VOLATILITY OF CASH CORN PRICES BY DAY-OF-THE-WEEK[*]

by

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Introduction

In the economics and finance literature, considerable attention given has been given to calendar anomalies in the prices of financial instruments. Articles by Fortune; Coutts and Hayes; Chang, Pinegar and Ravichandran; Davidson and Faff; Wang, Li and Erickson; and Hiraki, Maberly and Taube describe some of the anomalies which have been studied. Calendar anomalies in the prices of agricultural commodities seem to have received less attention. This more limited attention by agricultural economists may be appropriate. Nonetheless, the possible existence of certain types of calendar anomalies is of interest to us.

Most of the anomalies which have been studied have been in changes in prices and/or rates of return for holding financial instruments[1]. Although analogous anomalies in agricultural commodity prices are of interest to us, and are considered in this paper, we are more interested in calendar anomalies in the volatility of commodity prices. In fact, this study was prompted by a minor inconsistency in the way that volatility is treated in option pricing.

On the one hand, the Black model treats price change and volatility as being continuous. As if the per hour volatility is the same on weekends and holidays and during non-trading hours as on days and at times when futures markets are operating. On the other hand, most of the formulas which are used to estimate volatility from previous prices are more consistent with the suspension of price change and volatility (and the forces which cause it) on holidays and on weekend days.

We realize that the continuous treatment in the Black and other option pricing models is partly for convenience. In a sense, futures prices don't change except when exchanges and other means of trading are operating. Although the forces which influence prices don't always stop while markets are closed some of them may operate at a slower rate. For example, fewer crop condition reports are issued on weekends.

Although we suspect that the minor disparity in the treatment of volatility has limited practical importance, it did stimulate our interest in the possibility of weekend and holiday effects on the volatility of agricultural commodity prices. Perhaps the most natural data to use to look for these effects are futures contract prices. Since local cash prices are of more interest to us, we use corn prices at St. Louis.

A preliminary investigation applied an *ad hoc* approach. The results suggested greater volatility on Mondays (larger change from the previous Friday) than on other days (relative to corresponding previous business days). They also suggested greater volatility on Fridays than during the middle of the week.

Unfortunately, our *ad hoc* approach has several limitations. One is that it is based on intuition rather than on a formal model. A second limitation is that the relative volatility estimates include the effects of drift or trend, if they exist, as well as volatility. This second limitation might not be serious if we used futures contract prices and believe that the efficient market hypothesis is valid. But one possible motive for owning a physical commodity is the anticipation of a price increase sufficient to cover storage and other ownership costs. Thus, it might be appropriate for us to remove trend or drift, if any, prior to estimating relative volatilities.

Data

The data which we use are truck bids for corn at St. Louis for the period September 1, 1992 through August 31, 1999. St. Louis corn prices have several advantages. The range of corn prices reported for St. Louis is usually shorter than for other Missouri locations. The fact that we receive corn price data for St. Louis in both electronic and printed form (Missouri Department of Agriculture) increases the probability that we can correct some of the reporting errors[2].

The period which we use is selected partly because we believe that our corn price data for that period are reasonably complete and accurate. A second reason is that the period begins and ends at about the time that the marketing year for corn begins and ends. Including complete marketing years gives us an almost balanced design.

We use midpoints of the reported price ranges. Each day is classified as being one of eleven types. Types M, T, W, R and F are Mondays, Tuesdays, Wednesdays, Thursdays and Fridays for which we have corn prices and for which we also have prices for the immediately preceding Fridays, Mondays, Tuesdays, Wednesdays and Thursdays, respectively. Types HM, HT, HW, HR and HF are Mondays, Tuesdays, Wednesdays, Thursdays and Fridays following holidays which fall (or are observed) on what would otherwise be a business day. These types include only days which follow "one day" holidays (in the case of HW, HR or HF) or three holiday weekends (in the case of HM or HT) and for which we also have corn prices for the business day immediately preceding the holiday or holiday weekend. Type O includes all other days. Thus, it includes business days for which we do not have corn prices. It includes business days which follow business days for which we do not have corn prices. It also includes business days which follow two or more consecutive holidays or which follow four day or longer holiday weekends. Prices for type O days are not used in our analyses.

Models

We use variance, rather than standard deviation, as the measure of volatility. This reflects the fact that estimation and hypothesis testing theories more commonly use variance than standard deviation to measure variability. Except where otherwise noted our models assume day-to-day independence of corn prices.

We used three general types of models. The first is a multiplicative model which is developed to partially justify our *ad hoc* relative volatility estimates.

Multiplicative Model

Our multiplicative volatility model has the form

(1) $V_{ij} = MY_i D_j B$

where V_{ij} is the volatility of type j days in month/year i, MY_i is the (relative) volatility effect of month/year combination i, D_j is the (relative) volatility effect of day type j and B is a base volatility.

The only measure of return used with our multiplicative volatility model is the natural logarithm of the ratio of the current price to the price for the most recent previous business day. We call this measure the rate of price change. When using the multiplicative model we ignore trend or drift. That effectively means that the observed volatility for any given day is the square of the return for that day. We estimate relative volatility by day type using a four step method:

1. For each month/year combination, the average volatility is computed for each day type.

2. For each month/year combination, the overall average volatility is computed.

3. For each month/year combination, we estimate day type relative volatilities by dividing the average volatilities from step 1 by the month/year average volatility computed in step 2. That gives us 84 estimates of the relative volatilities for day types M through F and smaller numbers of estimates for day types MH through FH.

4. For each day type, we estimate an overall relative volatility by computing a weighted average of its month/year average volatilities. The weights are proportional to the numbers of days of that type in the various month/year combinations.

This approach clearly has some limitations. It ignores the possibility of drift. Bias could be introduced in step 3 because the numbers of various day types is not the same for each month/year combination. Thus, the implicit estimates of month/year relative volatilities include some day type effects which could, in turn, induce some bias in day type relative volatility estimates. Another limitation is that (1) includes no error term.

Some of these limitations could be corrected or mitigated. Rather than do that now, we use more common additive models to obtain an additional and perhaps different perspective.

Additive Models

Our additive models assume that day type and other effects are additive. The other effects which we consider are month-of-the-year and corn marketing year effects. As is the case with the multiplicative model month and year effects are included to partially correct for the possibility that the "base" drift and volatility are not constant. Unlike our multiplicative model, our additive models do not include month/year interaction effects. The decision to exclude them is motivated by a desire to avoid undue complexity and by the fact that preliminary analyses suggested that these interactions had little impact on the results.

Our estimation method (PROC GLM in SAS) makes it convenient to think of our additive models as (slightly) unbalanced ANOVA models. They are equivalent to dummy variable models.

Two measures of price change are used as dependent variables for our drift estimation models. One is the rate of price change. The other measure is simply day-to-day price change. A third measure, percentage price change, was considered. Although it is not exactly the same as the rate of price change, the two measures are so highly correlated that using the percentage of price change would add little.

There seem to be several ways of estimating volatility effects. Given that our approach to estimating drift involves a linear model, the computations associated with an heteroscedasticity test provide a way of exploring volatility effects. Our volatility effects are based on the estimation method associated with the Breusch-Pagan (BP) test. We chose the BP test partly because a linear model is used to compute its test statistic. An additional advantage is that, according to Judge et al., the BP test is consistent with a fairly wide class of heteroscedasticity formulations. Moreover, the BP test tends to reject the null hypothesis less frequently (rather than too frequently) for any selected level of significance.

Autoregressive Models

One explanation for weekend and other effects is that current price changes are closely related to recent price changes (Abraham and Ikenberry). To help determine whether this accounts for some of our day type results, we estimate the coefficients of several first order autoregressive models. One model is based on data for all but Type O days. The other autoregressive models are based on data for single day types.

Some Characteristics of Our Models

Our models do not include variables which reflect underlying economic forces or processes. Therefore, low explanatory power is expected.

The period which we chose gives us an almost orthogonal design. This means that, for the additive models, it shouldn't matter much whether day type drift effects are estimated in a model including only day types as explanatory variables or in a model which includes month-of-the-year and crop marketing year variables as well.

For much the same reason, we do not expect differences in volatility (heteroscedasticity) due to day type to have much effect on the estimates of day type drift effects. Differences in day type drift estimates obtained using our complete additive model should be very similar to the differences which could be computed from simple averages by day type. However, standard errors of these differences are likely to be biased. Moreover, heteroscedasticity due to volatility differences associated with month-of-the-year and crop marketing year could influence day type drift estimates and differences among them. For that reason, we attempt to correct our additive drift models for heteroscedasticity and then re-estimate the drift effects.

Results

Table 1 presents part of the day type results. As might be expected, there are more than 300 observations for each of the day types M through F. There are much fewer observations for days following one day holidays or three day holiday weekends.

Relative Volatilities

The third column in table 1 presents relative volatilities for the multiplicative model. The W volatility is the base for these relative volatilities. Inasmuch as the relative volatilities are ratios of variances, F tests are reasonably appropriate. The M, F, HT and HR volatilities are significant[3]. Non-zero drift for day types other than W would tend to cause an upward bias in the ratios while non-zero drift for W would tend to cause a downward bias.

The fact that the estimated relative volatility for day type M is greater than 1 but smaller than 3 is consistent with the idea that volatility or the forces which influence it don't completely stop over the weekend but may operate at a slower rate.

We are somewhat surprised by the estimated relative volatility for day type F. Given that we did not anticipate this result, we don't have a good explanation for it. Additional evidence is offered by the autoregressive model results.

We expected the relative volatility for day type HM to be at least as large as the relative volatility for day type M. Instead it is smaller.

As we expected, the estimated relative volatility for day type HT is larger than for day type M. Many days of type HT follow holidays which are observed more by government offices and exchanges than by businesses. Taken together, the F, M and HT results are consistent with a one day suspension of volatility per weekend. For many of us, it is natural to think of that day as being Sunday. The title of an article by Plaut suggests that there may be another view about that.

The largest estimated relative volatility is for day type HR. There were only four such days in the period which we consider.

Estimated Effects of Day Type in Rate of Price Change Model

The fourth column in table 1 reports differences in drift effects for the various day types in the rate of price change model. We continue to treat the W day type as the base. The fact that, collectively, day types do not have a significant effect on drift suggests that failure to eliminate drift effects when computing the relative volatility estimates presented in the third column of table 1 may not be serious. The mostly negative drift effect estimates do not mean that the drift is negative for day types H, T and R through HW. They simply mean that the drift tends to be *algebraically* smaller for these day types than for the W day type.

The estimated levels for all of these day types depends on the model's intercept term and the specific month-of-the-year and crop marketing year. That is one disadvantage of including variables other than day type in the model. This disadvantage is partially mitigated by the fact that month-of-the-year effects on drift are collectively significant. From largest to smallest the month-of-the-year effects are November, October, March, February, December, January, April, May, June, September, July and August. This means, among other things, that, for any given crop marketing year and day type, the rate of price change tends to be (algebraically) larger from October through March than it is in September and from April through August.

Collectively, the crop marketing year drift effects are not significant.

The estimates in the fifth column are related to the volatility effects of day type. We say related to, rather than estimate, because although the BP test for heteroscedasticity involves linear regression for which the inverse of a constant times the squares of the prediction error (which in our case is for the drift effects model) is the dependent variable, the class of alternative hypotheses against which the null hypothesis of homogeneous error variances is tested includes many functions of the linear form which is used for the test[4]. It does seem reasonable to assume that the estimated coefficients in the fifth column of table 1 have an ordinal relationship to the relative volatility effects of day type. When considered in that way, they are rather consistent with the relative volatility estimates in the third column of table 1.

Collectively, the day type volatility coefficients are significant. However, the month-of-the-year and crop marketing year volatility effects are much "more" significant. The largest month-of-the-year volatility effects are for July and August while the smallest are for December through February. It should come as no surprise to those who remember the difficulties with hedge-to-arrive corn contracts that the 1995 crop marketing year has the largest crop marketing year volatility effect.

Estimated Effects of Day Type in Price Change Model

For the price change model no group of variables is significant. The differences (from W) in the estimated day type drift coefficients are presented in the sixth column of table 1.

As is true for the rate of price change model, the volatility coefficients for each group (day type, month of the year and crop marketing year) of variables are collectively significant. The coefficients of the linear form are presented in the last column of table 1. Note that they suggest a greater volatility effect for day type F than for day type M. At least to this extent they differ from our other volatility results.

Table 2 presents the estimated drift coefficients which are obtained after adjusting for heteroscedasticity. As noted earlier, rejection of the null hypothesis of homogeneous error variances does not provide definitive guidance about the form of the heteroscedasticity. For our analyses, it is clear that the estimated linear form can not be used directly because doing so would imply negative variances for some of the error terms. To obtain the estimates in table 2, we use the estimates implied by the linear form as exponents of the natural constant, e, to estimate error variances and use the inverses of these estimated error variances as weights in weighted regression. This approach is consistent with the BP test. The resulting differences in the estimated day type drift coefficients are, as expected, somewhat different from the corresponding differences presented in columns four and six of table 1.

Autoregressive Results

Table 3 presents least squares estimates of the coefficients of our autoregressive models. In view of the potential problems with least squares estimators of autoregressive models, we use them only to suggest relationships.

The estimated coefficient for the rate of price change autoregressive model which uses all relevant data is .077[5]. This suggests that, overall, the rate of price change for any day is not highly related to the rate of price change for the previous business day. Somewhat different results are obtained for the disaggregated version of the rate of price change autoregressive model. Relatively small or negative coefficient estimates were obtained for all but HF, W, R, and F day types. The largest coefficient is for F. It is .16. The smallest (in absolute value) estimated coefficients are for M and T day types. Collectively, these results suggest that the rate of price changes early in the week tend to be independent of previous price changes. This provides little support for the idea that volatility on Mondays may simply be a continuation of Friday volatility. The estimated coefficients for day types, W, R and F suggest some autoregressive effect.

The estimated coefficients for the price change autoregressive model are somewhat different. The most obvious differences are a relatively large estimated coefficient for W and a rather small estimated coefficient for R.

Concluding Remarks

The analyses reported here paid more attention to, and provide more support for, the importance of day-of-the-week on volatility than most other studies of calendar anomalies. They also support the practice which seems to exist of using Wednesday or other mid-week prices when price for a single day is used as a proxy for a weekly price.

We do not intend to suggest that volatility of prices is always undesirable. In fact, volatility can provide the opportunity for gains. If anything, a problem with the apparently greater volatility of corn price on Mondays and Fridays is that our results may reflect tendencies rather than regular occurrences.

Inasmuch as we have considered prices for only one commodity at one location and for only one time period, it is premature to suggest that the results which we report are generally valid for cash grain prices. Thaler suggests that searches for economic anomalies such as calendar effects on prices are important because they may provide disconfirming evidence of economic hypotheses such as the efficient market hypothesis. It may also be important to verify or refute the validity of disconfirming evidence.

One of the minor problems with our corn price data is that the treatment of holidays is not consistent from year to year. This is mostly due to changes in the holidays which are observed by our state government. A concomitant change has been the tendency for the state agency which collects and reports cash grain prices to do this for more days on which most state employees are not required to work. Presumably, this latter change is related to the fact that initial dissemination of cash grain prices is now through a USDA Web site. Although we suspect that the minor changes in state holidays have little effect on the results reported here, it would be interesting to determine whether that is in fact true.

One of us is particularly interested in local basis behavior. A logical extension of the present work would be to see if there are calendar anomalies in basis behavior and/or whether the anomalies which we found for cash corn prices are present in the prices of corn futures contracts.

Table 1. First Stage Drift and Volatility Estimates

			Rate of Price Change Model		Price Change Model	
Day Type	# of Obs.	Relative Volatility	Drift Difference[a]	Volatility Difference	Drift Difference	Volatility Difference
M	301	1.692	-1.533	.293	-.402	.243
T	323	1.043	-.023	.036	-.096	.007
W	357	1.000	0	0	0	0
R	348	1.004	-1.236	-.002	-.248	-.059
F	334	1.390	-2.083	.155	-.497	.366
HM	16	1.185	-4.403	.049	-.800	.049
HT	38	2.273	-2.720	.997	-.710	.622
HW	1	.145	3.572	-1.402	1.157	-1.518
HR	4	4.981	15.125	1.258	3.443	.677
HF	6	.841	1.919	-.735	.966	.932

[a]Estimated coefficients are .001 times the numbers in this column.

Table 2. Second Stage Drift Estimates

Day Type	Drift Difference: Rate of Price Change Model[a]	Drift Difference: Price Change Model
M	-1.412	-.392
T	-.280	-.040
W	0	0
R	-.956	-.257
F	-2.145	-.623
HM	-4.874	-1.034
HT	-.804	-.226
HW	3.225	.916
HR	16.744	4.185
HF	.123	-.363

[a]Estimated coefficients are .001 times the numbers in this column.

Table 3. Estimated Autoregression Coefficients

	Estimated Autoregression Coefficients	
Day Type	Rate of Price Change Model	Price Change Model
All	.0773	.1054
M	.0345	.0467
T	-.0381	.04487
W	.1258	.2391
R	.1033	.0759
F	.1606	.1351
HM	.2954	.2808
HT	.5349	.7280
HW	[a]	[a]
HR	-.9183	-.3586
HF	.1379	.4712

[a]Not estimable; only one observation for this day type.

Footnotes

1. The study by Fortune is one of the exceptions to this statement.

2. Even though our experience is that the St. Louis corn price data are more accurate than the price data for other locations in Missouri, reporting errors do occur. For example, in the initial report of Tuesday prices, all grain prices for St. Louis are sometimes the same as Monday prices. Fortunately, these prices are usually corrected in the later printed report.

3. We use five percent as the level of significance throughout this paper.

4. It is not completely accurate to say that number by which the square of each prediction error is divided is a constant. Statistically, it is an estimate and thus a random variable. However, for computational purposes, it is treated as a constant.

5. The number of observations for the autoregressive model is slightly smaller than the number of observations for other models because the lagged value was not always available for an appropriate day.

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