is seasonality, especially in the case of grains.

Anderson and Danthine (1983) generalized the Samuelson hypothesis by noting that price variability is related to the distribution of underlying supply-and-demand "state" variables. As uncertainty regarding these variables is resolved, prices move to incorporate information, increasing the variability of prices. This state-variable hypothesis encom-

[2]Time to maturity is essentially a linear trend variable when used in a model for a single contract. Thus, linear seasonality patterns cannot be distinguished from time-to-maturity effects.

passes seasonality and the Samuelson hypothesis in that the resolution of uncertainty about state variables may itself be seasonal and may coincide with the maturity of a contract. Hennessy and Wahl (1996) found significant seasonality but could not confirm the significance of time-to-maturity effects. Streeter and Tomek (1992) found that time to maturity has a nonlinear effect on price variability, with price variability diminishing in the months immediately preceding contract expiration. This result is not entirely consistent with the Samuelson effect and may suggest that little new information is added during the period immediately preceding contract expiration.

A related line of research has investigated the extent to which variance is related to underlying supply and demand factors. This research evaluates the extent to which economic factors affect price variability. Kenyon et al. (1987) found that the stocks-to-use ratio had a negative, but not statistically significant, influence on grain price variability. Their research also found that the ratio of prices to loan rates had a significant positive influence on variability. Streeter and Tomek (1992) found that a variable representing total supply did not have a significant relationship with soybean price variability. Their research also implied that higher stocks had an unexpected positive influence on price variability. Likewise, these investigators found a correlation between increased disappearance and less variability. Considerable previous research has established that price levels are significantly related to variability (see, e.g., Glauber and Heifner, 1986; Kenyon et al., 1987; Streeter and Tomek, (1992). In particular, this work has confirmed that higher prices tend to be associated with higher levels of price variability. Streeter and Tomek (1992) argued that price levels may represent the effects of supply and demand factors and thus that it may be difficult to identify supply and demand effects on price variability when price levels are also included in the analysis.

Intraseason variability in prices is clearly dependent on growing conditions, which are influenced by weather and other stochastic elements. Hennessy and Wahl (1996) evaluated the effect of rainfall and temperature on price variability. Their results found that high temperatures together with low rainfall increase variability. Likewise, high temperatures and plentiful rains tend to decrease price variability.

A third avenue of research has evaluated a number of futures market "structure" variables. The activities of futures market traders may influence the realized variability of futures prices. Peck (1981) argued that speculative activity should be negatively related to price variability, since when speculation is high relative to hedging activity, hedgers have more liquidity.[3] A significant negative relationship between an index of speculative activity and soybean futures price variability was confirmed by Streeter and Tomek (1992). Scalping activity has also been hypothesized to be related to futures price variability. “Scalping” refers to traders entering and exiting the market often without having open positions at the end of the closing day.[4] A standard measure of scalping is the ratio of volume to open interest. In that scalpers add liquidity to a market, it is often argued that their activities should reduce bid-ask spreads and thus reduce price variability. Brorsen (1991) argued, however, that scalping may allow prices to adjust to information more quickly and thus increase price variability. Thus, the overall relationship between scalping activity and price variability is unclear. Significant positive relationships between scalping and price variability have been confirmed by Peck (1981) and Streeter and Tomek (1992). Finally, market concentration may have an effect on price variability. If the activities of large traders inhibit liquidity or result in large price adjustments, price volatility may increase, although the expected link between concentration and variability is unclear. Streeter and Tomek (1992) found that increased market concentration tended to increase volatility.

The existing literature has almost entirely used indirect measures of price variability rather than estimating variability together with movements in the means of prices. For example, Kenyon et al. (1987), Streeter and Tomek (1992), and Hennessy and Wahl (1996) use the variance of the change in daily log prices as a measure of volatility. A somewhat different approach to modeling price variance is taken in this analysis. Maximum likelihood estimation of conditional heteroscedasticity models with autoregressive variance terms are estimated using weekly data. This approach allows variability to vary from week to week, rather than assuming that variation is constant within a month. It is complemented by estimates of a nonstructural vector autoregressive model that uses option market based estimates of price variability.

ECONOMETRIC PROCEDURES AND EMPIRICAL FRAMEWORK

The empirical analysis of price variability is conducted in four steps, each using closely related though distinct econometric approaches. The basic model of price variability adopts a specification of the following form:

[3]It should be noted that structural conditions in futures markets are likely to be most relevant to analyses of high-frequency (tick, hourly, or daily) data.
[4]Such behavior is often referred to as “day trading.”

$$y_t = \alpha + X_t\beta + e_t \tag{1}$$

where

$$E(e_t^2) = \mathrm{Var}(e_t) = \sigma_t^2 = f(Z_t\gamma). \tag{2}$$

The second equation relates the variability of conditional prices to a set of explanatory factors represented by Z_t. In the basic conditional heteroscedasticity model, we use the following functional relationship for the variance expression:

$$\sigma_t^2 = \sigma^2 \exp(Z_t\gamma). \tag{3}$$

If Z_t contains a column of 1s, representing an intercept term, the intercept of the variance equation represents an estimate of exp (σ^2).[5]

An extensive literature has recognized that conditional variance terms often exhibit autocorrelation. In particular, periods of large variability tend to followed by periods of further large movements in prices. Fackler (1986) explains this phenomenon in terms of the "clumpy" nature of the arrival of new information, which tends to occur with greatest frequency during the summer growing months for agricultural commodities. A large class of ARCH and GARCH models have been developed. ARCH models were first introduced by Engle (1982) and were generalized and extended by Bollerslev (1986). Specification of an ARCH-type model is accomplished by amending eq. (2) to contain lagged squared error terms:

$$\mathrm{Var}(e_t) = \sigma_t^2 = \alpha_0 + \sum_{i=1}^{k} \alpha_i e_{t-i}^2 + Z_t\gamma \tag{4}$$

Bollerslev's (1986) generalization of the ARCH process includes lags of the variance terms:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{k} \alpha_i e_{t-i}^2 + \sum_{i=1}^{j} \delta_i \sigma_{t-i}^2 + Z_t\gamma \tag{5}$$

Estimation of the conditional heteroscedasticity models is usually accomplished by assuming a parametric distribution for the dependent variable, y_t, and maximizing the appropriate likelihood function using the sample of data. This approach is adopted in this case, where we define y_t to be the changes in the logs of weekly average futures prices. We assume that

[5]This model is discussed at length by Harvey (1976).

y_t is normally distributed with a variance of σ_t^2. This specification is standard and corresponds to the assumption that prices are log-normally distributed.

A second component of the empirical analysis involves the application of nonstructural vector-autoregressive models to market-based measures of price volatility. In particular, implied volatilities from options premia are used as a measure of price volatility. These are included in a four-equation VAR system. The autoregressive models are analogous to the ARCH and GARCH-type models, in that lagged volatility is an important determinant of volatilities. Orthogonalized impulse responses are generated from the estimated vector autoregressive models and used to interpret the dynamic linkages among variables hypothesized to be relevant to realized volatilities. Impulse responses represent the time path of adjustments to shocks to each of the variables included in the VAR system.

Our analysis will be applied to weekly averages of futures settlement prices observed between 1986 and 1997. Corn futures prices are taken for the December contract, while spring wheat futures prices are taken for the September contract.[6] Table I presents definitions and summary statistics for the variables considered in the empirical analysis. Chicago Board of Trade price, volume, and open interest data for corn were taken from the Bridge database of futures prices. Minneapolis spring wheat futures and options prices along with volume and open interest data were also taken from the Bridge database.[7]

One of the most important factors hypothesized to be related to the variability of agricultural prices pertains to weather and other growing conditions. Hennessy and Wahl (1996) confirmed that rainfall and temperature have important influences on the variability of agricultural commodity prices. During the growing season (i.e., from immediately after planting until harvest), the National Agricultural Statistics Service (NASS) releases a weekly report that describes the progress of crops in each state and on an (acreage-weighted) national basis. One of the measures given in this weekly report pertains to the proportion of the crop that falls into each of five condition categories: very poor, poor, fair, good, and excellent. An index of crop quality was constructed by taking a weighted average, using proportions in each category as weights, and assuming a simple numerical scale, where 1 = very poor, . . . , 5 = excel-

[6]These choices correspond to contracts currently being used in the measurement of price risk in the construction of revenue insurance contracts.

[7]We considered both spring and winter wheat prices. Results were similar, although we found that, because of the timing of the reports, our measure of growing conditions was more relevant to spring planted crops.

TABLE I

Variable Definitions and Summary Statistics

Variable	*Definition*	*Corn* *Mean*	*Corn* *SD*	*Wheat* *Mean*	*Wheat* *SD*
Return	$\ln(p_t/p_{t-1})$	0.0000	0.0348	0.0001	0.0296
Growing conditions	Growing condition index (deviations from mean)	0.0000	0.2159	−0.0057	0.2305
Use/stocks	WASDE forecasts of annual total use (domestic use plus exports) relative to ending total stocks	6.2012	5.0703	4.0252	1.7474
Speculation index	Ratio of speculation short positions to total hedging positions (if short hedge volume exceeds long hedge volume) or speculation long positions to total hedging positions (otherwise)	1.0543	0.0413	1.0116	0.0181
Volume/open interest	Total volume/open interest	0.0908	0.0463	0.1821	0.0906
Concentration	Percentage of short open interest held by four largest traders	16.0902	5.6266	38.4790	13.1657
Time to maturity	Days until contract expiration	197.3304	105.1892	185.6740	99.3498
Implied Volatility	Volatility implied from option contracts using Black-Scholes formula	16.6411	8.6216	14.9765	8.0864

WASDE, World Agricultural Supply and Demand Estimates; SD, standard deviation.

lent.[8] The growing conditions index was set at the value of the mean of the index (over the entire period of study) for those weeks of the year when the NASS assessments of growing conditions were not reported (i.e., the nongrowing portion of the crop year). Growing conditions were then represented by deviations from the mean value of the index, such that the growing condition variable had a value of zero during portions of the year when no information about crop progress was available and was positive (negative) when growing conditions were above (below) average levels. We also included a discrete indicator variable having the value of 1 during periods when NASS reports were unavailable. This variable was not statistically significant in any specification considered and was therefore omitted from the final model specification.

Weekly averages of the ratio of volume to open interest (for all contracts of each crop) were used to represent scalping and day trading. Unpublished commitments of traders data were obtained from the Commodity Futures Trading Commission (CFTC) and used to construct measures of market concentration (the percentage of short open interest held

[8]Such an index is admittedly ad hoc and is not invariant to monotonic transformations. The index was found to be superior to other modeling approaches considered.

by the four largest traders) and the speculation index. The speculation index was given by the ratio of speculative short positions to total hedges when the short hedge volume exceeded the long hedge volume and the ratio of speculative long positions to total hedges when the long hedge position exceeded the short hedge position. This measure of speculation was used by Streeter and Tomek (1992).

Most existing studies that have evaluated the effects of supply and demand factors on price volatility have used quarterly or monthly USDA estimates. A somewhat different measure of such variables is adopted in this analysis. The USDA provides monthly forecasts of stocks and supply and demand variables in its World Agricultural Supply and Demand Estimates (WASDE) report. These forecasts are typically provided for the current crop year and for the forthcoming crop year. We use estimates of domestic stocks, domestic demand, and exports for the current crop year. We move to the new crop year each September (for corn) and June (for wheat). These forecasts are often taken to be important indicators of market conditions for market participants and we thus hypothesize that the estimates should be relevant to price movement in the corn and wheat markets. A problem generic to many such analyses of finely sampled price data involves the fact that many pertinent variables (such as the stocks and demand variables) are only available on a more aggregated (monthly or quarterly) basis. To obtain weekly measures on stocks and demand variables, we used cubic spline interpolation. Such a procedure may be reasonable for disaggregation of series that tend to move slowly from week to week (i.e., nonvolatile series) (see de Boor, 1981), for a discussion of this point). Stocks and aggregate demand factors are likely to be rather slow in adjusting because of their highly aggregate nature. Thus, we maintain that such an approach provides a reasonable means of using timewise aggregated data in our study of price volatilities. The relative effects of stocks and overall demand are evaluated using the ratio of total use (domestic plus exports) to total stocks.

A single contract is used for each commodity (December for corn and September for wheat). A consecutive series of futures prices was constructed by using quotes on each contract up until the last week of the month preceding expiration of the contract. At this point, the following crop year's contract is used. Dummy variables are incorporated into the models having autoregressive effects in variance terms in order to capture the effects of switching contracts.

Finally, it is hypothesized that strong patterns of seasonality may be present in volatility patterns for corn and wheat. Previous research has confirmed the presence of strong seasonality in price volatility. In particular, volatility appears to peak in the summer months for most agricultural commodities. This may correspond to the arrival of new information during peak growing (for corn) and harvest (for wheat) periods. We incorporate deterministic seasonal components into the models of variability by adding a sum of trigonometric functions corresponding to the week of the year. If we define d_t as the week of the year corresponding to observation t, the seasonal component can be written as:

$$s_t = \sum_{i=1}^{k} [\theta_i \cos(2\pi i d_t/52) + \phi_i \sin(2\pi i d_t/52)] \tag{6}$$

This specification provides a seasonal function with a period of one year and can be interpreted as providing a kth order Fourier approximation to the unknown seasonal function. We use $k = 3$ in representing the seasonal components. Time to maturity (i.e., days until expiration of the contract) also represents a linear component of seasonality, which is added to s_t in representing overall seasonality.

EMPIRICAL RESULTS

Maximum likelihood techniques (under the assumption of normally distributed residuals) were used to estimate the conditional heteroscedasticity (CH), and ARCH and GARCH models of price variability. Parameter estimates and summary statistics for the application to corn prices are presented in Table II. We allow the mean of returns to be influenced by growing conditions, although an efficiency of markets perspective might imply that returns should not be predictable. The estimates demonstrate several significant determinants of price volatility. In addition, strong autoregressive effects are shown in the heteroscedasticity terms. In several cases, it was not possible to identify both causal determinants of heteroscedasticity and autoregressive ARCH and GARCH terms. In particular, estimation frequently failed when ARCH and GARCH terms were included along with the exogenous explanatory factors associated with price variability. Such a result is not surprising. A shortcoming of the extensive literature on models that account for persistence in variance (i.e., GARCH models) is that intuitive interpretations of the autoregressive patterns in variances are seldom offered. Fackler (1986) points out that "lumpiness" in the arrival of new information about upcoming harvests results in persistence in volatilities. In other words, information about future price levels is itself autocorrelated and thus tends to result in autoregressive patterns in variance terms. In this context, difficulties

TABLE II

Maximum Likelihood Parameter Estimates and Summary Statistics: Corn

Parameter	CH Model	ARCH Model	GARCH Model
	Mean		
Intercept	0.0001	−0.0006	−0.0003
	(0.0011)[a]	(0.0010)	(0.0011)
Growing conditions	−0.0100	−0.0170	−0.0124
	(0.0086)	(0.0056)*	(0.0053)*
	Variance		
Intercept	0.0118	0.0000[b]	0.0000[b]
	(0.0091)	(0.0000)[b]	(0.0000)[b]
ARCH(1)		0.3407	0.3347
		(0.0589)*	(0.0582)*
ARCH(2)		0.0000[b]	
		(0.0000)[b]	
ARCH(3)		0.1111	
		(0.0005)*	
GARCH(1)			0.1940
			(0.0379)*
Growing conditions	−1.3938		
	(0.3384)*		
COS_1	−0.9608		
	(0.0968)*		
COS_2	−0.0265		
	(0.1025)		
COS_3	−0.3531		
	(0.0963)*		
SIN_1	−1.2702		
	(0.1183)*		
SIN_2	−0.5233		
	(0.0824)*		
SIN_3	−0.0666		
	(0.0829)		
Use/stocks	0.0282		
	(0.0123)*		
Speculation index	−0.9962		
	(1.4408)		
Volume/open interest	7.0847	0.0052	0.0049
	(1.3884)*	(0.0005)*	(0.0007)*
Concentration	0.0176		
	(0.0137)		
Time to maturity	0.0086		
	(0.0008)*		
Contract switch dummy		0.0032	0.0055
		(0.0001)*	(0.0021)*
Ln likelihood Fn.	1227.5320	1201.4368	1203.5882

[a]Numbers in parentheses are standard errors. Asterisks (*) indicate statistical significance at the $\alpha = 0.10$ or smaller level.
[b]Number <0.00005 in absolute value.

in identifying both autoregressive patterns in variances and causal patterns of explanatory factors representing new information about crops is not unexpected. In most cases, the estimates imply that better (i.e., above average) growing conditions tend to correspond to lower mean returns, although the effect is statistically significant in only two of the six models.

Estimates of the conditional heteroscedasticity model for corn confirm expectations regarding the effect of various factors on corn price volatility, though some surprises are reflected in the estimates. As expected, better than average growing conditions (crop conditions) tend to be associated with lower variation in corn prices. This effect is highly significant and confirms the findings of other research (see, e.g., Hennessy & Wahl, 1996) that maintain that weather and other factors pertinent to growing conditions are important determinants of the variability of futures prices. The trigonometric seasonality terms are also highly significant, confirming that strong seasonality exists, even after information about the condition of the crop is incorporated.

In accordance with expectations, the ratio of total use to stocks has a strong positive influence on the variability of corn prices. Higher levels of demand, relative to a given level of stocks, tend to increase the variability of corn prices. Likewise, larger levels of stocks relative to a given level of total demand tend to reduce corn price variability. This result is in agreement with our expectations, though we should note that it does not agree with the results of other studies. In particular, Streeter and Tomek (1992) unexpectedly found a positive relationship between stocks and price variability for soybeans. They attributed this result to correlation between price levels and stocks.[9] Streeter and Tomek (1992) also found an unexpected negative relationship between demand variables and price variability.

Of the three futures market structure variables, only the ratio of volume to open interest variable is statistically significant. In particular, the ratio has a significant positive influence on corn futures price variability. A similar result was obtained by Peck (1981) and by Streeter and Tomek (1992). As Streeter and Tomek (1992) point out, this result may reflect the fact that day traders and scalpers are likely to be more active in markets with high volatility, raising concerns of simultaneity. Our results suggest that speculative activity and market concentration do not significantly influence futures price variability.

[9]In light of this correlation among price levels and the other explanatory variables, we do not include the lagged level of price as an explanatory variable. We should note, however, that evidence of this correlation was strong in that several variables lost their significance when price levels were included. These results are available from the authors on request.

Time to maturity has a significant positive effect, which is counter to the standard Samuelson effect. However, as noted above, in light of the fact that our analysis considers only a single futures contract, this effect cannot be separated from the seasonality effects implied by the trigonometric terms which were also highly significant. As we note below, a consideration of the overall pattern of seasonality confirms a nonlinear version of the Samuelson effect whereby price volatility increases to a point during the growing season and then falls as contract maturation nears.

The ARCH and GARCH models confirm strong autoregression in variance effects. The parameter estimates are reasonable and correspond to a stationary variance for prices. The ARCH specification contains three lags, chosen by testing the significance of successive lags.[10] Although, as noted, considerable difficulty was associated with incorporating explanatory factors and autoregressive variance terms in the same model, it was possible to include the ratio of volume to open interest. The coefficient on this variable again confirms that greater day trading tends to increase price volatility.[11] Finally, dummies corresponding to contract switch points are significant and have large positive values. A similar result was obtained by Myers and Hanson (1993). These indicator variables account for the discontinuity implicit in the price time series at contract switch points.

Maximum likelihood estimates of conditional heteroscedasticity models of wheat price variability are presented in Table 3. These results again confirm the significance of several factors in explaining patterns of price variability as well as ARCH and GARCH terms. As was the case for corn, growing conditions have a positive effect on price volatility, though the effect narrowly misses being statistically significant at the $\alpha = 0.10$ level. Above-average growing conditions throughout the spring and summer months are correlated with lower levels of price volatility. The trigonometric seasonality components are statistically significant in several cases, confirming the significance of seasonality in the volatility of wheat prices.

Larger levels of use relative to stocks again appear to exert a positive influence on the variability of wheat prices. In like fashion, larger levels

[10]That is, lags were added until they were no longer significant.

[11]It should be pointed out that this variable was observable on a weekly basis, making it one of a small number of explanatory factors that was not subject to smoothing. Considerable variation existed from observation to observation—implying weaker patterns of autocorrelation in this explanatory variable. In contrast, the smoothed weekly observations of the variables which could only be observed on a monthly or quarterly basis were quite slow to change. This makes identification of their effects in the presence of autoregressive variance terms difficult, if not impossible.

TABLE III

Maximum Likelihood Parameter Estimates and Summary Statistics: Wheat

Parameter	*CH Model*	*ARCH Model*	*GARCH Model*
	Mean		
Intercept	0.0003	−0.0017	−0.0012
	(0.0010)	(0.0009)*	(0.0010)
Growing conditions	−0.0082	−0.0002	−0.0011
	(0.0052)	(0.0046)	(0.0043)
	Variance		
Intercept	0.0186	0.0001	0.0000[b]
	(0.0422)	(0.0000)[b]*	(0.0000)[b]
ARCH(1)		0.3849	0.3254
		(0.0664)*	(0.0612)*
ARCH(2)		0.2036	
		(0.0626)*	
ARCH(3)		0.1235	
		(0.0439)*	
GARCH(1)			0.5634
			(0.0722)*
Growing conditions	−0.5840		
	(0.3617)		
COS_1	−0.8386		
	(0.1265)*		
COS_2	0.2988		
	(0.0831)*		
COS_3	−0.1188		
	(0.0824)		
SIN_1	0.0300		
	(0.0813)		
SIN_2	0.4209		
	(0.0852)*		
SIN_3	−0.0300		
	(0.0953)		
Private stocks	0.1311		
	(0.0325)*		
Speculation index	−0.1341		
	(4.4273)		
Volume/open interest	3.4582	0.0013	0.0006
	(0.6802)*	(0.0002)*	(0.0002)*
Concentration	−0.0166		
	(0.0056)*		
Time to maturity	0.0007		
	(0.0008)		
Contract switch dummy		0.0000[b]	0.0000[b]
		(0.0000)[b]	(0.0000)[b]
Ln likelihood Fn.	1248.5522	1218.2219	1218.8112

CH, conditional heteroscedasticity; ARCH, autoregressive conditional heteroscedasticity; GARCH, generalized ARCH.
[a]Numbers in parentheses are standard errors. Asterisks (*) indicate statistical significance at the $\alpha = 0.05$ or smaller level.
[b]Number <0.00005 in absolute value.

of total stocks, given total demand, are correlated with lower levels of wheat price variability. The extent of scalping or day trading, represented by the ratio of volume to open interest, again appears to have a statistically significant positive influence on price variability. The coefficient is small relative to the estimates for corn. In contrast to corn, market concentration appears to have a significant negative influence on wheat price variability.

Time to maturity again has a positive, though statistically insignificant, relationship with price variability. This must, however, be interpreted within the context of seasonality components. As was true for corn, significant autoregressive effects are apparent in variance patterns, although such influences cannot be identified when most of the explanatory factors are included in the empirical models. The ARCH and GARCH terms are consistent with stationary variances. In both the corn and wheat models, the conditional heteroscedasticity models appear to do a better job in explaining determinants of price levels and variances. This is evidenced by the larger log likelihood function values obtained for the conditional heteroscedasticity models.

Figures 2A and 2B illustrates patterns of seasonality implied by the conditional heteroscedasticity models. In both cases, variance seems to peak in the summer months. This same result has been demonstrated in other research (see, e.g., Streeter & Tomek, 1992; Fackler, 1986). In terms of the implications for the Samuelson effect, it can be noted that variance does appear to increase as time to maturity falls—to a point. During the period immediately preceding contract expiration, however, price variance falls considerably. The extent of the increase in variability is much stronger for wheat, suggesting stronger support for Samuelson's prediction that variability increases as a futures contract nears maturity.

A second component of the empirical analysis involved the application of a four-equation nonstructural vector autoregressive model to market volatilities implied by observed options premia.[12] These models were used to evaluate dynamic lead/lag relationships among a subset of variables representing factors conceptually relevant to futures price variability. The VAR models also contained the deterministic trigonometric seasonality terms as well as days to maturity and contract switch dummies.

The dynamic paths of adjustments of volatilities to shocks in the other variables can be illustrated using impulse response analysis. Orthogonalized impulse responses to 1-standard deviation (SD) shocks to each of the variables, along with a 2-SD confidence band, are illustrated in

[12]The volatilities are based on the standard Black-Scholes formulation, which assumes lognormality for commodity prices.

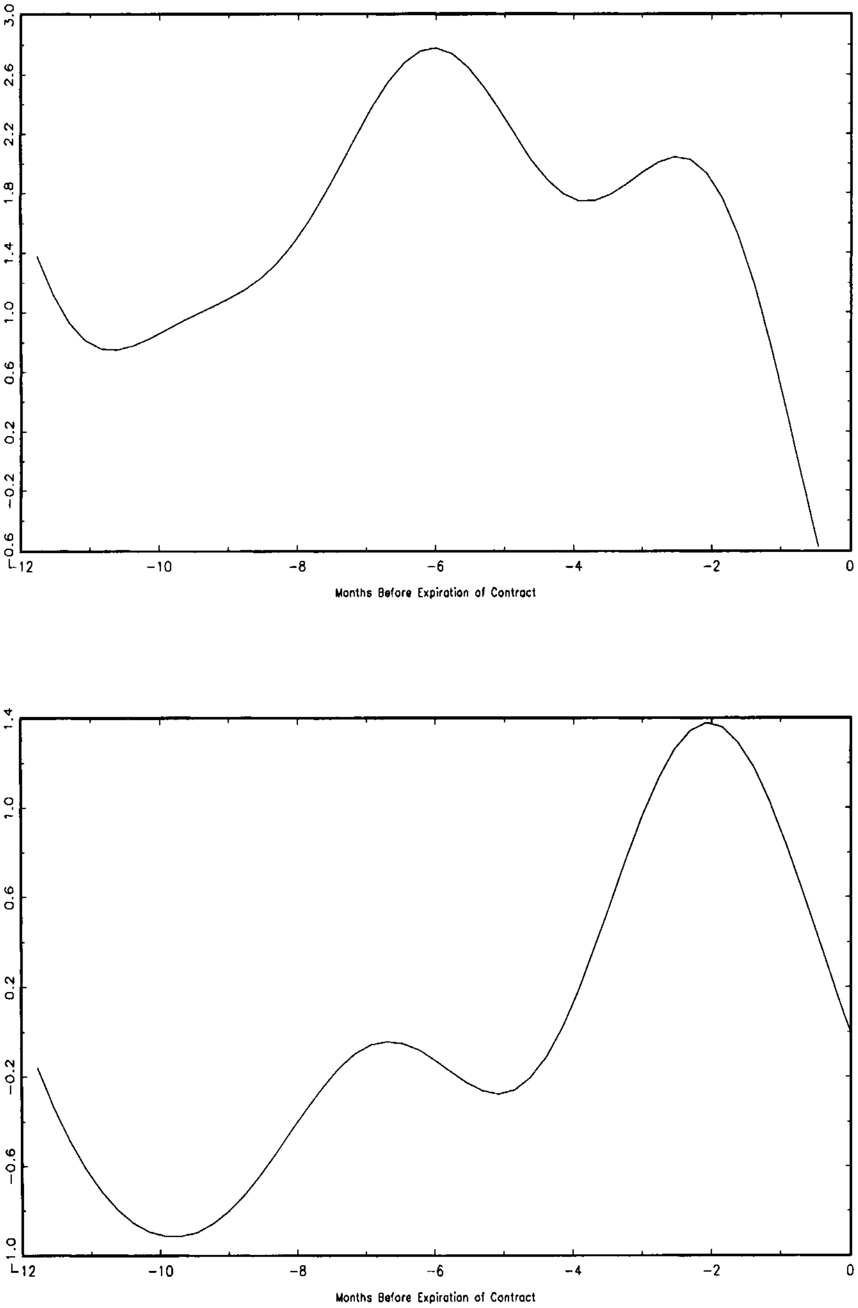

FIGURE 2
Deterministic seasonality in (**A**) December corn futures prices, and (**B**) September wheat futures prices.

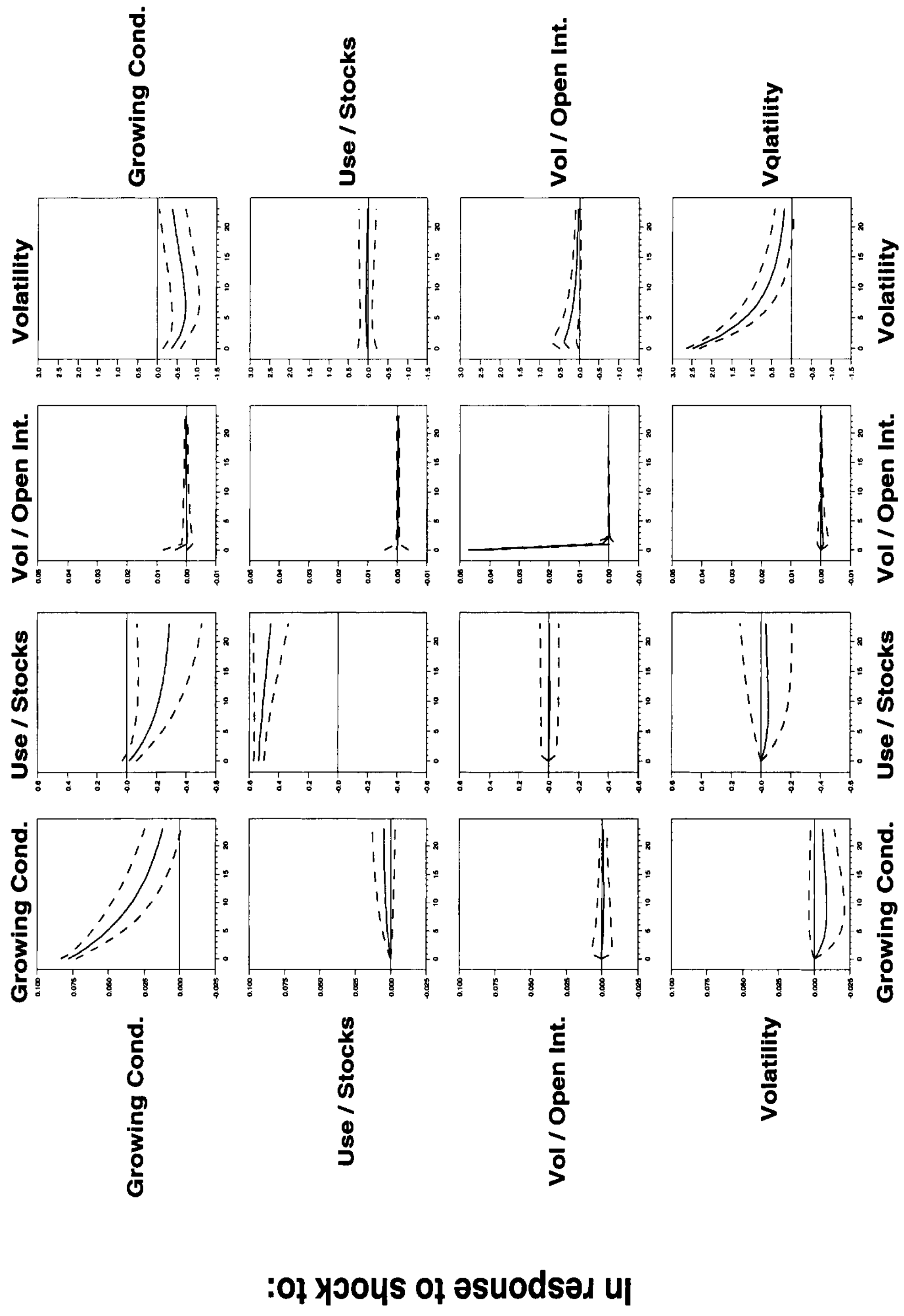

FIGURE 3
Corn impulse responses.

Figures 3 and 4. Standard errors were generated through the use of Monte Carlo integration (Kloek and Van Dijk, 1978). A total of 1,000 replications (with antithetic acceleration) were used in the Monte Carlo procedures to generate standard error bands. Statistically significant responses in corn price volatility are revealed in response to shocks to growing conditions. Likewise, a positive shock to the ratio of volume to open interest appears to exert a significantly positive influence on corn price volatility. Responses to the use over stocks variable are modest. An exogenous shock to volatility results in considerable persistence, with the response remaining significantly positive for approximately 12 weeks after the response. Such a result is analogous to the type of effects represented in the preceding GARCH models. In the case of wheat, volatility responds modestly to growing conditions. As was the case for corn, better than average growing conditions result in lower levels of volatility, although the effect is much smaller for wheat than for corn. An increase in the ratio of use to stocks exerts a modest influence on price variability. Again, considerable persistence in response to exogenous volatility shocks is revealed in the estimates—again a result analogous to GARCH effects.

In all, the nonstructural VAR models applied to implied options market volatility largely confirm the results obtained using futures price data. One of the major factors influencing corn and wheat price variability is the condition of the crop, which reflects growing conditions.

SUMMARY AND CONCLUDING REMARKS

This analysis evaluates determinants of weekly price variability in U.S. corn and wheat futures markets. Our results identify a number of factors that are significantly related to price variation. The strongest effects are revealed for crop-growing conditions. As expected, above-average crop conditions are related to lower levels of price variability. This effect is present for both corn and spring wheat, although the results are statistically significant only in the case of corn. We also identify strong seasonality in the patterns of corn and wheat price variation, with variance peaks occurring during the summer months. Increased levels of use relative to stocks tend to increase price variability for both corn and wheat. Likewise, smaller levels of stocks relative to total use tend to increase price variability.

Factors related to the structure of the corn and wheat futures markets are also shown to have important influences on corn price variation. Market structure variables reflecting the actions of futures market traders are also significant determinants of futures price variability. In particular,

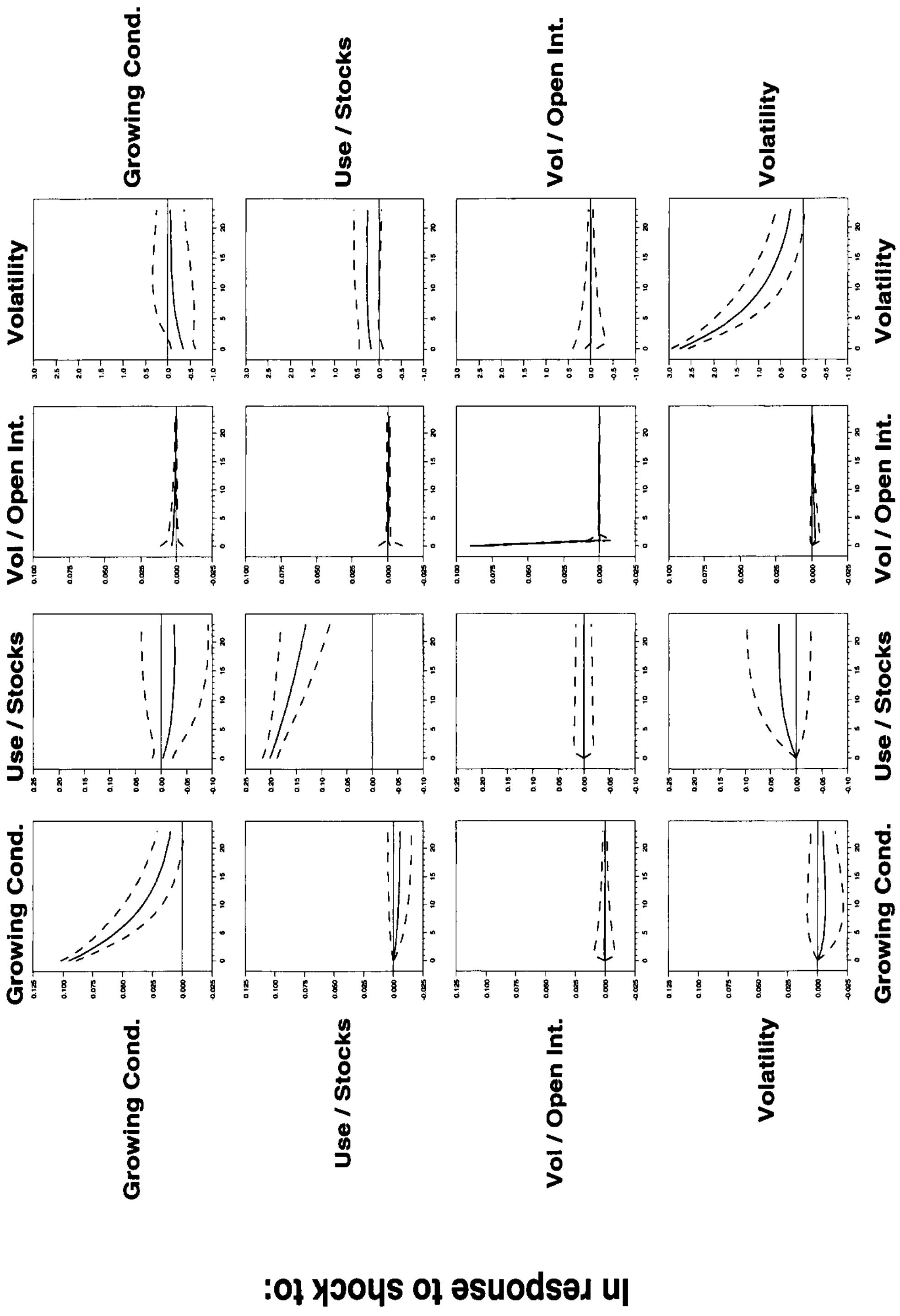

FIGURE 4
Wheat impulse responses.

an increase in day trading, as represented by the ratio of volume to open interest, has a significant positive influence on price variability. Higher levels of market concentration have a significant negative effect on price variability for wheat prices, although this effect is not significant for corn.

An interesting implication of our analysis pertains to the modeling of autoregressive relationships for price variance terms. ARCH and GARCH models confirm strong autoregressive relationships among conditional heteroscedasticity terms. When other explanatory factors are added to the conditional heteroscedasticity models, however, it becomes difficult to identify both ARCH/GARCH terms and the effects of such explanatory factors. This provides an intuitive explanation for the autoregressive terms. In particular, these terms probably reflect the lumpy autocorrelated nature that characterizes the arrival of new information.

We also pursue nonstructural VAR models that evaluate determinants of the price volatilities implied by corn and wheat option markets. These results are largely consistent with those generated in the conditional heteroscedasticity models.

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