Measuring Seasonalities in Commodity Markets and the Half-Month Effect

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INTRODUCTION

Recently, an extensive amount of research has been devoted to the issue of empirical anomalies in financial markets. In time series data involving individual issues and/or market indices, seasonalities have been documented with respect to *the turn of the year* (Keim (1983), Roll (1983), Haugen and Lakonishok (1988)), *the day of the week* (French (1980), Gibbons and Hess (1981), Keim and Stambaugh (1984)), *the half-month*[1] period (Ariel, 1987), and *the time of the day* (Harris, 1986), among others. The consistent recurrence of these seasonalities raises questions about market rationality and market efficiency, and has led to new theoretical models to explain such anomalies (Rock (1989), Admati and Pfleiderer (1988)). However, even when attempts are made to reduce incidental noise from the data with the use of different and larger datasets (Lakonishok and Smidt, 1988), most of the regularities remain intact.

While researchers in the stock and bond markets cannot fully explain the existence of all seasonalities on the basis of market rationality alone, the existence of seasonalities in the commodity markets is potentially explainable by the cyclic nature of production. Because agricultural commodities must follow their own crop cycle which repeats the same seasonal patterns year after year, observed commodity prices exhibit nonstationarities along the same seasonal lines. Crop cycle-related seasonalities in agricultural commodities are documented by Roll (1984), Anderson (1985), Milonas and Vora (1985), Kenyon et al. (1987), and Fama and French (1987). However, since commodities are traded in markets similar to the financial markets, it is an empirical question whether the seasonalities found in financial markets are also present in commodity markets.

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[1]Lakonishok and Smidt (1988) refer to the "time of the month" effect in an attempt to correct the inappropriate term "month effect" used by Ariel. Even this term, however, suffers from precise interpretation. Throughout this study, we attempt to correct this by referring to the same phenomenon as the "half-month effect."

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Recent studies use the Commodity Research Bureau Index (CRB) and the Dow Jones Commodity Index (DJC) to study financial-related seasonalities on commodities (Gay and Kim (1987), Chang and Kim (1988), Chang (1988)). While stock price indices principally lend themselves to a time series analysis of various seasonalities, commodity price indices do not. This is because commodity indices are portfolios of commodities with and without a crop cycle.[2] If the crop-related seasonality exhibited by each commodity for each point in time is not controlled, its effect on the behavior of the index cannot be assessed or identified. Furthermore, because commodity seasonalities may be unique to each commodity, their effect is not diversifiable in the same way stock indices are assumed diversifiable. As a result, the evidence on commodity seasonalities using time series of commodity indices may be a statistical artifact, and not a true representation of existing seasonalities.

The need to adjust commodity prices for crop-related seasonalities is provided by a growing realization that commodity price movements follow a mixture of normal distributions (Clark (1973), Tauchen and Pitts (1983), Hudson et al. (1987), Hall et al. (1989)). As Hall et al. (1989) suggest, these normal distributions have different variances which appear to be serially correlated. Since the main factor for the generation of the nonconstant variance is commodity seasonality, any statistical tests using commodity prices must make adjustments for the seasonality and the resulting heteroskedasticity.[3]

This article documents the existence of crop-related seasonalities in agricultural commodity prices which are examined individually. It is argued that when dealing with commodities, the crop-related seasonalities must be accounted for prior to examining any seasonalities found in the financial markets. Five agricultural commodities are utilized to study *the half-month effect.* The evidence shows that while crop-related seasonalities seriously affect the behavior of commodity prices, the half-month effect has an independent and nontrivial influence on commodity prices.

THREE SOURCES OF SEASONALITIES IN AGRICULTURAL COMMODITIES

Although there is a natural tendency among researchers to investigate certain hypotheses proven in one set of markets of another, the investigation of empirical regularities in commodity markets after such regularities have been documented in the financial markets must make at least one consideration: the seasonal nature of a commodity's extant supply. While not all commodities have seasonal patterns (e.g., metals), all agricultural crop commodities must follow the stages of development from planting to harvest. As the crop enters the growing season, information about the factors which affect its ultimate size and quality at harvest is continuously disseminated in the markets. At the crucial points of development (i.e., summer months) information about the level of heat and moisture exert their greatest influence on the commodity. Such information is translated into price at the equilibrium of expected demand and supply. Consequently, the resulting volatilities are greater in months where the changing weather conditions lead to significant price adjustments, than in months where production yields are not affected seriously, so

[2]According to Cox (1984), the CRB Index consists of the following mixture of commodities: grains, oilseeds, livestock and meats, industrial, precious metals, and miscellaneous. Furthermore, as of 1982, the *DJC Index* included, on an equally weighted basis: cattle, coffee, copper, corn, cotton, gold, hogs, lumber, silver, soybeans, sugar, and wheat.

[3]This point is also made by Taylor (1985).

that price adjustments are rather small. This type of seasonality is known as the *month effect.*

The month effect is also related to storage. After their highest level at harvest, stock levels decline as the year progresses. During the following summer, stocks are much lower than at harvest, and any news affecting the supply and/or demand of the commodity will have a greater impact on prices. This will lead to differential price volatility across months so that the month effect will be manifested.

Another form of seasonality is the *year effect.* The year effect is a statistical manifestation of higher price volatilities during entire crop years in which events with worldwide effects on commodities occur. Political decisions, such as the imposition of a grain export embargo to the Soviet Union by President Carter; economic policies, such as government programs which set price support levels; or major accidents, such as the Chernobyl nuclear accident; as well as unfavorable weather conditions affecting harvest levels, such as droughts, lead to new price and volatility levels which may last for more than one crop cycle. In fact, year effects may be stronger influences than month effects. This does not necessarily mean that the month effect is dependent on the year effect. It means, however, that to statistically detect a month effect, the year effect may have to be controlled (Milonas and Vora, 1985).

Month and year effects influence both cash and futures prices. Futures prices, however, are susceptible to a third effect known as the *maturity effect.* Samuelson (1965), who first analyzed the maturity effect, states that futures price changes exhibit increasing variability as contract maturity nears. This is so, intuitively because, as maturity nears, the futures price is forced to react increasingly stronger to any new information since, upon maturity, it must exactly equal the cash price. This form of regularity which is independent of either the month or year effects, is documented empirically on a large number of commodities and financial assets by Anderson (1985), Milonas (1986), and Fama and French (1988).

OTHER PRICE REGULARITIES IN AGRICULTURAL COMMODITIES?

The price behavior documented in the stock markets is usually an invitation to examine them in the commodity markets as well. However, proven methodologies in the stock market may not necessarily fit the type of data or price behavior in commodity markets. For example, Gay and Kim (1987), Chang and Kim (1988), and Chang (1988) utilize price series of commodity indices to study seasonalities found in the stock market. Their analyses of the *day of the week effect* and the *half-month effect* provide evidence that such seasonalities also exist in commodity markets. However, those studies make no effort to address the year, month, and maturity effects mentioned earlier; so their findings should be viewed with caution, because the possibility of a statistical artifact cannot be ruled out. In particular, the use of a commodity index averages out the price effect of the included commodities. Since some of the included commodities do not have a crop cycle, while others do, and since the production cycle of all commodities does not coincide, the net effect of the averaging procedure is not known. Due to possible systematic bias from such averaging procedures, the results may not be attributed to the price regularity under study.

One way of examining the existence of financially related empirical regularities in commodity markets while simultaneously preventing potential bias, is to examine the individual commodities rather than indices, and to control for the known seasonalities of that commodity. Once the crop-related seasonalities are controlled, the residual price behavior can be used to examine other price regularities.

THE HALF-MONTH EFFECT

To demonstrate the hypothesis that crop-related seasonalities must be controlled before attempting to examine any other price regularity, three agricultural commodities with crop cycles (corn, wheat, and soybeans) and two without crop cycles (soybean meal and soybean oil) are chosen. The methodology is designed to test the recently discovered *half-month* effect by Ariel (1987). Since this effect is tested in the futures markets by Chang (1988) using the CRB commodity index, the results can be compared directly.

Ariel (1987) studies 19 years (1963–1981) of the CRSP (Center for Research in Security Prices) Indices' stock returns in the first and second half of a month. He finds that the average stock return for the first half is positive and significantly higher than the overall stock return in the second half of the month. He finds this seasonality to be independent of any known anomalies such as the January effect. No particular reason or rationality is cited to explain this phenomenon. However, the plausible explanation that the risk faced by market participants may be different in the two halves of the month has not been examined. If the risk in the first half of the month is higher, the higher return found may simply be compensation for higher risk.

More recently, Lakonishok and Smidt (1988) examine the half-month effect over 90 years of price series of the Dow Jones Industrial Average. In contrast to Ariel's definition of the first half-month, Lakonishok and Smidt define the first half of a month to include the first 15 calendar days. When the fifteenth day is not a trading day, the next trading day is included with the first half of the month. The second half consists of all remaining days. Their evidence offers only mild support for the half-month effect. The authors argue that Ariel's result is due, first, to the particular period examined, and, second, to Ariel's definition of the first month to include the last trading day of the previous month.

METHODOLOGY, DATA, AND STATISTICAL CONSIDERATIONS

An examination of nonstationarities in commodities requires the use of a volatility measure. In an effort to reduce potential bias, volatility is estimated with the variance of logarithmic price changes as in Anderson (1985) and Milonas (1986). The logarithm of daily cash price changes on day t, DP_t is calculated as:[4]

$$DP_t = \ln(P_t/P_{t-1}) \tag{1}$$

where P_t is the cash price of a specific commodity observed at time t.[5]

Daily cash prices of the five agricultural commodities are collected for the period 1966 to 1986 from the Chicago Board of Trade Statistical Annuals.[6,7] The choice of cash price data is made because they cover a 21-year period. Also, by us-

[4]This measure was also utilized by Rutledge (1976), Milonas and Vora (1985), and Hall et al. (1989), among others.

[5]Price changes in eq. (1) can also be considered as daily returns for an investor with zero capital investment (0% margin investment). This specification coupled with the use of logarithms eliminates any nonstationarity due to changes in the price level.

[6]The cash price series selected were: Chicago no. 2 yellow corn, Chicago no. 2 soft red winter wheat, Chicago no. 1 yellow soybeans, Decatur soybean meal, and Decatur soybean oil.

[7]In 1966, daily cash price data for corn and soybeans begin in April and for wheat, soymeal, and soyoil in June. Furthermore, soybean prices for the first 6-month period in 1984 are missing.

ing cash price data, the seasonality due to the maturity effect disappears so that the other forms of seasonalities can be studied. Furthermore, the use of cash prices alleviates the problem of daily price limits which, at times, may bias prices from truly reflecting all available information. Since the cash markets of the five agricultural commodities examined are traded in an over-the-counter fashion, to effectively compete under rules of an organized association, cash prices are expected to reflect adequately all existing information.

To show the existence of crop-related seasonalities, the length of one trading month is used to estimate the variance of daily price changes computed from eq. (1).[8,9] Therefore, the statistical tests of analysis of variance employed here implicitly assume that the distribution of price changes within any month is stationary, even though it may be nonstationary from month to month. The estimation period of one month is not so long as to invite within-month nonstationarities while, at the same time, is not so short that it results in an inefficient estimation of volatility. The estimated variances are then arranged according to years and according to months. Therefore, the null hypothesis tests for the equality of the mean variance of daily price changes across years and across months:

$H(0)$: $m(1) = m(2) = \ldots = m(n)$,

i.e., the n population means of variances are equal,

where $n = 1, 2, \ldots, 12$ when testing the month effect, and

$n = 1966, 1967, \ldots, 1986$ when testing the year effect.

The alternative hypothesis is:

$H(1)$: At least one of the population means of variances differs from the rest.

The standard tests of the Analysis of Variance and the nonparametric test of Kruskal–Wallis are utilized to test the null hypothesis.

To test for the half-month effect Lakonishok and Smidt's (1988) methodology is followed with some modifications. To allow for a balanced number of observations in both halves of each month, the first half includes the first 15 calendar days, and the second half includes all the remaining days. If either of the two halves has 5 or fewer observations, the entire month is eliminated from the sample. The final sample, therefore, consists of equal numbers of half-month periods. Within these half-month periods, daily cash logarithmic returns are computed according to eq. (1), and their mean and standard deviations are estimated. The null and alternative hypotheses are as follows:

$H(0)$: $\mu(1) = \mu(2)$, i.e., the mean logarithmic return in the first half period is equal to the mean logarithmic return in the second-half period.

$H(1)$: $\mu(1) > \mu(2)$, i.e., the mean logarithmic return in the first-half period is greater that the mean logarithmic return in the second-half period.

The null hypothesis is tested using a t test.

EVIDENCE ON THE CROP-RELATED SEASONALITIES

Year Effects

Table I presents the evidence of seasonality due to the year effects. The average of 12 or fewer months within each year of cash-based volatility are shown for the

[8]The choice of one trading month as the estimation period is also necessitated by the fact that we need to utilize its two halves in order to study the half-month effect.

[9]The largest number of trading days within a month is 23. While the number of observations used to derive monthly variances changes, months with fewer than 16 observations were excluded from the study.

Table I
THE YEAR EFFECT IN CASH PRICES
Estimation Period: One Month (1966–1986)

	Average Monthly Variances (%) of Daily Price Changes				
Calendar Year	**Corn**	**Wheat**	**Soybeans**	**Soymeal**	**Soyoil**
1966	.0093	.0177	.0142	.0254	.0239
1967	.0118	.0114	.0026	.0118	.0057
1968	.0109	.0074	.0025	.0079	.0087
1969	.0098	.0084	.0027	.0105	.0295
1970	.0155	.0166	.0072	.0242	.0517
1971	.0132	.0142	.0079	.0066	.0238
1972	.0136	.0213	.0126	.0244	.0313
1973	.0739	.1422	.1723	.2419	.2176
1974	.0715	.0923	.0666	.2333	.1219
1975	.0393	.0630	.0487	.0658	.0628
1976	.0261	.0332	.0460	.0509	.1062
1977	.0187	.0243	.0567	.0790	.1362
1978	.0106	.0391	.0276	.2246	.1256
1979	.0167	.0526	.0220	.0330	.0221
1980	.0466	.0416	.0405	.0419	.0615
1981	.0163	.0561	.0206	.0305	.0394
1982	.0179	.0265	.0129	.0119	.0162
1983	.0209	.0204	.0284	.0340	.0367
1984	.0187	.0518	.0377	.0340	.0427
1985	.0132	.0162	.0143	.0261	.0232
1986	.0229	.0053	.0142	.0139	.0307
Obs	248	243	244	246	246
DF	20/227	20/222	20/223	20/225	20/225
F-value	5.79*	10.85*	22.70*	15.92*	13.75*

*Significant at the 1% level.

5 commodities. As the statistical tests of ANOVA suggest, there is strong evidence that volatility is different across the 21 years.[10] In fact, volatilities are higher during years with extended worldwide influences. For all commodities, the 1973 period of the Russian grain deal and the 1974 period of midwest drought exhibit larger volatilities than in all other years. The grain-export embargo to the Soviets imposed by President Carter in 1980 combined with a small crop due to a drought produces the second highest volatility for corn (primarily affected by the embargo), and among the highest volatilities for wheat. However, soybeans and soybean-related products exhibit only mild volatility during that time. The US dominance in soybean production, and the growing demand for soybeans seem to have partially offset any strong soybean reaction to the grain embargo.

The year effect is illustrated graphically in Figure 1. Except the period 1976–78 where soymeal and soyoil exhibited different volatilities, the volatilities of all

[10]Throughout our statistical analysis, whenever, ANOVA tests were required, we also performed the nonparametric test of Kruskal–Wallis. In all cases, the resulting Chi-square test agrees wtih the statistical significance of the *F* test so we do not report it.

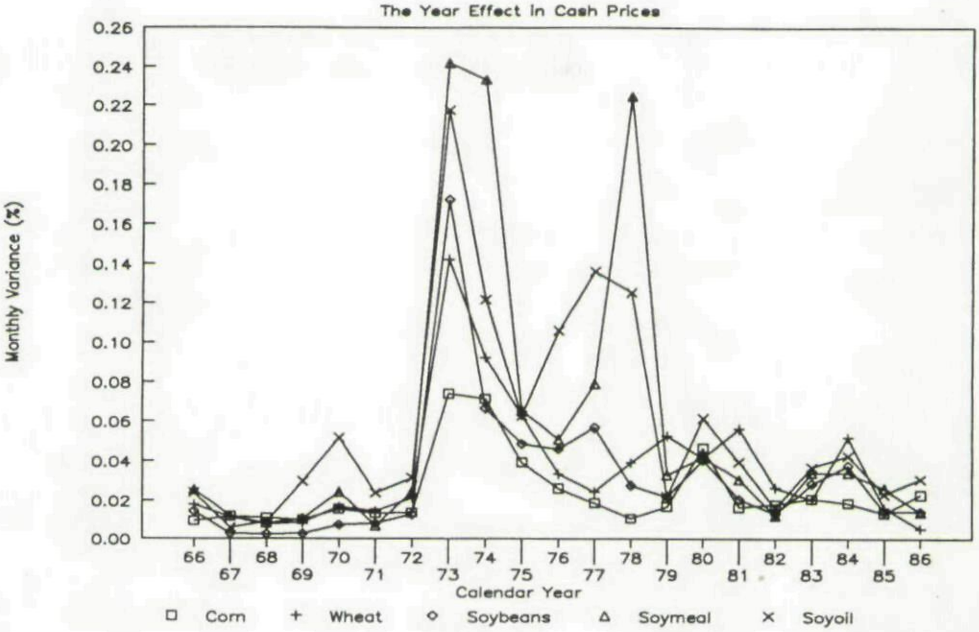

Figure 1
The Year Effect in Cash Prices

5 commodities follow a similar pattern. This suggests that domestic and worldwide events affect commodity price volatility simultaneously and in the same direction.

Month Effects

Panel A of Table II and Figure 2 show the average monthly variances of logarithmic daily price changes arranged by the calendar month of observation. These averages increase substantially during the summer months of June to August. In the case of corn, they are high up to the month of harvest (October). This systematic volatility is followed also by soymeal and soyoil which do not have a crop cycle themselves. In this case, it seems that the seasonality effect exhibited in soybeans is spilled over to its two derivatives through perhaps the crushing margin.

Despite the obvious differences in monthly volatilities, only corn and soybeans exhibit statistical support for the month effect. No statistical support for the month effect is found for the remaining commodities. One possible explanation for this phenomenon is the existence of a strong year effect (found in Table I) which may prevent the month effect from being detected statistically. This is a case where the year effect is stronger than the month effect.

To examine the possibility that the month effect exists but is dominated by the year effect, a methodology which controls for the latter effect is applied for each calendar year. The arithmetic and geometric average of the variance is found. Then, each of the 12 monthly variances of that year is divided by the two averages of the same year. Two datasets with normalized variances are created in which the year effect is equalized across years.[11]

[11]ANOVA and Kruskal–Wallis tests on the two normalized datasets do not show statistical support of the year effect.

Table II
THE MONTH EFFECT IN CASH PRICES
Estimation Period: One Month (1966–1986)

Calendar Month	Corn	Wheat	Soybeans	Soymeal	Soyoil
Panel A: Raw Variances					
Average Monthly Variances (%) of Daily Price Changes					
January	.0184	.0313	.0268	.0476	.0355
February	.0199	.0406	.0164	.0231	.0357
March	.0133	.0277	.0174	.0341	.0428
April	.0122	.0356	.0183	.0804	.0354
May	.0157	.0453	.0206	.0258	.0328
June	.0200	.0524	.0375	.1001	.0792
July	.0333	.0362	.0773	.1182	.1428
August	.0294	.0582	.0471	.0830	.0566
September	.0335	.0561	.0387	.0601	.0449
October	.0448	.0245	.0287	.0490	.0568
November	.0266	.0328	.0261	.0440	.0968
December	.0200	.0236	.0175	.0427	.0358
Grand mean	.0239	.0388	.0313	.0595	.0580
Obs	248	243	244	246	246
DF	11/236	11/231	11/232	11/234	11/234
F-value	5.54*	1.00	2.46*	1.00	1.09
Panel B: Arithmetically Normalized Variances					
F-value	9.36*	1.98**	8.71*	2.53*	2.78*
Panel C: Geometrically Normalized Variances					
F-value	9.81*	2.09**	9.35*	2.81*	3.25*

*Significant at the 1% level.
**Significant at the 5% level.

Panels B and C of Table II present the statistical results of the month effect on arithmetically and geometrically normalized variances, respectively. In all 5 commodities, the existence of the month effect is supported. This evidence also suggests that in the cases of wheat, soymeal, and soyoil, the year effect dominates the effect from trading in different months.

EVIDENCE ON THE HALF-MONTH EFFECT

Table III shows the mean logarithmic return for each half-month period and their difference over the entire 21-year period. For all 5 commodities, the average logarithmic return in the first half is positive, and in the second half is negative. As a result, their mean difference is positive. However, the difference in the two half-month returns is statistically significant only in the case of corn and wheat. Therefore, the evidence on the half-month effect cannot be considered conclusive on all commodities. Furthermore, the year and month effects documented earlier may prevent the half-month effect from appearing statistically. To examine the latter

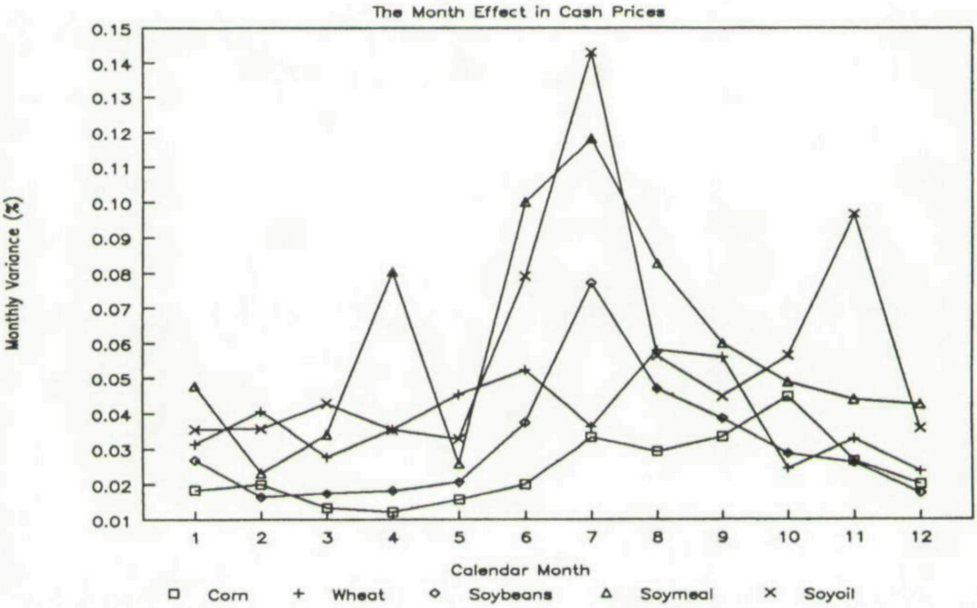

Figure 2
The Month Effect in Cash Prices

possibility, the year and month effects are re-examined using half-month period estimates of volatilities. The results appear in Table IV.

For all commodities, the average standard deviation for the first half is very close to the average standard deviation in the second half. This suggests that there are no differences in the risk level of price changes between the two halves. The *F*-statistics show that the year effect is significant in both halves for all commodities. In contrast, the month effect is significant only in the case of corn and soybeans. Once again, the month effect in the remaining three commodities is overshadowed by the year effect, a result also obtained earlier (see Table II, panel A).

The evidence in Table IV has at least three implications. It strengthens the argument that the month and year effects are an integral part of the pricing process as both effects are identified using small estimation periods. It suggests that the small half-month estimation periods produce efficient volatility estimates. Since the

Table III
THE HALF-MONTH EFFECT IN CASH PRICES.
HALF-MONTH LOGARITHMIC PRICE CHANGES (DP) (1966–1986)

		First Half		Second Half		Mean Difference	
Commodity	**Obs**	**Mean (%)**	***t*-stat**	**Mean (%)**	***t*-stat**	**Mean (%)**	***t*-stat**
Corn	249	0.052	2.01*	−0.045	−1.49	0.097	2.44*
Wheat	245	0.089	2.35*	−0.048	−1.32	0.137	2.81*
Soybeans	243	0.046	1.24	−0.023	−0.70	0.069	1.56
Soymeal	246	0.051	1.10	−0.029	−0.68	0.080	1.38
Soyoil	245	0.011	0.23	−0.018	−0.40	0.029	0.45

*Significant at the 5% level.

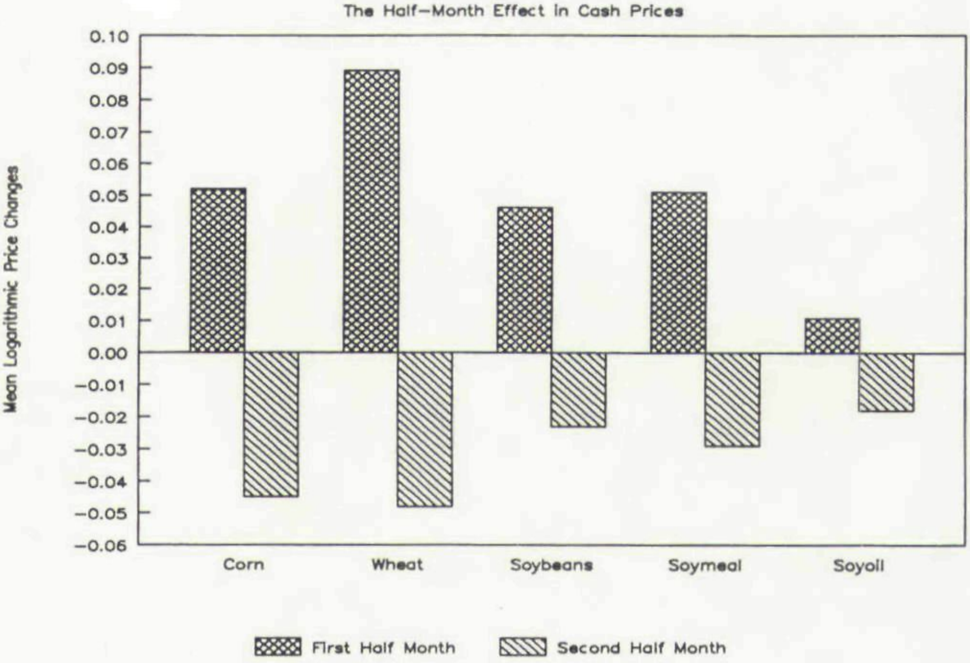

Figure 3
The Half-Month Effect in Cash Prices

month and year effects are present in half-month periods, it is necessary to adjust for them before the half-month effect can be tested.

One simple way of adjusting for existing seasonalities is by calculating the risk return tradeoff, RRT_{it} for month t and half-month period i ($i = 1$ for first half and $i = 2$ for second half):

$$RRT_{it} = \frac{\overline{DP_{it}}}{\sigma_{it}} \tag{2}$$

where:

$\overline{DP_{it}}$ is the mean of the daily logarithmic price changes defined in eq. (1), and
σ_{it} is the standard deviation of daily logarithmic price changes for month t and half-month period i.

Intuitively, this measure standardizes the level of return observed in each period with its associated estimated volatility, so that the returns become part of the same population without regard to the month or year they are observed. Since the average volatilities of the two half-periods are equal for a given month (according to the evidence in Table IV), no systematic bias is introduced during the standardization process. To examine whether this procedure effectively neutralizes the existing month and year effects, an ANOVA test is performed on the two half-month period difference of risk-return tradeoff. The difference in the risk-return tradeoff between the two halves in month t is defined as:

$$\Delta RRT_t = RRT_{1t} - RRT_{2t} \tag{3}$$

Table V shows that the estimated risk-return tradeoff does not exhibit any seasonality either in calendar years or in calendar months. All associated F-statistics

Table IV
THE YEAR AND MONTH EFFECT IN CASH PRICES
Estimation Period: Half Month (1966–1986)

		First Half			Second Half		
		Average	F-Statistics		Average	F-Statistics	
Commodity	Obs	Standard Deviation	Year Effect	Month Effect	Standard Deviation	Year Effect	Month Effect
Corn	249	.0132	5.86*	2.21*	.0127	4.25*	4.36*
Wheat	245	.0163	5.98*	1.58	.0166	5.27*	0.78
Soybeans	243	.0141	10.35*	1.97*	.0143	10.37*	2.25*
Soymeal	246	.0187	8.13*	1.66	.0180	6.91*	1.02
Soyoil	245	.0197	3.26*	1.85	.0190	4.49*	1.06

Note: Risk-return tradeoff (RRT) for month t and half-month i ($i = 1,2$) is:

$$RRT_{it} = \frac{\overline{DP}_{it}}{\sigma_{it}}$$

where: $\overline{DP}$ = mean daily logarithmic price change defined in eq. (1) and
σ = standard deviation of daily logarithmic price changes.
The difference in the RRT between the two halves in month t is:

$$\Delta RRT_t = RRT_{1t} - RRT_{2t}$$

*Significant at the 1% level.

are small and insignificant at any conventional level, suggesting that the behavior of the risk-return tradeoff is stationary.

Table VI presents averages of the risk-return tradeoff for the two halves as well as their difference. The pattern of positive (standardized) returns in the first half and negative returns in the second half also appears here. The mean difference is positive and statistically significant in all commodities except soybean oil. This evidence on the half-month effect is stronger than the evidence in Table III. It also suggests that when other seasonalities are controlled, the half-month effect can be detected.

After having accounted for the basic sources of seasonality in each commodity separately, it is puzzling why all 5 agricultural commodities examined show positive average returns during the first half of an average month and negative returns in the second half. The explanation of this phenomenon in financial markets, called "window dressing," does not seem to exist in commodities.

Table V
THE YEAR AND MONTH EFFECT IN THE HALF-MONTH PERIOD DIFFERENCE OF THE RISK-RETURN TRADEOFF (ΔRRT) (1966–1986)

			F-Statistics	
Commodity	Obs	Average ΔRRT	Year Effect	Month Effect
Corn	249	.0975	0.99	1.38
Wheat	245	.0868	1.12	1.29
Soybeans	243	.1221	0.94	1.07
Soymeal	246	.0920	0.84	1.11
Soyoil	245	.0877	1.07	1.09

Table VI
THE HALF-MONTH EFFECT IN CASH PRICES
HALF-MONTH RISK-RETURN TRADEOFF IN CASH PRICES (1966–1986)

Commodity	Obs	First Half Mean	First Half *t*-stat	Second Half Mean	Second Half *t*-stat	Mean Difference Mean	Mean Difference *t*-stat
Corn	249	0.0669	3.38*	−0.0306	−1.37	0.0975	3.22*
Wheat	245	0.0595	2.85*	−0.0273	−1.31	0.0868	2.95*
Soybeans	243	0.1017	3.63*	−0.0204	−0.96	0.1221	3.47*
Soymeal	246	0.0574	1.99**	−0.0346	−1.32	0.0920	2.37*
Soyoil	245	0.0534	0.94	−0.0343	−1.43	0.0877	1.42

*Significant at the 1% level.
**Significant at the 5% level.

In an attempt to examine whether this pattern holds for each month and is not due to systematic behavior in certain calendar months, the average difference of the risk-return tradeoff between the two halves by month is presented in Table VII. In the case of the three-crop cycle-related commodities (corn, wheat, and soybeans), 83% of the total combined months show that the return difference in the two halves is positive. This suggests that the half-month effect is not due to some outlier. However, there seems to be some tendency of larger standardized returns in the second half-month period during the months in the fall and December. Both corn and wheat have higher second half returns in December. This phenomenon may be explained by the seasonal tendency of corn and wheat prices to increase in the fall of the year through December. Overall, the half-month effect seems to hold uniformly.

Table VII
THE MONTH EFFECT IN THE TWO-HALF MONTH
DIFFERENCE OF RISK-RETURN TRADEOFF (1966–1986)

Calendar Month	Corn	Wheat	Soybeans	Soymeal	Soyoil
	Average Difference of the Risk-Return Tradeoff (ΔRRT)				
January	.0830	.1538	.2152	.0998	−.0946
February	.1769	.2665	.1828	−.0556	.0506
March	.1033	.0818	.0387	.2039	.0450
April	.0214	.1237	.0881	−.0220	.0220
May	.0619	.1681	.2851	.1659	.1167
June	.1913	.0414	.0937	.0122	−.1752
July	.3587	.0951	.2337	.2495	.0746
August	.1975	.0778	.2015	.1085	.7754
September	.0880	.1426	−.0574	−.0031	.0622
October	−.0041	.0103	−.0920	.1258	−.0479
November	−.0413	.0970	.1332	−.1322	.1368
December	−.0631	−.1938	.1542	.3609	.0713
Grand mean	.0975	.0868	.1221	.0920	.0877

CONCLUSIONS

This article examines the various sources of seasonalities present in agricultural commodities. The evidence shows that the month and year effects are major factors in the commodity pricing process and are caused by the systematic flow of information. Because the flow of information which affects commodities follows a seasonal pattern, commodity prices exhibit strong seasonalities which are captured in their volatility. While these results are in line to existing evidence, they expand the understanding of microseasonal patterns of commodity price behavior according to the type of information and during a particular time period.

This study advances the argument that unless the crop-related seasonalities are controlled, other types of seasonalities found in financial markets (i.e., weekend effect, January effect, half-month effect) cannot be examined properly. The error may be even greater if, instead of individual commodities, one uses commodity indices. Unlike stock indices, commodity indices cannot diversify all nonsystematic risk (in the form of seasonalities) related to each commodity in the index. The remaining nonstationarities may potentially bias the results in an unknown direction. It is, therefore, appropriate that the quest for various seasonalities focus on individual commodities rather than indices.

The hypothesis was tested on the newly discovered anomaly of the half-month period using cash prices of 5 individual commodities over a 21-year period. After controlling for the crop-related seasonalities, it is found that the half-month effect holds in 4 of the 5 examined commodities. In particular, for corn and wheat, the half-month effect is documented by simply following Lakonishok and Smidt's (1988) methodology. However, only after standardizing the level of return for its particular volatility is it possible to document the half-month effect for soybeans and soybean meal. This simple methodology is shown to effectively neutralize the existing month and year effects. Hence, it has potential use for the study of other phenomena which affect commodity prices.

Although the existence of the half-month effect is documented here, no explanation surfaces about its cause. In fact, some of the practices followed by money managers that could potentially explain this phenomenon are not as relevant in the case of commodities. Furthermore, because both halves show similar volatility, it is unlikely that the half-month effect is generated by a disproportionate number of information releases in the two halves. Nevertheless, despite the lack of obvious economic foundation, since it can be considered another empirical regularity, the half-month effect should be taken into account: when pursuing deals in the cash commodity markets so that sales are promoted during the first half while purchases are made during the second half of the month; and, in statistical testing involving disproportionate numbers of observations from the first or the second half of the month.

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