Putting on the Crush: Day Trading the Soybean Complex Spread

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INTRODUCTION

In recent years, spread trading strategies for financial commodities have received considerable attention [Rentzler (1986); Poitras (1987); Yano (1989)] while, with some exceptions, spreads in agricultural commodities have been relatively ignored. Limited or no information is available, for example, on the performance of various profit margin trading rules arising from production relationships between tradeable agricultural input and output prices, e.g., soybean meal, corn and live hogs [Kenyon and Clay (1987)]. Of the agricultural spreading strategies, the so-called "soy crush" or soybean complex spread is possibly the most well known.[1] Trading rules arising from this spread exploit the gross processing margin (GPM) inherent in the processing of raw soybeans into crude oil and meal. The primary objective of this study is to show that it is possible to use the GPM, derived from the known relative proportions of meal, oil, and beans, to specify profitable rules for day trading the soy crush spread.[2]

This article first reviews relevant results of previous studies on the soybean complex and its components followed by specifics on the GPM-based, intraday trading rule under consideration. Assumptions on contract selection, transactions costs, and margin costs are discussed. Simulation results for the trade on daily data over the period February 1, 1978 to July 30, 1991 are presented. The results indicate that, for sufficiently large filter sizes, the trading rule under consideration is profitable during the sample periods examined. It is argued that the results of this study reflect the potential profitability of floor trading in the soybean pits.

PREVIOUS RESULTS

With some exceptions, previous studies of the soybean complex have ignored the interrelationships inherent in the crush spread opting instead to focus on the

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[1] A number of sources provide descriptive treatments of the trade, e.g., Rose and Sheldon (1984) or Arthur (1971).

[2] See Thompson and Waller (1988) for background on day trading.

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individual markets. In many cases, the objective was to assess whether specific criteria for "market efficiency" were satisfied. For example, Stevenson and Bear (1970) examined soybean futures, 1957–1968, and identified a tendency toward negative dependence over short intervals and positive dependence over longer periods. Rausser and Carter (1983) used monthly average cash prices for soybeans, oil and meal, 1966–1980, and provided results to "support the necessary relative accuracy condition for futures market inefficiency" (p. 447). Finally, Helms, Kaen, and Rosenman (1984) used both the proportionate daily change in prices for soybean, oil and meal contracts, 1976–1977, and the proportionate intraday (minute-by-minute) price changes for a number of days in 1977 and 1978 for CBOT soybeans, and found that "there are non-periodic cycles (persistent dependence) in both daily and intraday futures prices." While there may be questions about the methodology used in these studies, on balance, the evidence indicates that price changes in the soybean complex are not completely independent.

Of the small number of previous studies directly concerned with the soybean complex spread, the Johnson et al. (1991) article is of immediate interest.[3] With the objective of verifying market efficiency in the soybean complex, Johnson et al. deduct an estimate of the cost of crushing from the GPM and use the resulting net profit margin (NPM) to identify long-term trading opportunities. When the NPM $>$ 0, a normal crush position (long beans, short meal, short oil) is established; when NPM $<$ 0, a reverse crush (short beans, long meal, long oil) is used. Five trades are initiated at the closing price on the 15th of every month and then lifted at preset intervals: 1.5, 3.5, 5.5, 7.5, and 9.5 months. (Being held for monthly frequencies, the Johnson et al. strategy differs from the day trading strategy under present consideration.) Contract delivery date selection is determined by using the maturity date nearest to but still later than the calendar day when the trade is to be lifted. Simulation results are presented for 1966–1988.

Using the trading rule described, Johnson, et al. find that: "Significant profits above transactions costs are not found at trade lengths of 1.5 and 3.5 months, but are found at trade lengths of 5.5 months or longer," This leaves a number of important questions unanswered. For example, is this outcome dependent on how execution costs are determined, e.g., underestimated for the longer horizons? What would be the profitability if the trader was able to lift the trade at any time between the start date and the fixed termination date or use a filter to select the start date, e.g., NPM $>$ k, some constant? This article indirectly addresses the latter question by illustrating how a profitable day trading rule can be specified. Johnson et al. (especially Table II) do observe that their aggregate results indicate "larger profits and a higher percentage of profitable trades as implied margins become more positive." Similar results hold for the reverse crush. In addition, their results indicate that longer trade lengths combined with filters $>$ 20 cents almost always produce a profitable trade.

TRADING RULE SPECIFICATION

On balance, evidence from previous studies of the soybean complex suggests the potential for exploitable futures trading opportunities in the soy crush spread. In contrast to previous studies, which examined interday and longer term trading horizons, this study examines the profitability of intraday trades based solely on

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[3] Hieronymous (1949) and Dueringer (1972) are other academic studies directly on the soy crush spread. Tzang and Leuthold (1990) examine the problem of estimating hedge ratios for the soybean complex processor.

the GPM. More precisely, the spread involves combining a long (short) position in soybeans with short (long) positions in meal and oil. The number of contracts used is determined by duplicating the physical processing relationship for the soybean complex, the GPM, where a (60 lbs.) bushel of soybeans yields 11 lbs. of oil and 48 lbs. of meal [USDA (1988)]. Specifically, in terms of futures contracts:

$$\mathrm{GPM}(t,T) = 48\,\frac{\mathrm{FM}(t,T)}{2000\ \mathrm{lbs.}} + 11\,\frac{\mathrm{FO}(t,T)}{100\ \mathrm{lbs.}} - \mathrm{FS}(t,T)$$

where: $\mathrm{GPM}(t,T)$ is the per bushel gross processing margin observed at time t using CBOT futures contracts with maturity at time T $(T > t)$, $\mathrm{FM}(t,T)$ is the associated price of meal, $\mathrm{FO}(t,T)$ is the price of oil, and $\mathrm{FS}(t,T)$ is the price per bushel of soybeans.

Given the CBOT contract specifications, this translates into 10 soybeans, 12 meal, and 9 oil contracts for a balanced position. When used as a hedging strategy, the soy crush spread can be used by processors to hedge the GPM associated with their operations.[4]

While it is possible to develop fundamental rationales for trading strategies based on the GPM, the approach used here is closer to a technical approach; e.g., Lukac, et al. (1988) and Lukac and Brorsen (1990). Specifically, the GPM is used to specify a naive day trading rule which tracks whether the GPM at the open is below (above) the GPM at the previous close. This leads to the following trading rule:

> If the GPM on the open is less (greater) than the previous day's close, a reverse crush (normal crush) spread is placed. In all cases, the position is liquidated on the close of the same day.

In keeping with similar naive trading rules, filters are imposed on the GPM, reducing the number of days during which trades are initiated. Ex ante, the expected (monotonic) relationship between filter size and trade performance is: as filter size increases, mean profit per trade and the percentage of profitable trades will increase while the number of trades will decrease.

To facilitate profit calculations, when trading 10 soybean, 12 meal, and 9 oil contracts, a 1-cent per bushel change in the GPM represents a \$500.00 change in the value of the position. However, in what follows, if all trade sizes are doubled, i.e., results for a 20–24–18 trade are evaluated,[5] a 1-cent per bushel change in the GPM represents a \$1000 change in the position. Given this, roundtrip transaction costs per trade are estimated to be 1.5 cents per bushel. This value is composed of both execution costs and commissions. Following the approach used by Johnson et al. (p. 30) and others, it is assumed that one tick is required both to get in and to get out of a given contract. Based on price ticks for beans, meal, and oil of 1/4 cent per bushel, 10 cents per ton, and 1 cent per 100 lbs., this translates into $0.5 + 0.48 + 0.216 = 1.196$ cents per bushel for execution costs. This leaves 0.304 cents per bushel for commission costs and is consistent with payments incurred by floor traders employed by clearinghouse members.

This estimate for trading costs is assumed for testing the trading rule. Specifically, the strategies examined here are designed to "replicate" floor trading activity in the (CBOT) soybean complex pits where: transactions take place at or near

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[4] The methods required for implementing such a hedging strategy are discussed in Tzang and Leuthold (1990).

[5] This approach also differs from Johnson et al. who used a 1–1–1 spread.

clearinghouse commission rates, margin costs are minimal because positions are not carried overnight, and all gains or losses must be settled in cash at the end of the day (with corresponding cash flow implications). Costs savings arising from execution gains, i.e., being able to "hit" offers rather than "placing" bids, are assumed to offset distortions arising due to potentially noisy opening and closing prices.[6] Distortions in these prices can occur for a number of reasons. For example, small unrepresentative trades occurring at the open (or close) do not reflect attainable profit opportunities. There is also a general inability to place the first or last trade of the day.[7]

EMPIRICAL RESULTS[8]

A daily GPM is calculated using the opening and closing transaction price quotations for CBOT soybean, soybean meal and soybean oil futures contracts. A continuous series is constructed using four-month trading periods for each of the March, August, and December contracts from February 1, 1978 to July 31, 1991. In presenting evidence on the components of the complex and the GPM, the sample is decomposed into two parts, February 1978 to May 1987 and June 1987 to July 1991. In addition, due to different trading cycles and data availability, the March GPM uses March contracts for each of the three commodities, the August GPM uses July soybeans and August meal and oil, while the December series uses November beans and December meal and oil. Given this, the March GPM trading period runs from October 1 to January 31, February 1 to May 31 for the August GPM, and June 1 to September 30 for the December GPM. In this fashion, about 85 observations from a given delivery month are used in constructing the continuous series, in a given year.[9] In addition, the contracts being used are relatively close to delivery, negating concerns about contract liquidity.

Tables IA and IB provide a number of summary statistics for the GPM and the three components of the complex: beans, meal, and oil over the two subsamples. Closer inspection of these empirical results reveals the rationale for the use of two subsamples, i.e., at conventional α levels, there is a statistically significant difference in the mean values for the component series over the two periods. In effect, while prices and GPM are relatively constant over the first subsample, the second subsample is characterized by an uptrend. Given this, combining the samples and presenting results for only the full sample may provide a substantially less accurate picture of the empirical evidence. Examining the results for the individual components reveals

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[6] Another offset to the use of opening and closing prices occurs when the trade is lifted at some point in the day prior to the close. Hence, it would have been possible to evaluate this trade using open, high, low, and closing prices to ascertain the maximum possible profit which could have been achieved. However, this would lead to a number of significant complications in specifying the form of the trading rule.

[7] Useful discussions are available regarding the problems that arise in specifying trading rules and the associated profit simulations, e.g., Lukac and Brorsen (1990) and Poitras (1989). Regarding trading floor execution of the soy crush trade, it is typical for the (large) floor trading operations of clearinghouse members to have a designated trader coordinating activity in various pits. While it is common practice for trading firms to quote a specific dollar value for the GPM spread to customers, e.g., Johnson et al. (p. 30), the trading firm has to execute the trades for the components of the GPM in the individual pits.

[8] The transaction price data is from Commodity Systems, Inc., located in Boca Raton, Florida. The open price is for the first transaction of the day while the close price is for the last transaction.

[9] This method of constructing a continuous series leads to "rollovers" which are days on which one contract ceases to trade the nearest delivery month and begins to trade the subsequent contract used. Even though the number of rollover dates is small relative to the total number of trading days, e.g., 27 of 2351in the first subsample, these dates are omitted from the simulations to avoid the bias associated with the pricing implications.

that, over the two specified time intervals, the mean price changes are relatively small compared to the size of the standard deviations. In addition, while significant differences in the means for the three commodities over the two subsamples can be observed, this may be an artifact of the subsample selection process.

Table IA[a]

OPENING AND CLOSING PRICE CHANGES: GPM, SOYBEANS, SOYBEAN MEAL, AND SOYBEAN OIL

Sample: Daily, February 1, 1978 to May 29, 1987, selected contracts
Gross Processing Margin (GPM) (cents/bu.): mean GPM: 34.7 cents; std. dev.: 10.2 cents

Price Changes	Mean Change	Std. Dev.	Skewness	Kurtosis
ΔOpen	0.0021	3.655	0.11	6.54
ΔClose	0.0042	2.789	−0.29	18.5
$\text{Open}_t - \text{Close}_{t-1}$	−0.081	2.727	−0.90	25.3
$\text{Close}_t - \text{Open}_t$	0.085	2.837	0.22	6.57

Variables	Correlations
ΔOpen_t and ΔOpen_{t-1}	−0.39 (−18.9)
ΔClose_t and ΔClose_{t-1}	−0.26 (−12.9)
$(\text{Close}_t - \text{Open}_t)$ and $(\text{Open}_t - \text{Close}_{t-1})$	−0.49 (−23.7)

Components of the Complex

A. Soybeans (cents/bu.)

Price Changes	Mean Change	Std. Dev.	Skewness	Kurtosis
ΔOpen	−0.0107	10.97	−0.53	9.62
ΔClose	−0.0127	10.50	−0.62	9.79
$\text{Open}_t - \text{Close}_{t-1}$	0.116	6.599	−0.65	34.70
$\text{Close}_t - \text{Open}_t$	−0.128	8.033	−0.11	3.16

Variables	Correlations
ΔOpen_t and ΔOpen_{t-1}	−0.043 (−2.08)
ΔClose_t and ΔClose_{t-1}	0.0003 (0.15)
$(\text{Open}_t - \text{Close}_{t-1})$ and $(\text{Close}_t - \text{Open}_t)$	0.015 (0.73)

B. Soybean Meal (dollars/ton)

Price Changes	Mean Change	Std. Dev.	Skewness	Kurtosis
ΔOpen	0.0038	3.04	0.30	6.22
ΔClose	0.0040	2.86	0.22	3.59
$\text{Open}_t - \text{Close}_{t-1}$	0.025	1.83	1.67	15.10
$\text{Close}_t - \text{Open}_t$	−0.021	2.24	−0.10	4.89

Table IA (continued)

Variables	Correlations
$\Delta Open_t$ and $\Delta Open_{t-1}$	−0.0558 (−2.70)
$\Delta Close_t$ and $\Delta Close_{t-1}$	0.011 (0.53)
($Open_t - Close_{t-1}$) and ($Close_t - Open_t$)	−0.019 (−0.92)

C. Soybean Oil (dollars/100 lbs.)

Price Changes	Mean Change	Std. Dev.	Skewness	Kurtosis
ΔOpen	−0.00163	0.461	−1.30	22.37
ΔClose	−0.00164	0.422	−1.86	31.4
$Open_t - Close_{t-1}$	−0.00225	0.278	−5.74	143.7
$Close_t - Open_t$	0.00062	0.327	0.23	2.32

Variables	Correlations
$\Delta Open_t$ and $\Delta Open_{t-1}$	−0.059 (−2.86)
$\Delta Close_t$ and $\Delta Close_{t-1}$	0.045 (2.18)
($Open_t - Close_{t-1}$) and ($Close_t - Open_t$)	−0.035 (−1.70)

[a] Values in brackets beside correlations are t-values for the null hypothesis of zero correlation and normally distributed variables. ΔOpen = daily change in the level of the opening price; ΔClose = daily change in the level of the closing price; $Open_t - Close_{t-1}$ = difference between the opening price and the previous day's closing price, the "overnight" price change; $Close_t - Open_t$ = difference between the same day closing and opening price levels, the intraday price change. Values for kurtosis are centered at 3. See also footnote to Table II.

Table IB[a]
OPENING AND CLOSING PRICE CHANGES: GPM, SOYBEANS, SOYBEAN MEAL, AND SOYBEAN OIL

Sample: Daily, June 1, 1987 to July 31, 1991, selected contracts
Gross Processing Margin (GPM) (cents/bu.): mean GPM: 62.9 cents; std. dev.: 12.5 cents

Price Changes	Mean Change	Std. Dev.	Skewness	Kurtosis
ΔOpen	0.0569	4.315	1.55	20.9
ΔClose	0.0560	3.410	1.61	44.2
$Open_t - Close_{t-1}$	−0.0016	3.241	4.21	73.4
$Close_t - Open_t$	0.058	3.133	−0.44	5.03

Variables	Correlations
$\Delta Open_t$ and $\Delta Open_{t-1}$	−0.306 (−10.1)
$\Delta Close_t$ and $\Delta Close_{t-1}$	−0.134 (−4.44)
($Close_t - Open_t$) and ($Open_t - Close_{t-1}$)	−0.43 (−14.2)

Table IB (continued)

Components of the Complex

A. Soybeans (cents/bu.)

Price Changes	Mean Change	Std. Dev.	Skewness	Kurtosis
ΔOpen	0.0303	11.66	−0.61	11.7
ΔClose	0.0349	10.74	−0.62	5.65
$\text{Open}_t - \text{Close}_{t-1}$	0.278	7.48	−1.61	33.1
$\text{Close}_t - \text{Open}_t$	−0.243	7.94	−0.31	2.41

Variables	Correlations
ΔOpen_t and ΔOpen_{t-1}	−0.008 (−0.26)
ΔClose_t and ΔClose_{t-1}	0.098 (3.25)
$(\text{Open}_t - \text{Close}_{t-1})$ and $(\text{Close}_t - \text{Open}_t)$	−0.030 (−0.99)

B. Soybean Meal (dollars/ton)

Price Changes	Mean Change	Std. Dev.	Skewness	Kurtosis
ΔOpen	0.0202	3.76	−0.05	6.83
ΔClose	0.0225	3.38	−0.33	3.55
$\text{Open}_t - \text{Close}_{t-1}$	0.052	2.36	−0.26	14.9
$\text{Close}_t - \text{Open}_t$	−0.0296	2.59	−0.22	2.19

Variables	Correlations
ΔOpen_t and ΔOpen_{t-1}	−0.058 (−1.92)
ΔClose_t and ΔClose_{t-1}	0.104 (3.44)
$(\text{Open}_t - \text{Close}_{t-1})$ and $(\text{Close}_t - \text{Open}_t)$	−0.067 (−2.22)

C. Soybean Oil (dollars/100 lbs.)

Price Changes	Mean Change	Std. Dev.	Skewness	Kurtosis
ΔOpen	0.00351	0.389	0.41	10.17
ΔClose	0.00335	0.351	0.08	2.74
$\text{Open}_t - \text{Close}_{t-1}$	0.01377	0.220	1.14	16.6
$\text{Close}_t - \text{Open}_t$	−0.01042	0.295	−0.53	4.20

Variables	Correlations
ΔOpen_t and ΔOpen_{t-1}	−0.022 (−0.73)
ΔClose_t and ΔClose_{t-1}	0.127 (4.21)
$(\text{Open}_t - \text{Close}_{t-1})$ and $(\text{Close}_t - \text{Open}_t)$	−0.08935 (−2.95)

[a] See footnotes to Tables IA and II.

Turning to the distributional evidence, there is a marked difference, as indicated by the skewness and kurtosis, of the distribution for the open minus the previous close from those of the other price differences considered. The persistence of this behavior across both subsamples is of particular importance to interpreting the trading rule under consideration. In turn, there are numerous instances of differences between the subsamples. For example, while the distribution for oil is decidedly different from those for beans and meal in the earlier subsample, this does not persist into the latter period where the observed skewness and kurtosis for the three components is relatively similar. Similar discrepancies can be found in the serial correlation coefficients. For example, the daily changes in all the opening prices, as well as the closing prices for oil, are significantly different from zero (at the 5% level) in the earlier sample, with all other price changes insignificant. This is not replicated in the later subsample. In any event, given the size and behavior of these correlation coefficients, it would appear that naive, trend-based, trading strategies for the individual commodities would almost surely not be highly profitable.

The results for the components of the complex can be contrasted with those for the GPM where, even though the mean changes are also small relative to the standard deviations, highly significant correlations are found for all the GPM differences considered across both subsamples. Of these, the largest in absolute magnitude is the correlation between close-to-open and open-to-close GPM. This is important for present purposes, because it provides indirect support for the possibility of "opening reversals"; or, in other words, the tendency of GPM to change direction at the open. More direct evidence for opening reversals is provided by the signs of the mean values for the "overnight" and intraday GPM changes, which indicate that the GPM at the opening tends to be lower than the previous close and then "trade up" during the day. However, this evidence can be qualified because the distribution for the open minus the previous close (again) exhibits the highest skewness and kurtosis values.

While certain aspects of GPM behavior persist across both subsamples, there are some noticeable differences—especially in the skewness and kurtosis values which are noticeably higher in the later subsample. Even though the tendency for opening reversals continues in the face of the uptrend which characterizes the latter subsample, the substantial difference in the average GPM over the two periods does raise some concern. Specifically, while the statistical results for the earlier subsample are consistent with the longer term evidence provided by Johnson et al., which suggested a mean-reverting process for the GPM (assuming the costs of crushing are relatively constant), this is arguably not the case with the latter subsample. Given that this could be due to subsample selection bias and, insofar as rule performance is better during periods when the GPM is relatively constant around some mean value, it is possible that the rule under consideration could be improved by adjusting for trends, e.g., by using the NPM instead of the GPM. However, these possibilities are not pursued here.

Turning to the results for the GPM-based day trading rule, Table II provides a summary of the profit simulations for the full sample, grouped by size of filter. The results are intuitive and consistent with expectations for a profitable, filter-based trading rule [e.g., Poitras (1987)]: as the size of the filter increases, mean profit per trade increases and the number of profitable trades decreases. Significantly, the relationship between filter size and *aggregate* profit (mean profit per trade times the number of trades) is not monotonic from 2 to 3 cents. This arises because the reduction in aggregate profits due to the diminishing number of transactions is not fully offset by the increase in the return per trade. Hence, it follows that there is likely to be an optimal filter/trade size which maximizes aggregate profit. The effect of transactions costs is also evident, e.g., both in the low percentage of profitable transactions and the negative mean return per trade for the zero filter case.

Table II[a]
AGGREGATE TRADE PERFORMANCE: 1978–1991, GROUPED BY FILTER SIZE, NET OF TRANSACTIONS COSTS

	Filter Size			
	0.0	1-Cent	2-Cent	3-Cent
Mean profit per trade	−0.36	0.35	1.02	1.74
Std. dev. profit per trade	2.71	2.97	3.40	4.00
Skewness	0.96	0.87	0.90	0.81
Kurtosis	6.94	7.22	6.67	5.62
Rho	0.010	−0.061	−0.077	−0.068
Chi-square ($df = 2$)	849	453	229	104
Studentized range	15.4	14.0	12.3	10.4
t-Value	−7.69	5.08	9.10	9.30
Number of trades	3352	1861	922	457
Percentage trades profitable	39.6	52.3	62.3	69.0

[a] The mean and standard deviation of trade profits are expressed in terms of cents per bushel. For a 20–24–18 trade, cents per bushel can also be taken to be $ '000. Interest revenue arising from cumulative profits (losses) has been ignored. Skewness and kurtosis are the standardized third and fourth moments where the value for kurtosis has been centered about its value for the normal distribution. Rho is the first-order serial correlation coefficient. The chi-square test (two degrees of freedom) is the omnibus test for normality recommended in D'Agostino and Stephens (1986, chaps. 7 and 9) as the preferred test for combining the information contained in skewness and kurtosis. SR is the studentized range. t-Value is calculated for null hypothesis of a mean value of zero.

Table II also provides results for a substantial number of distributional tests which indicate that the profit distribution, across all filter sizes, is positively skewed with a high degree of kurtosis. These results are similar to those reported for other studies of (technical) trading rules applied to individual markets, e.g., Lukacs and Brorsen (1990). Among other things, the significantly non-normal profit distribution complicates the hypothesis testing problem. In the present context of evaluating the performance of a specific trading rule, the key null hypothesis to be tested is whether mean profits are less than or equal to zero against the alternative hypothesis that mean profits are non-negative. Observing from Table II that profits are serially independent, and assuming that the central limit theorem applies to the underlying profit distribution, conventional one-tailed t-tests can be directly applied to test the relevant null hypothesis. The resulting t-values reject the null, indicating that mean profits for the 1-, 2-, and 3-cent filters are all significantly greater than zero.[10]

Tables III and IV disaggregate the summary results given in Table II by year (Table III) and by whether a long or short crush position is traded (Table IV). The year-by-year results confirm that substantial variability in trading rule performance over time is common to all filter sizes. For example, in some years, i.e., 1983 and 1984, profits are relatively strong for the non-zero filter sizes. In other years, i.e., 1980 and 1986, the results are weak. In both 1982 and 1986, only a small number of trades are triggered by the 3-cent filter. In addition, the shape of the profit distribution, as reflected in skewness and kurtosis, also varies substantially

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[10] For a one-tailed test, the $\alpha = 5\%$ t-value is 1.645, while $\alpha = 0.05\%$ is 2.576.

across time with 1984 exhibiting the most "non-normal" behavior. Comparison with the aggregate distribution reveals that most years are decidedly more "normal," illustrating the impact that a relatively small number of non-normal observations can have on statistics for the upper moments. In many cases, precise hypothesis testing is restricted due to the presence of significant serial correlation.

Table III[a]

ANNUAL SUMMARIES OF THE TRADING SIMULATIONS: 1978–1991, GROUPED BY FILTER AND YEAR, NET OF TRANSACTIONS COSTS

	Filter Size			
Year	0.0	1-Cent	2-Cent	3-Cent
1978 (from Feb. 1)				
Mean profit per trade	0.12	0.58	1.22	2.27
Std. dev. profit per trade	2.74	2.66	2.81	3.07
Skewness	0.47	0.74	0.79	0.67
Kurtosis	1.28	1.89	1.82	1.90
Rho	0.09	−0.08	−0.03	−0.02
Number of trades	225	152	89	43
Percentage trades profitable	50.2	55.6	67.0	84.1
1979				
Mean profit per trade	−0.13	0.52	1.08	1.50
Std. dev. profit per trade	2.86	2.93	3.18	3.80
Skewness	0.78	0.68	0.36	0.35
Kurtosis	1.26	1.41	1.30	0.97
Rho	−0.01	−0.05	−0.10	−0.32
Number of trades	247	144	66	31
Percentage trades profitable	42.1	50.7	62.1	57.1
1980				
Mean profit per trade	−0.62	−0.04	0.38	0.37
Std. dev. profit per trade	3.05	3.28	3.67	4.39
Skewness	0.30	−0.03	−0.20	0.15
Kurtosis	6.58	7.61	8.34	6.90
Rho	−0.06	−0.22	−0.39	−0.43
Number of trades	247	154	89	51
Percentage trades profitable	39.2	49.3	56.2	58.0
1981				
Mean profit per trade	−0.39	0.38	1.13	2.20
Std. dev. profit per trade	2.47	2.65	2.98	3.76
Skewness	1.16	1.24	1.12	0.99
Kurtosis	3.72	3.53	2.85	1.16
Rho	−0.08	−0.12	−0.20	0.29
Number of trades	249	137	74	28
Percentage trades profitable	39.0	50.4	62.2	73.9

Table III (continued)

Year	Filter Size			
	0.0	1-Cent	2-Cent	3-Cent
1982				
Mean profit per trade	−0.75	−0.08	0.65	2.05
Std. dev. profit per trade	1.34	1.42	1.71	—
Skewness	0.85	1.24	1.20	—
Kurtosis	2.37	2.89	1.52	—
Rho	−0.05	0.06	−0.22	—
Number of trades	247	87	30	5
Percentage trades profitable	25.5	43.7	70.0	83.3
1983				
Mean profit per trade	−0.36	0.49	1.46	2.27
Std. dev. profit per trade	3.33	3.70	4.02	4.44
Skewness	0.65	0.55	0.89	0.77
Kurtosis	4.04	3.18	1.51	1.00
Rho	0.15	0.19	0.21	0.35
Number of trades	246	144	79	45
Percentage trades profitable	39.0	52.8	63.2	71.2
1984				
Mean profit per trade	−0.07	0.75	1.57	2.44
Std. dev. profit per trade	3.20	3.41	3.78	4.16
Skewness	2.10	2.38	2.62	3.31
Kurtosis	14.6	15.4	14.9	16.9
Rho	−0.03	−0.07	−0.06	0.09
Number of trades	249	158	94	51
Percentage trades profitable	45.8	57.0	69.1	77.1
1985				
Mean profit per trade	−0.57	0.12	0.86	2.36
Std. dev. profit per trade	2.31	2.48	2.80	3.00
Skewness	0.86	0.86	0.99	1.65
Kurtosis	2.91	2.99	3.58	4.53
Rho	0.002	0.003	−0.01	−0.25
Number of trades	250	130	54	21
Percentage trades profitable	37.6	50.0	61.1	73.7
1986				
Mean profit per trade	−0.55	0.14	0.41	0.75
Std. dev. profit per trade	1.90	2.04	2.23	—
Skewness	0.58	0.67	0.01	—
Kurtosis	1.95	1.84	0.30	—
Rho	−0.02	0.03	0.11	—
Number of trades	250	119	45	13
Percentage trades profitable	32.8	47.1	51.1	60.0

Table III (continued)

Year	Filter Size 0.0	1-Cent	2-Cent	3-Cent
1987				
Mean profit per trade	−0.66	0.16	0.69	1.15
Std. dev. profit per trade	2.03	2.05	1.85	2.02
Skewness	0.59	0.69	0.32	−0.04
Kurtosis	1.25	0.49	−0.58	−0.63
Rho	−0.01	0.02	−0.14	−0.31
Number of trades	250	126	47	23
Percentage trades profitable	32.0	47.6	59.6	66.7
1988				
Mean profit per trade	0.25	0.69	1.08	1.95
Std. dev. profit per trade	4.21	4.48	5.02	5.25
Skewness	0.57	0.49	0.53	0.48
Kurtosis	3.86	3.84	2.96	3.01
Rho	−0.09	−0.23	−0.09	−0.19
Number of trades	250	179	117	82
Percentage trades profitable	47.6	54.1	54.7	57.1
1989				
Mean profit per trade	−0.11	0.54	1.29	1.50
Std. dev. profit per trade	2.81	2.94	2.98	3.21
Skewness	0.41	0.22	0.40	0.23
Kurtosis	0.94	1.06	0.78	0.89
Rho	−0.07	0.09	−0.16	−0.29
Number of trades	249	148	73	39
Percentage trades profitable	47.4	58.1	65.8	58.0
1990				
Mean profit per trade	−0.68	0.04	0.63	1.55
Std. dev. profit per trade	2.08	2.23	2.43	2.01
Skewness	0.07	−0.45	−0.26	1.40
Kurtosis	0.72	1.53	0.17	2.76
Rho	0.05	−0.05	−0.21	−0.46
Number of trades	250	121	41	15
Percentage trades profitable	38.4	55.3	63.4	73.9
1991 (to July 31)				
Mean profit per trade	−0.45	0.18	0.90	0.84
Std. dev. profit per trade	1.53	1.39	1.59	—
Skewness	0.71	0.99	1.15	—
Kurtosis	1.64	3.34	2.54	—
Rho	−0.10	−0.06	−0.24	—
Number of trades	143	62	24	11
Percentage trades profitable	35.7	53.2	79.2	83.3

[a] The mean and standard deviation of trade profits are expressed in terms of cents per bushel. For a 20–24–18 trade, cents per bushel can also be taken to be $ '000. Some values for the 3-cent filter were not calculated due to small sample size. For description of statistics see footnote to Table II.

Table IV[a]
AGGREGATE TRADE PERFORMANCE: 1978–1991, GROUPED BY FILTER SIZE AND TYPE OF POSITION NET OF TRANSACTIONS COSTS

Type of Position	Filter Size 0-Cent	1-Cent	2-Cent	3-Cent
Long crush positions only:				
Mean profit per trade	−0.31	0.33	1.06	1.71
Std. dev.	2.62	2.86	3.28	3.96
Skewness	1.07	1.04	1.11	1.01
Kurtosis	8.18	8.60	8.30	6.83
Number of trades	1747	986	475	229
Percentage trades profitable	40.5	48.0	65.1	72.1
Short crush positions only:				
Mean profit per trade	−0.40	0.38	0.97	1.70
Std. dev.	2.80	3.07	3.51	4.02
Skewness	0.85	0.69	0.71	0.64
Kurtosis	5.77	5.99	5.39	4.80
Number of trades	1650	901	463	238
Percentage trades profitable	38.7	52.5	59.4	66.0

[a] The mean and standard deviation of trade profits are expressed in terms of cents per bushel. For a 20–24–18 trade, cents per bushel can also be taken to be $ '000.

Examining the performance of trade since 1987, the year-by-year results reveal the continuing profitability of the trading rule over this period, especially in 1988. While the mean profits for 1989–1990 are not as large as those reported for the aggregate case, the difference is not found to be statistically significant. Similarly, the mean profits for the 2- and 3-cent filters are found to be greater than zero at high α values. However, the small number of trades in 1990 combined with the poor performance of 1991 does raise concern. Examination of the raw data (not reported) reveals a substantial upward shift in the GPM starting with the June 1, 1989 rollover date. It follows that rule performance could be affected during a period that involves an underlying shift in GPM behavior; e.g., because the rule depends on a GPM process which is mean-reverting and the GPM experienced a mean-value shift in this period. Unfortunately, because the relevant behavior occurs at the end of the sample, further analysis of this point is difficult.

On balance, while the year-to-year evidence indicates occasionally erratic performance, the performance of the 2- and 3-cent filters is generally acceptable. Subject to the caveat about serial correlation, profits are usually significant (at appropriate α levels). Given the asymmetry (skewness) in the underlying generating process for profits, it is useful to consider the possibility of improving trade performance by identifying whether a long (normal crush spread) or a short (reverse crush spread) trade is being established. The results in Table IV reveal that while mean returns per trade are virtually equal for the 3-cent filter, there is a small amount of not-statistically-significant divergence for the other filter sizes. In addition, there is a decided difference in the shape of the profit distributions for the short and long trades. However, on balance, the ratio of the number of long to short trades, as well as the mean and standard deviation of returns per trade, indicate basically equal performance at all filter sizes. Hence, it can be concluded that both long and short positions contribute equally to the trade's profitability.

CONCLUSIONS

An important practical implication of this study is that participants in the soybean complex pits can *potentially* pursue profitable "naive" day trading strategies based on the GPM. In particular, the open-to-close day trading strategies examined here could be exploited by floor traders operating in those pits. In keeping with previous trading rule studies, it is natural to ask what implications these results have for evaluating the "market efficiency" of the soybean complex pits. In this vein, even though there is evidence of potential profit opportunities, it is difficult to draw direct implications about "market efficiency." This is because, among other reasons, it is not possible to verify whether the traders' returns are abnormal since the trading simulations cannot determine how much trading activity is required to have an offsetting effect on the associated prices.[11] In general, trading rule profitability studies provide, at best, only indirect evidence on whether price behavior conforms with expectations about how "efficient" prices should behave.

Given this, the results of this study do raise a number of other questions. For example, what market fundamentals could give rise to the profitability of the trading rule under consideration? One possible explanation could be based on the market dictum: "While the public is in on the close only the trading floor is in on the open." In other words, because price behavior at the close is the end-product of the (publicly observable) trading day's activities, trading at the close is accessible to the public. Hence, closing prices should reflect the GPM relationship. On the other hand, there is no (publicly observable) price information, i.e., immediately preceding prices, to permit identification of where prices will be at the opening. Given the relevant supply and demand factors in the respective component markets, the opening GPM can deviate significantly from the previous day's close. The practical implication is that open-to-close reversals will occur through the trading day.[12] Closing prices will track the GPM while opening prices depend more on specifics driving the individual components of the complex. Further empirical research is required to assess the validity of this hypothesis.

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[11] Lukac et al. (1988) and Lukac and Brorsen (1990) provide a number of rationales why the results of trading rule simulations only indicate the presence of "market disequilibrium" and not market inefficiency.

[12] These reversals may also occur in other markets. A tendency to short-term reversals is consistent with evidence on the New York foreign exchange market provided by Dooley and Shafer (1983).

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