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Components of Grain Futures Price Volatility

Berna Karali and Walter N. Thurman

We analyze the determinants of daily futures price volatility in corn, soybeans, wheat, and oats markets from 1986 to 2007. Combining the information from simultaneously traded contracts, a generalized least squares method is implemented that allows us to clearly distinguish among time-to-delivery effects, seasonality, calendar trend, and volatility persistence. We find strong evidence of time-to-delivery (Samuelson) effects and systematic seasonal components with volatility increasing prior to harvest times—an indirect confirmation of the theory of storage.

Key Words: futures markets, Samuelson effect, seasonality, time to maturity, volatility

Introduction

Agricultural commodity prices, particularly futures prices, are subject to considerable variability. It is important to identify factors underlying futures price variability in order to properly interpret futures price time series and improve production and risk management decisions. Price variability has been attributed to a number of factors. Its level has been explained by reactions to information flows (Kyle, 1985; Andersen and Bollerslev, 1997), by levels of physical inventories (Thurman, 1988; Williams and Wright, 1991), by time to delivery (Samuelson, 1965; Milonas, 1986), by production seasons (Anderson, 1985), by persistence in variability (Kenyon et al., 1987), and by trade volumes (Streeter and Tomek, 1992).

We empirically analyze daily price changes in North American grain futures markets, focusing on seasonality, time to delivery, and persistence as factors explaining volatility. To identify these effects, we use data on multiple traded contracts with different delivery dates across four commodities and apply the generalized least squares (GLS) method of Karali and Thurman (2009) to account for contemporaneous correlation among overlapping contracts. The importance of a multiple-contract approach was stressed by Goodwin and Schnepf (2000), who argued that it is difficult, if not impossible, to distinguish time-to-delivery effects from seasonality when a single futures contract is analyzed.

Our analysis of daily price volatility in U.S. corn, soybeans, wheat, and oats futures markets considers two definitions of volatility. One is based on changes in closing price from one day to the next; the other is based on intra-day transactions price ranges. The latter measure has been proposed by Gallant, Hsu, and Tauchen (1999) and Alizadeh, Brandt, and Diebold (2002) in a stochastic volatility context as a superior proxy for asset price volatility.

Our findings show that price volatility in these markets varies substantially throughout a year and increases in months preceding harvest periods. We also find support for Samuelson's argument that volatility increases as futures contracts approach delivery dates.

Berna Karali is assistant professor, Department of Agricultural and Applied economics, the University of Georgia; Walter N. Thurman is William Neal Reynolds Professor, Department of Agricultural and Resource Economics, North Carolina State University.
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Prior Literature

A venerable literature considers time patterns of volatility and connects volatility with time to delivery and seasonality. Samuelson (1965) originally argued that price volatility of a futures contract should increase as a contract approaches its delivery date. The so-called Samuelson effect has been investigated by a number of authors and has received mixed support. There exists more consistent empirical support for predicting seasonal volatility in grain futures markets. In general, volatility increases in the spring, peaks in the summer, and declines toward the end of a year.

Anderson (1985) finds that seasonality is a primary factor in explaining futures price volatility in grain markets and that contract maturity is a secondary factor. Kenyon at al. (1987) show that corn, soybeans, and wheat futures price volatility is affected by seasons, lagged volatility, and loan rates. Although Hennessy and Wahl (1996) observe significant seasonal effects on the volatility of corn, soybeans, Chicago wheat, Kansas wheat, and Minneapolis wheat futures prices, they fail to find inventory and time-to-delivery effects. In their study of soybean futures, Streeter and Tomek (1992) show that time to delivery has nonlinear effects on price volatility and that volatility decreases in months immediately prior to contract expiration. They also find significant seasonal effects, with volatility increasing in summer months. Furthermore, lagged volatility had a significant positive effect on price volatility.

Yang and Brorsen (1993) report evidence of seasonality in corn, soybeans, and wheat futures price variability. However, they find time-to-delivery effects only for soybeans and oats. Based on findings by Goodwin and Schnepf (2000), corn and wheat price variability is significantly affected by inventories, growing conditions, trading volume, open interest, and seasonality. Their results show evidence of positive time-to-delivery effects for corn but no effects for wheat. Chatrath, Adrangi, and Dhanda (2002) show that daily returns (log price changes) on soybean, corn, wheat, and cotton futures contracts are significantly affected by seasonality and lagged daily returns. They study time-to-delivery effects for soybean and corn and find support for the Samuelson effect. Sørensen (2002) considers seasonal price patterns for corn, soybeans, and wheat futures, and concludes that the seasonal components for all three commodities peak about two to three months before the beginning of harvest.

Some prior work analyzes the nearest delivery contract, rolling forward to the next contract month as a maturity date approaches. Other work analyzes individual months' contracts (e.g., the December corn contract) separately. These approaches are limited in their ability to reveal time-to-delivery effects—i.e., the analysis of single months' contracts makes seasonal comparisons difficult and the use of rolled-over series limits the range of time to delivery that can be studied. In contrast to these approaches, Smith (2005) studies simultaneously traded corn futures contracts using a partially overlapping time series (POTS) model and finds support for the Samuelson effect and the theory of storage. [See also Suenaga, Smith, and Williams (2008) for another application of Smith's latent factor model.] More recently, Kalev and Duong (2008) provide evidence of the Samuelson effect in agricultural futures markets using seemingly unrelated regressions (SUR). They construct time series of the nearest delivery contract, the second-nearest delivery contract, and so on to measure the relationship between time to delivery and price volatility.

Our study augments and updates this literature by simultaneously modeling time to delivery, seasonality, trend, and volatility persistence in North American grain futures markets. We use data from simultaneously traded contracts, applying the GLS estimation procedure developed in

Karali and Thurman (2009)[1] and Karali, Dorfman, and Thurman (2010a, b).[2] We compare results derived from two distinct measures of daily price volatility. Our analysis differs from previous work in its comprehensive use of recent daily data on all traded contracts for the grains studied and in its comparison of results for two different volatility measures.

Empirical Framework

The daily return on a futures contract can be written as the product of a time-varying volatility factor and a white noise disturbance:

$$y_t = \sigma_t u_t , \tag{1}$$

where $y_t = \ln(P_t) - \ln(P_{t-1})$ is a continuously compounded daily return. The disturbance in (1) is assumed to be covariance stationary with the following properties: $E(u_t) = 0$, $\mathrm{Var}(u_t) = 1$, and $E(u_t u_{t-1}) = 0$. The nonstochastic volatility term, σ_t, is positive and time-varying.

The zero mean of u_t implies that daily returns have a zero mean. We take this as an approximation appropriate to daily returns data, in which any nonzero expected return will be small. Market efficiency in futures markets (i.e., an inability to predict price changes) implies serial noncorrelatedness of both u_t and returns. Normalizing $\mathrm{Var}(u_t) = 1$ implies that $\mathrm{Var}(y_t) = \sigma_t^2$.

The absolute value of (1) yields:

$$| y_t | = \sigma_t | u_t | , \tag{2}$$

and the expected value of (2) is given by:

$$E | y_t | = \sigma_t E | u_t | = \sigma_t k , \tag{3}$$

where k is a positive constant. We do not assume normality, but note that if u_t is standard normal, the distribution of $| u_t |$ is half-normal with a mean of $k = \sqrt{2/\pi} = 0.8$.

We specify volatility as dependent upon observable covariates: a contract's time to maturity, day of the year, a time trend, and the lagged value of absolute returns. The latter allows for potential serial correlation in volatility not accounted for by time to maturity, trend, and seasonal factors. Thus, we write volatility as:

$$\sigma_t = \omega + \mathbf{z}_t' \gamma + \alpha | y_{t-1} | , \tag{4}$$

where $\mathbf{z}_t$ contains covariates representing time to delivery, seasonality, and trend.[3]

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[1] Karali and Thurman (2009) study the effect of housing starts announcement surprises on lumber futures prices and find that the price response to observed information flows depends on inventories and time to delivery. They model the conditional mean of daily returns, whereas the current study models the second moment to represent volatility. Accordingly, the specification of disturbance variances differs across these studies. In Karali and Thurman (2009), the disturbance variances and correlations among contracts are allowed to vary by delivery horizon to account for time-to-delivery effects on volatility. In the current study, the variances and correlations are constant across delivery horizons and time-varying volatility is handled by using time to delivery explicitly as a regressor in the model.

[2] Karali, Dorfman, and Thurman (2010a, b) are two related studies that focus on volatility in grain and lumber futures markets, respectively. These studies adopt a Bayesian point of view and examine how the volatility determinants change by delivery horizon and futures contract. While the work of Karali, Dorfman, and Thurman (2010a) studies grain market volatility, it differs from the current study primarily in its Bayesian methodological approach, but also in the proposed determinants of volatility. In contrast to the current study, they explain volatility by an interpolated quarterly measure of inventories. Further, they model seasonality differently: a calendar year is divided into planting, pre-harvest, and post-harvest periods.

[3] The variable σ_t is a conditional volatility—conditioned on time to delivery, seasonality, and lagged absolute return. This is not a stochastic volatility model because there is no error term in (4). Given the right-hand side of (4), volatility is deterministic.

Equations (2), (3), and (4) can be combined to derive a regression model representing the conditional mean of absolute returns:

$$
\begin{aligned}
(5) \qquad |y_t| &= E|y_t| + \varepsilon_t \\
&= k\sigma_t + \varepsilon_t \\
&= k\left(\omega + \mathbf{z}_t'\gamma + \alpha|y_{t-1}|\right) + \varepsilon_t,
\end{aligned}
$$

where $\varepsilon_t = |y_t| - E|y_t|$, $E(\varepsilon_t) = 0$, $\text{Var}(\varepsilon_t) = \sigma_\varepsilon^2$, and $E(\varepsilon_t \varepsilon_{t-1}) = 0$. Our empirical model is based on (5), adopting particular functional forms for the time to delivery, seasonality, and trend covariates.

Further, we expand the model to represent volatility of simultaneously traded futures contracts. For each grain, 10 to 15 contract months are listed on any given day. Each has a different delivery date of up to three and one-half years into the future. We trim the data so that each contract's history has an equal number of observations—the number of trading days of the shortest-lived contract. This results in at most seven contracts on a given day for corn and soybeans, six contracts for wheat, and five contracts for oats.[4]

Our empirical specification based on (5) is:

$$
\begin{aligned}
(6) \qquad |\%\Delta CC_{it}| &= \alpha + \beta_1 TTD_{it} + \beta_2 TTD_{it}^2 + \delta_1 t + \delta_2 t^2 + \psi|\%\Delta CC_{i,t-1}| \\
&\quad + \sum_{j=1}^{m}\left[\theta_j^s \sin(2\pi j x_t/365) + \theta_j^c \cos(2\pi j x_t/365)\right] + \varepsilon_{it}, \\
i &= 1, 2, ..., k_t \text{ and } t = 1, 2, ..., T,
\end{aligned}
$$

where $|\%\Delta CC_{it}| = 100 \times |\ln(P_{it}) - \ln(P_{i,t-1})|$, the absolute percentage return from buying a futures contract at one day's settlement price and selling the contract at the following day's settlement price. Other terms are defined as follows: k_t is the number of contracts traded on day t (between one and seven for corn and soybeans, one and six for wheat, and one and five for oats); T is the total number of trading days; TTD_{it} is the ith contract's time to delivery on day t; and x_t is the number of days since January 1st in each year.

The sum of trigonometric functions in (6) provides a periodic function with a period of one year.[5] Larger values of m allow the annual cycle to depart from strict sine and cosine waveforms. We choose $m = 4$ for the seasonal components.[6]

Volatility of daily asset returns can be represented by different measures related to the second moment of returns, with daily squared or absolute values of returns being the most obvious. Research by Gallant, Hsu, and Tauchen (1999); Alizadeh, Brandt, and Diebold (2002); and others has advocated the use of daily high-low range as a second-moment proxy

[4] Because we study only complete contract histories from inception to expiration, at the beginning of our sample as new contracts are introduced, the number of traded contracts in the sample increases. Similarly, at the end of the sample period, as the contracts we analyze expire, the number of contracts falls until the last contract has expired.

[5] We model seasonality as a function of trading day—a measure of when trading takes place in a calendar year—not contract month. This approach assumes the same seasonal volatility for all contract months (e.g., March and July contracts are assumed to have the same seasonal component of volatility on the days when both are traded). It is consistent with seasonal variation in the flow of information to the market.

[6] Higher-order sinusoidal polynomial coefficients were estimated and sometimes found to be significant. However, a visual inspection of predicted volatility with higher-order polynomials suggested an unreliable fluctuation. To avoid high-frequency oscillations, we limited the number of polynomials to four. On this issue, see also Fackler and Livingston (2002).

in stochastic volatility modeling. Because highs and lows are necessarily derived from continuously monitored markets, they provide more information than daily closing values. We focus our empirical analysis on variation in the absolute value of daily returns, but also offer a comparison with estimates that use daily high-low ranges as an alternative volatility measure. This alternative is presented as:

$$\%HL_{it} = \alpha + \beta_1 TTD_{it} + \beta_2 TTD_{it}^2 + \delta_1 t + \delta_2 t^2 + \psi(\%HL_{i,t-1}) + \sum_{j=1}^{m} \left[\theta_j^s \sin(2\pi j x_t / 365) + \theta_j^c \cos(2\pi j x_t / 365) \right] + \varepsilon_{it}, \quad (7)$$

where $\%HL_{it} = 100 \times [\ln(P_{it}^H) - \ln(P_{it}^L)]$, and P_{it}^H and P_{it}^L are the high and low price observations, respectively, for contract i on day t; $\%HL_{it}$ is the percentage return from buying at the day's low price and selling at the day's high price.

Our econometric approach separately estimates equations (6) and (7) as systems of seemingly unrelated regressions for each commodity. For example, equation (6) comprises a system of equations for all contracts of a specific commodity traded on any given day. The number of contracts traded varies from day to day as old contracts expire and new contracts are introduced. However, the identity of the *k*th contract changes as the most nearby contract expires.[7] Furthermore, the contemporaneous disturbances of equation (6) are correlated across contracts. The GLS method estimates the cross-contract correlations from OLS residuals and, in a second step, applies a GLS transformation to equation (6) to obtain consistent and asymptotically efficient parameter estimates. The method is described in detail in Karali and Thurman (2009) and implemented in MATLAB.

Data and Empirical Results

We study corn, soybeans, wheat, and oats futures contracts traded at the Chicago Board of Trade from 1986 to 2007. Prices are quoted in cents per bushel and contract sizes are 5,000 bushels for all four commodities. Delivery months for corn, wheat, and oats are March, May, July, September, and December; delivery months for soybeans are January, March, May, July, August, September, and November. Sample periods and the number of contracts studied for each commodity are given in table 1.

Table 2 presents summary statistics for the variables used in our analysis. Using the close-to-close measure, the four grain contracts have similar mean volatilities, with corn being the smallest (0.886 absolute daily percentage return) and oats being the largest (1.203 absolute daily percentage return). The four commodities' daily high-low measures are similar to one another, but each is approximately 50% larger than its close-to-close counterpart. Again, corn is the lowest (1.403) and oats is the highest (1.709).[8]

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[7] Note that our method of data construction—no rolling over of contracts—guarantees that no price changes across contract months are included.

[8] Grain futures contracts are subject to daily price move limits. The daily price limits in the beginning of our sample period were 10 cents per bushel for corn and oats, 30 cents for soybeans, and 20 cents for wheat (Park, 2009; Park and Irwin, 2005; Hatchett, Brorsen, and Anderson, 2009). The limits on all four commodity markets have increased over our sample period and they are currently as follows: 30 cents per bushel for corn (expandable to 45 cents and then to 70 cents), 70 cents for soybeans (expandable to \$1.05 and then to \$1.60), 60 cents for wheat (expandable to 90 cents and then to \$1.35), and 20 cents for oats (expandable to 30 cents and then to 45 cents). Based on the earliest limits regarding our sample period, which are lower than the current ones, 2.26%, 1.39%, 0.71%, and 1.44%, respectively, of the corn, soybeans, wheat, and oats price movements in our sample are limit moves. Because they represent a small portion of our data, we do not make any adjustments for limit move days (see also Park, 2000).

Table 1. Sample Characteristics

Description	Corn	Soybeans	Wheat	Oats
Sample Period	9/15/1986 to 9/14/2007	9/30/1986 to 9/14/2007	9/24/1986 to 9/14/2007	9/24/1986 to 9/14/2007
Contract Months	3, 5, 7, 9, 12	1, 3, 5, 7, 8, 9, 11	3, 5, 7, 9, 12	3, 5, 7, 9, 12
No. of Observations	32,188	34,855	25,351	21,318
Total No. of Trading Days	5,294	5,283	5,287	5,287
Total No. of Contracts	100	142	101	102
Maximum Contracts/Day	7	7	6	5

Table 2. Summary Statistics of Daily Variables

Description	Corn	Soybeans	Wheat	Oats
Return, Close-to-Close: $\mid \%\Delta CC \mid$				
Mean	0.886	0.938	1.003	1.203
Median	0.655	0.705	0.791	0.870
Minimum	0.000	0.000	0.000	0.000
Maximum	9.426	11.665	23.296	20.294
Standard Deviation	0.853	0.891	0.893	1.180
Return, High-Low: $\%HL$				
Mean	1.403	1.449	1.671	1.709
Median	1.183	1.243	1.487	1.463
Minimum	0.000	0.000	0.000	0.000
Maximum	9.031	10.771	39.255	20.498
Standard Deviation	0.916	0.911	1.009	1.337
Time to Delivery (Days ÷ 1,000)				
Mean	0.160	0.122	0.125	0.104
Median	0.160	0.122	0.125	0.104
Minimum	0.000	0.000	0.000	0.000
Maximum	0.321	0.246	0.250	0.208
Standard Deviation	0.093	0.071	0.072	0.060

Notes: $\mid \%\Delta CC_{it} \mid = 100 \times \mid \ln(P_{it}) - \ln(P_{i,t-1}) \mid$ and $\%HL_{it} = 100 \times [\ln(P_{it}^H) - \ln(P_{it}^L)]$, $i = 1, 2, ..., k_t$, $t = 1, 2, ..., T$, where k_t is the number of contracts traded on day t, T is the number of trading days in the sample (T = 5,294 for corn, 5,283 for soybeans, and 5,287 for wheat and oats); $\ln(P_{it})$ is the natural logarithm of settlement price on day t, during which a total of k_t contracts were traded; $\ln(P_{it}^H)$ and $\ln(P_{it}^L)$ are the natural logarithms of the highest and the lowest futures prices, respectively, on day t. Time to delivery is measured as the number of trading days (i.e., not counting weekends and holidays) remaining to contract maturity divided by 1,000.

Table 2 also gives descriptive statistics for time to delivery, measured as trading days (excluding weekends and holidays) normalized by dividing by 1,000. The longest time to delivery is 321 days for corn, followed by 250 days for wheat, 246 days for soybeans, and 208 days for oats. With multiple contracts, the numbers of observations are 32,188 for corn, 34,855 for soybeans, 25,351 for wheat, and 21,318 for oats (table 1).

Estimates of the volatility models for the four grains and the two measures of daily volatility are presented in table 3. Standard errors appear in square brackets and *t*-statistics in parentheses. The presence of a lagged dependent variable allows for the estimation of short- and long-run effects. We focus only on the short-run effects.

Time-to-Delivery Effects

The time-to-delivery variable and its square are both used in the empirical specification. Table 3 shows that almost all of the individual linear and quadratic coefficients are statistically significant, and the pair of coefficients is jointly and strongly significant for all four grains and both volatility measures.

The Samuelson hypothesis asserts that volatility increases with time to delivery, and the estimated coeffcients presented in table 3 support this conjecture. This can also be seen in figure 1, which plots the predicted paths of volatility. The top panel of figure 1 plots predicted close-to-close volatility for time-to-delivery values. Corn contracts have the longest trading horizons. The maximum value for corn time to delivery is 321 trading days (approximately 1.3 calendar years). The horizontal axis is ordered such that time to delivery declines moving from left to right as calendar time advances. The levels of the curves are positioned using the sample means of the other covariates. Figure 1 shows that volatility increases as time to delivery declines for all four commodities.

The lower panel of figure 1 displays the time-to-delivery relationship for the high-low volatility measure. The volatility curves in the lower panel are more concave than those in the upper panel, indicating greater volatility. The top panel of table 4 also illustrates this relationship in the row labeled "TTD effect over life of contract." [9]

The measured time-to-delivery effects in table 4 are sizable. Over the life of a corn contract, close-to-close volatility increases by 0.352 percentage points (compared to mean volatility of 0.886), and high-low range volatility increases by 0.604 (compared to mean volatility of 1.403). For both measures, corn volatility increases by more than 40% of its mean over the life of a contract. For soybeans, the life-of-contract increase in close-to-close volatility is 17% of its mean, while for high-low range volatility the increase is 31% of the mean. For wheat, the life-of-contract increase in close-to-close volatility is 32% of its mean; for high-low range volatility the increase is 43% of the mean. Finally, the life-of-contract increase in oats close-to-close volatility is 39% of its mean and 67% of the mean for high-low range volatility. We also computed marginal time-to-delivery effects by evaluating the derivative of each volatility measure with respect to the time-to-delivery variable's minimum, mean, and maximum values. Almost all the derivatives are negative and statistically significant.[10]

Because we are interested in the full life of each contract, we include observations over each contract's delivery period. This period begins on the first business day of the delivery month and ends on the second business day after the last trading day of the delivery month. It is possible that increased volatility during this period is driven by factors different from those relevant in earlier months. To explore this possibility, we excluded daily observations occurring one month prior to contract expiration and reestimated the models. The bottom panel of table 4 reports the resulting life-of-contract maturity effects as well as estimated trends.

The estimated life-of-contract effects excluding the month prior to expiration are, as in the full data set, highly statistically significant. However, they are smaller. The close-to-close

[9] Contracts distant from delivery often have low volume. While this has no obvious effect on close-to-close volatility, low volume will dampen the high-low range measure because it is based on order statistics, the distributions for which depend on the number of observations. The high-low range estimates should be understood in this context. Further, the close-to-close measure spans a 24-hour period (between weekdays) while the high-low range is derived from trading hours only. It can be argued, therefore, that the two measures reflect different notions of volatility. We are grateful to a referee for bringing these points to our attention.

[10] We checked the robustness of our time-to-delivery effects by excluding the trend and/or seasonality terms from our models, and found only trivial changes in the results. We also estimated our models excluding the data from 2006 and 2007 due to concern over the effect of recent commodity price booms and found little substantive change in our results.

Table 3. Volatility in Grain Futures Markets

	Corn		Soybeans	
Item	$\|\%\Delta CC\|$	$\%HL$	$\|\%\Delta CC\|$	$\%HL$
Intercept	1.178	1.343	1.048	1.130
	[0.034]	[0.031]	[0.035]	[0.032]
	(34.978)	(43.705)	(30.294)	(35.644)
Time to Delivery	−0.850	−0.282	−0.149	0.239
	[0.080]	[0.095]	[0.085]	[0.113]
	(−10.566)	(−2.956)	(−1.754)	(2.115)
Time to Delivery^2	−0.773	−4.986	−2.052	−8.498
	[0.227]	[0.274]	[0.307]	[0.424]
	(−3.400)	(−18.221)	(−6.683)	(−20.031)
Calendar Time	−0.267	−0.288	−0.153	−0.141
	[0.028]	[0.024]	[0.029]	[0.026]
	(−9.477)	(−11.774)	(−5.220)	(−5.430)
Calendar Time^2	0.056	0.071	0.034	0.037
	[0.005]	[0.004]	[0.005]	[0.005]
	(10.906)	(15.809)	(6.293)	(7.857)
Lagged Dependent Variable	0.067	0.282	0.034	0.329
	[0.006]	[0.005]	[0.006]	[0.005]
	(11.626)	(51.500)	(6.172)	(63.981)
$\sin_1$	0.030	−0.016	−0.036	0.014
	[0.015]	[0.013]	[0.016]	[0.014]
	(1.999)	(−1.279)	(−2.321)	(0.991)
$\cos_1$	−0.275	−0.202	−0.269	−0.204
	[0.015]	[0.013]	[0.016]	[0.014]
	(−18.193)	(−15.599)	(−17.028)	(−14.734)
$\sin_2$	−0.008	−0.009	0.054	0.051
	[0.015]	[0.013]	[0.016]	[0.014]
	(−0.517)	(−0.718)	(3.443)	(3.722)
$\cos_2$	0.100	0.053	0.124	0.102
	[0.015]	[0.013]	[0.016]	[0.014]
	(6.666)	(4.119)	(7.932)	(7.432)
$\sin_3$	0.001	0.007	−0.042	−0.047
	[0.015]	[0.013]	[0.016]	[0.014]
	(0.064)	(0.543)	(−2.668)	(−3.397)
$\cos_3$	−0.042	−0.025	−0.059	−0.046
	[0.015]	[0.013]	[0.016]	[0.014]
	(−2.796)	(−1.981)	(−3.740)	(−3.366)
$\sin_4$	0.026	0.058	0.024	0.037
	[0.015]	[0.013]	[0.016]	[0.014]
	(1.772)	(4.533)	(1.566)	(2.715)
$\cos_4$	0.067	0.042	0.030	0.004
	[0.015]	[0.013]	[0.016]	[0.014]
	(4.431)	(3.232)	(1.885)	(0.287)

Notes: The models are $|\%\Delta CC_{it}| \equiv 100 \times |\ln(P_{it}) - \ln(P_{i,t-1})| = \alpha + \beta_1 TTD_{it} + \beta_2 TTD_{it}^2 + \delta_1 t + \delta_2 t^2 + \psi|\%\Delta CC_{i,t-1}| + \Sigma_{j=1}^{m}[\theta_j^s \sin(2\pi j x_t / 365) + \theta_j^c \cos(2\pi j x_t / 365)] + \varepsilon_{it}$ and $\%HL_{it} \equiv 100 \times [\ln(P_{it}^H) - \ln(P_{it}^L)] = \alpha + \beta_1 TTD_{it} + \beta_2 TTD_{it}^2 + \delta_1 t + \delta_2 t^2 + \psi(\%HL_{i,t-1}) + \Sigma_{j=1}^{m}[\theta_j^s \sin(2\pi j x_t / 365) + \theta_j^c \cos(2\pi j x_t / 365)] + \varepsilon_{it}$, where $\ln(P_{it})$ is the natural logarithm of the settlement price on day t, during which a total of k_t contracts were traded, and $\ln(P_{it}^H)$ and $\ln(P_{it}^L)$ are the natural logarithms of the highest and the lowest futures prices, respectively, on day t. TTD_{it} is time to delivery, the number of days remaining to contract expiration on day t; x_t is the number of days since January 1st of each year; and m = 4. Values in square brackets [ ] are standard errors; values in parentheses ( ) are t-statistics.

(extended …→)

Table 3. Extended

	Wheat		Oats	
Item	$\lvert\%\Delta CC\rvert$	$\%HL$	$\lvert\%\Delta CC\rvert$	$\%HL$
Intercept	1.018	1.166	1.543	1.706
	[0.033]	[0.034]	[0.044]	[0.044]
	(30.405)	(34.311)	(34.825)	(38.654)
Time to Delivery	−1.826	0.237	−2.434	1.361
	[0.122]	[0.164]	[0.224]	[0.321]
	(−14.910)	(1.449)	(−10.859)	(4.243)
Time to Delivery^2	2.088	−12.341	0.778	−32.860
	[0.454]	[0.626]	[0.985]	[1.487]
	(4.600)	(−19.714)	(0.790)	(−22.103)
Calendar Time	−0.025	−0.010	−0.136	−0.201
	[0.028]	[0.027]	[0.036]	[0.033]
	(−0.887)	(−0.362)	(−3.782)	(−6.077)
Calendar Time^2	0.020	0.023	0.016	0.033
	[0.005]	[0.005]	[0.007]	[0.006]
	(4.010)	(4.783)	(2.406)	(5.447)
Lagged Dependent Variable	0.048	0.327	0.097	0.337
	[0.007]	[0.007]	[0.007]	[0.007]
	(7.059)	(49.222)	(13.782)	(51.232)
$\sin_1$	0.051	0.046	0.025	0.046
	[0.015]	[0.014]	[0.019]	[0.017]
	(3.471)	(3.294)	(1.330)	(2.656)
$\cos_1$	−0.141	−0.145	−0.346	−0.253
	[0.015]	[0.014]	[0.019]	[0.018]
	(−9.426)	(−10.241)	(−17.910)	(−14.345)
$\sin_2$	−0.018	0.037	−0.034	−0.024
	[0.015]	[0.014]	[0.019]	[0.017]
	(−1.185)	(2.643)	(−1.809)	(−1.376)
$\cos_2$	0.005	−0.003	0.123	0.040
	[0.015]	[0.014]	[0.019]	[0.017]
	(0.367)	(−0.195)	(6.424)	(2.274)
$\sin_3$	0.013	−0.005	−0.026	−0.044
	[0.015]	[0.014]	[0.019]	[0.017]
	(0.912)	(−0.331)	(−1.384)	(−2.527)
$\cos_3$	−0.019	−0.005	−0.057	−0.072
	[0.015]	[0.014]	[0.019]	[0.017]
	(−1.260)	(−0.364)	(−2.982)	(−4.109)
$\sin_4$	0.005	0.042	0.034	0.057
	[0.015]	[0.014]	[0.019]	[0.017]
	(0.350)	(3.013)	(1.790)	(3.319)
$\cos_4$	0.043	0.026	0.058	0.030
	[0.015]	[0.014]	[0.019]	[0.018]
	(2.912)	(1.857)	(3.008)	(1.722)

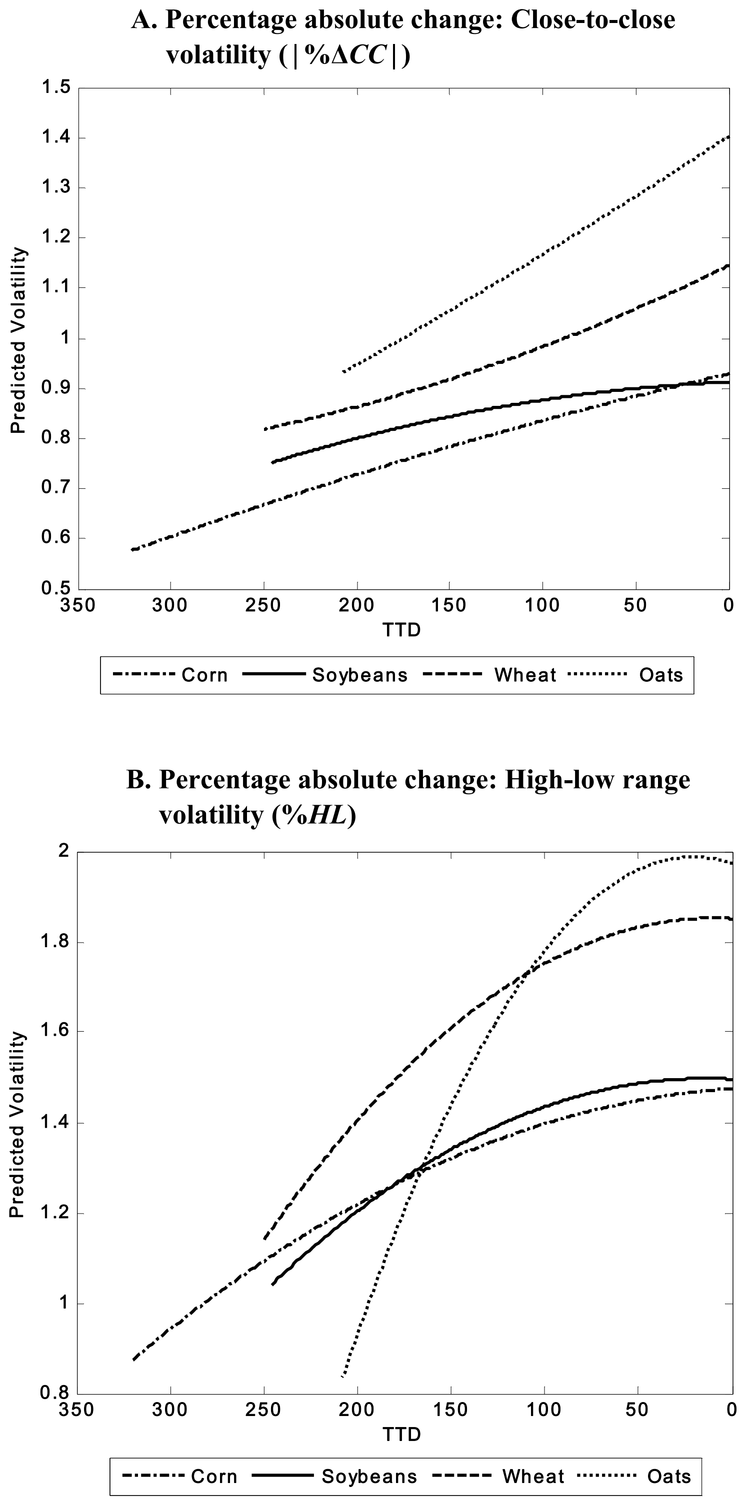


Figure 1. Time-to-delivery (Samuelson) effects

Table 4. Volatility Changes Implied by Changes in Time to Delivery and Calendar Time

PANEL A. FULL SAMPLE

Corn		Soybeans		Wheat		Oats	
$\lvert\%\Delta CC\rvert$	$\%HL$	$\lvert\%\Delta CC\rvert$	$\%HL$	$\lvert\%\Delta CC\rvert$	$\%HL$	$\lvert\%\Delta CC\rvert$	$\%HL$
TDD Effect over Life of Contract: $\beta_1(TTD_{\max} - TTD_{\min}) + \beta_2(TTD^2_{\max} - TTD^2_{\min})$							
−0.352	−0.604	−0.161	−0.455	−0.326	−0.712	−0.473	−1.139
Trend Effect over Sample Period: $\delta_1(t_{\max} - t_{\min}) + \delta_2(t^2_{\max} - t^2_{\min})$							
0.162	0.463	0.135	0.298	0.440	0.600	−0.275	−0.141

PANEL B. EXCLUDING DELIVERY PERIOD

Corn		Soybeans		Wheat		Oats	
$\lvert\%\Delta CC\rvert$	$\%HL$	$\lvert\%\Delta CC\rvert$	$\%HL$	$\lvert\%\Delta CC\rvert$	$\%HL$	$\lvert\%\Delta CC\rvert$	$\%HL$
TTD Effect over Life of Contract: $\beta_1(TTD_{\max} - TTD_{\min}) + \beta_2(TTD^2_{\max} - TTD^2_{\min})$							
−0.269	−0.578	−0.118	−0.459	−0.261	−0.712	−0.398	−1.222
Trend Effect over Sample Period: $\delta_1(t_{\max} - t_{\min}) + \delta_2(t^2_{\max} - t^2_{\min})$							
0.160	0.476	0.185	0.305	0.435	0.623	−0.232	−0.088

Notes: The models are $\lvert\%\Delta CC_{it}\rvert \equiv 100 \times \lvert \ln(P_{it}) - \ln(P_{i,t-1}) \rvert = \alpha + \beta_1 TTD_{it} + \beta_2 TTD^2_{it} + \delta_1 t + \delta_2 t^2 + \psi \lvert\%\Delta CC_{i,t-1}\rvert + \Sigma_{j=1}^{m}[\theta^s_j \sin(2\pi j x_t / 365) + \theta^c_j \cos(2\pi j x_t / 365)] + \varepsilon_{it}$ and $\%HL_{it} \equiv 100 \times [\ln(P^H_{it}) - \ln(P^L_{it})] = \alpha + \beta_1 TTD_{it} + \beta_2 TTD^2_{it} + \delta_1 t + \delta_2 t^2 + \psi(\%HL_{i,t-1}) + \Sigma_{j=1}^{m}[\theta^s_j \sin(2\pi j x_t / 365) + \theta^c_j \cos(2\pi j x_t / 365)] + \varepsilon_{it}$, where $\ln(P_{it})$ is the natural logarithm of the settlement price on day t, during which a total of k_t contracts were traded, and $\ln(P^H_{it})$ and $\ln(P^L_{it})$ are the natural logarithms of the highest and the lowest futures prices, respectively, on day t. TTD_{it} is time to delivery, the number of days remaining to contract expiration on day t; x_t is the number of days since January 1st of each year; and $m = 4$.

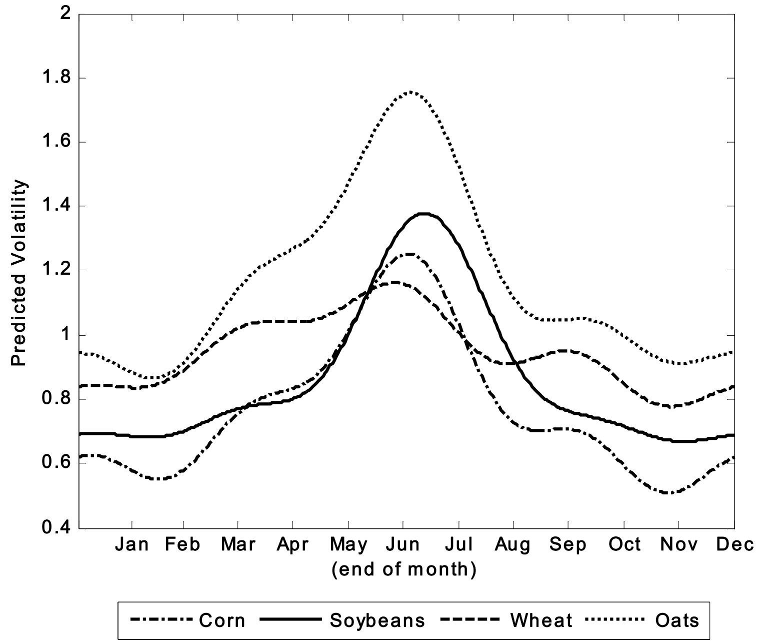
life-of-contract maturity effect for corn decreased by 24%, for soybeans 27%, for wheat 20%, and for oats 16%. It should be noted that some diminution in life-of-contract effect is to be expected because contract lives are between 7% and 9% smaller in the truncated data set, but the proportional reductions in life-of-contract effects are larger than the proportional reductions in contract lives. In contrast, time-to-delivery effects for the daily high-low volatility measures are similar between the two.

Seasonality

The quantity and quality of grain market information varies throughout a year. Planting and harvesting periods provide markets with important information regarding expected grain supplies and are likely to increase price volatility. Furthermore, grain inventories decline after harvest, which adds a seasonal component to price volatility. [See Karali and Thurman (2009) for analysis of the effects of inventories—in a nonseasonal context—on price volatility in lumber futures markets.] Given the collinearity between calendar time and grain inventories, our interpretation of seasonal patterns reflects the joint effects of seasonal changes in information flows and seasonal inventory regularities. Thus, a seasonal pattern with higher volatility during pre-harvest periods of low inventory can be considered an indirect confirmation of the theory of storage.

The coefficients on the sine and cosine terms are jointly significant in all models. Figure 2 plots the seasonal cycles implied by the estimated periodic coefficients. The seasonal cycles for

A. Percentage absolute change: Close-to-close volatility (|%Δ*CC*|)



B. Percentage absolute change: High-low range volatility (%*HL*)

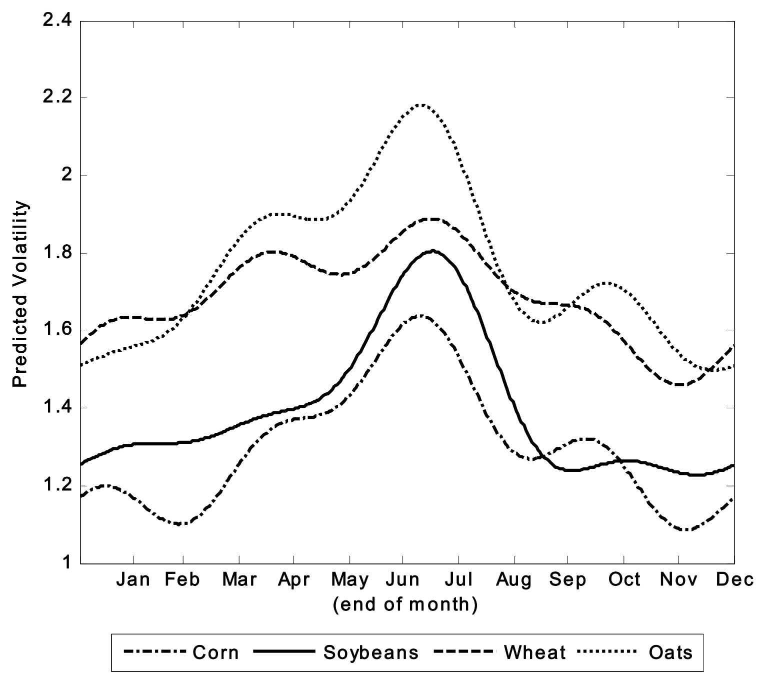


Figure 2. Seasonal volatility patterns

close-to-close volatility are displayed in the top panel of figure 2, while the seasonal cycles for high-low range volatility appear in the bottom panel. The tick labels in each figure represent the end of each month.

The most prominent cyclical feature is a peak in early or mid-July. The second most prominent feature, especially for the high-low range measure, is a shoulder for corn, wheat, and oats—but not soybeans—at the end of March. Further, corn, oats, and wheat—but again not soybeans—display a secondary shoulder at the end of September and October. Overall, the seasonal variations in volatility are dramatic. For example, peak-to-trough variation in high-low range volatility is almost 0.6 percentage points for soybeans, which represents 40% of mean volatility.[11]

Lagged Volatility and Time Trends

We include terms in our empirical models to capture volatility persistence and to allow for the possibility of volatility trends over the 21 years of our sample. Including lagged volatility results in a statistically significant coefficient in all specifications (table 3). The estimated coefficients cluster according to the selected volatility measure used as the dependent variable. For the close-to-close volatility models, the estimated lagged volatility coefficients are small, ranging from 0.034 (soybeans) to 0.097 (oats). The lagged effect is substantially larger in the high-low range volatility models. For those models, the estimated coefficients range from 0.282 (corn) to 0.337 (oats). Conditional volatility persistence is a much stronger feature for the high-low range volatility measure than it is for the close-to-close measure.

Calendar time is represented by linear and quadratic time trend variables. Almost all are highly significant in table 3 for both volatility measures. Figure 3 plots predicted variation due to calendar time based on the estimates presented in table 3. All commodities show convex trends. Those for corn, soybeans, and wheat are similar with downward trends in volatility for the first one-third of the sample, and offsetting upward trends thereafter. The net trend effects over the sample period are reported in table 4. Oats differs with respect to trend in that it displays a large monotonic decline in volatility over the sample period for both volatility measures.

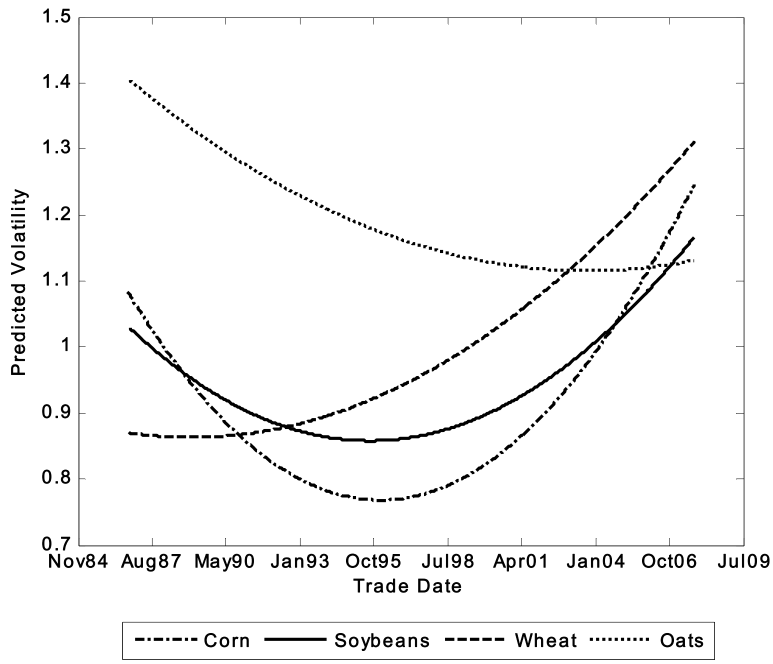
Conclusions and Discussion

We investigate the determinants of daily price volatility in U.S. corn, soybeans, wheat, and oats futures markets and identify two significant factors. From the multiple contracts traded each day, strong support is found for the existence of the Samuelson effect, with volatility increasing as maturity date approaches. Strong seasonality in the patterns of price volatility is identified as well. Similar to earlier studies, our results show that volatility peaks in summer, one to two months before harvest and when inventories are low.

Our analysis builds on and can be usefully compared with earlier studies. Anderson (1985) analyzed agricultural and nonagricultural contracts over the 1966–1980 period, finding both seasonal and maturity (time-to-delivery) effects. His estimated seasonal patterns are similar to ours, with monthly peaks occuring in July or June. Anderson also found maturity effects, though the statistical evidence was weaker and maturity explained much less of the variation in

[11] Seasonality patterns obtained from the data excluding one month prior to delivery show little deviation from the patterns in figure 2.

A. Percentage absolute change: Close-to-close volatility (|%Δ*CC*|)



B. Percentage absolute change: High-low range volatility (%*HL*)

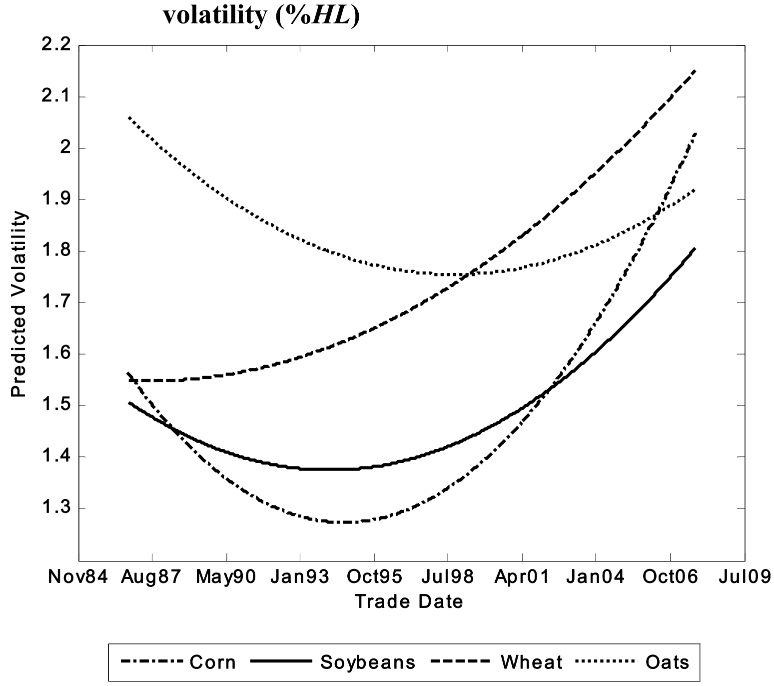


Figure 3. Quadratic time trends

return variance than did seasonal patterns. In contrast, over more recent data, we find that time-to-delivery effects are larger over the life of the contract than peak-to-trough seasonal effects.

Milonas (1986) analyzed agricultural (and other) daily futures price changes over 1972–1983, concluding that volatility increases over the life of a contract, but to a smaller extent than we observe in our sample. Yang and Brorsen (1993) studied the 1979–1988 period, using rolled-over contracts. In a GARCH setting, the authors concluded that maturity effects were small. They did not analyze full life-of-contract histories; thus they limited attention to the several-month period during which a contract is the near-delivery contract.

While we find some volatility persistence—as measured by the response to lagged absolute (or high-low) change—the effects are not large. In a model that controls for seasonality and time to delivery, we find statistically significant persistence in the form of an ARCH effect. The estimated AR effects are very small for the absolute close-to-close volatility proxy (less than 0.10 for all four grains) and somewhat larger for the daily high-low volatility proxy (near 0.30 for the four grains). Further, our estimates of seasonal and time-to-delivery effects are robust to the exclusion of ARCH effects. (We should also note that our linear system estimation procedure allows us to include only ARCH, and not GARCH effects.) In contrast, Jin and Frechette (2004) found substantial volatility persistence in grain futures prices. However, they did not account for systematic time-to-delivery and seasonal effects, which themselves could induce persistence.

Our results are broadly consistent for the two volatility measures we use, one based on close-to-close changes and one based on intra-day price ranges. The time-to-delivery and seasonal effects are also notably consistent across corn, soybeans, wheat, and oats models. Overall, our results show that daily price volatility can change by 40% of its mean volatility due to observable changes in underlying volatility factors.

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