The Intraday Behavior of Commodity Futures Prices

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I. INTRODUCTION

The behavior of prices in continuous auction markets has been the subject of extensive investigation during the past two decades. Most of this research has concentrated on the day-to-day movement of prices and has ignored their intraday characteristics.

This study examines the transaction-to-transaction behavior of futures prices and tests whether the behavior of prices is homogeneous over the life of a contract. In addition, the study investigates whether price behavior during a given day is related to such variables as trading volume or open interest for that day.

II. PREVIOUS RESEARCH

Using the random walk model as a framework, the dependency characteristics of daily and weekly commodity futures prices are studied by Houthakker (1961), Larson (1964), Smidt (1964), Stevenson and Bear (1970), Leuthold (1972), Martell and Philippatos (1974), and Cargill and Rausser (1975). With minor exceptions, serial correlation and runs analysis tend to support the hypothesis that successive price changes are independent. Only a small percentage of any price series is found to exhibit statistically significant dependencies.

The previously mentioned studies also use filter analysis to test a price series for serial independence. Filter analysis consists of comparing the profits generated by some trading rule to the expected value of profits that could be obtained if the price changes are random. Most previous studies assume that the maximum profit that can be obtained when price changes are random is given by the profitability of the buy-and-hold rule.

No previous research analyzes the sequential structure of transaction-to-transaction prices and relate it to maturity and the activity of the market. Such analysis is needed because there may exist systematic patterns which are not apparent in the day-to-day price series and because the individual transaction prices are the data actually reported to traders when the market is open.

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Working (1954) and Martell and Helms (1978) use transaction-to-transaction data and find the presence of strong negative serial correlation. A possible explanation for this large proportion of price reversals is suggested by Working (1954 and 1977) and Smidt who maintain that market orders to buy and sell the futures are filled at the asked and bid prices, respectively. If market orders are assumed to arrive at the market at random, prices tend to alternate between the bid and the asked prices causing the reversal tendencies.

The present study uses transaction-to-transaction prices but differs from the previous studies of intraday price behavior by examining each day separately. For each futures contract, the price series is divided into its component daily series. The intraday behavior of prices for each trading day is then individually analyzed. This eliminates the possibility of overlooking offsetting patterns that may occur if the price series is arbitrarily linked. In addition, this procedure allows a comparison of the intraday behavior of prices directly to the activity of the market and to the maturity of the contract and indirectly to the behavior of the floor trader.

III. DATA AND STATISTICAL ANALYSIS

The data consist of transaction-to-transaction prices for 26 commodity futures contracts traded between December 1975 and May 1978 on the Chicago Board of Trade. The commodities studied are wheat, corn, and soybeans-the three most active agricultural commodities.

Table I provides a list of the contracts used in this study, along with the number of trading days and total number of transactions for each contract. For the purposes of this study, the delivery month is excluded from the set of observations. Thus, the data file for the December 1977 corn contract contains 40,739 observations which represents a complete record of every price change recorded during the life of that futures contract with the exception of the delivery period.[1]

To examine the independence of successive price changes, serial correlation and runs tests are performed. The price series for each complete contract is divided into daily subseries and then the separate days are tested for the independence of intraday price changes. Thus, for each contract, as many tests are conducted as there are trading days in the life of that contract.

The results of the serial correlation analysis are also shown in Table I. For example, the March 1977 wheat contract has 270 trading days. Forty-eight percent of the 270 serial correlation coefficients are found to be significantly different fron zero at the .05 level. Not all are negative, however. Of all 131 significant correlations, 34 are positive and 97 negative.

As Table I shows, there is a large number of nonrandom days in each of the contracts examined. However a considerable number of the significant coefficients are positive.

In addition, a strong and consistent pattern is observed in the behavior of prices throughout the life of all the contracts analyzed. There is a tendency for positive autocorrelation at the beginning of the life of the contract and a tendency for negative autocorrelation towards the end of the life of a contract. Thus, an important find of this study is that the behavior of price changes differs over the life of a contract. Possible economic explanations for this pattern are offered below.[2]

[1]All trading days during which a limit move occurred are excluded from the data base. The data base is part of an earlier study (Martell and Helms (1978)). However, there have been no substantive changes since in the nature of the wheat, corn, and soybean markets that limits the usefulness of this data or the conclusions of this study.

[2]The results employing runs analysis are very similar and not reported here.

Table I
LIST OF THE CONTRACTS USED AND RESULTS OF SERIAL CORRELATION ANALYSIS

Contract	Symbol used in Tables	Number of Trading Days	Number of Transactions	Number of Significant Coefficients*	Positive Serial Coefficients	Negative Serial Correlation
Wheat Mar 1977	WMAR77	270	38,366	131	34	97
Wheat Mar 1977	WMAY77	207	22,282	96	31	65
Wheat July 1977	WJUL77	237	27,124	127	19	108
Wheat Sept 1977	WSEP77	211	13,751	45	16	29
Wheat Dec 1977	WDEC77	274	26,238	119	15	104
Wheat Dec 1976	WDEC76	230	55,817	120	10	110
Wheat Mar 1978	WMAR78	264	25,204	114	16	98
Wheat May 1978	WMAY78	261	25,406	66	17	49
Corn Mar 1977	CMAR77	310	36,391	156	3	153
Corn May 1977	CMAY77	292	23,945	133	14	119
Corn July 1977	CJUL77	242	24,013	148	7	141
Corn Sept 1977	CSEP77	238	12,633	63	5	58
Corn Dec 1977	CDEC77	274	40,739	202	1	201
Corn Sept 1976	CSEP76	191	19,396	71	1	70
Corn Dec 1976	CDEC76	253	54,133	212	0	212
Corn Mar 1978	CMAR78	270	22,967	168	5	163
Corn May 1978	CMAY78	257	22,967	142	2	140
Soybean Mar 1977	SMAR77	267	57,671	121	39	82
Soybean May 1977	SMAY77	307	64,869	157	75	82
Soybean July 1977	SJUL77	258	74,646	150	63	87
Soybean Aug 1977	SAUG77	191	29,605	54	23	25
Soybean Sept 1977	SSEP77	203	21,250	48	23	25
Soybean Nov 1977	SNOV77	248	83,153	174	4	170
Soybean Nov 1976	SNOV76	233	89,088	141	7	134
Soybean Jan 1978	SJAN78	250	51,514	88	18	70
Soybean Mar 1978	SMAR78	276	52,337	129	34	95

*$p \leq .05$

IV. FILTER PROFITABILITY ANALYSIS

Significant serial correlation coefficients do not necessarily indicate the existence of unexploited profit opportunities. To determine whether such opportunities do, in fact, exist, a filter profitability analysis is conducted.

Filter analysis consists of comparing the profits obtained by mechanically applying a trading rule to a sequence of prices against the profits obtained from buying and holding. If there are systematic patterns and the trading rule is sensitive to those patterns, the rule is termed "successful". However, a number of problems plague the use of filters. Of these, two require special attention. First, the statistical properties of filter profits are not well understood and biases can be easily introduced. The second problem is that no probabilistic statement is every made about the likelihood of the results since usually only one profit figure is obtained from a complete series.[3]

To circumvent these problems, following procedures are adopted. First, each contract is divided into days. Second, a trading rule is applied to the price series for the first day and a profit figure recorded. Third, the same trading rule is applied to the randomized price series of the first day. A randomized price series is obtained by assigning a random number to the sequence of price changes as they occurr and then reordering the sequence according to the random number assigned. Fourth, a profit difference for the first day is obtained by subtracting "random" profits (third step) from "actual" profits (second step). This procedure is repeated for every day. Thus, a contract that trades 270 days has 270 profit differences. By assuming that these daily profit differences constitute a random sample. This study tests that hypothesis the the mean of profit differences is equal to zero with a paired t-test.

Two different types of filter rules are employed in the study. The first type of trading rule, the inverse rule, assumes a contract is sold when the price moves up x cents. The short position is held until the price moves down x cents from the previous high, at which time the short position is covered and a long position is taken. The long position is held until the price moves up x cents from the previous low, at which time the long position is liquidated and a short created. This trading strategy is successful when the data exhibits strong tendencies toward reversals.

The second type of trading rule, the adaptive model, changes the filter rule based on the previous day's serial correlation coefficient. If the serial correlation coefficient on day T-1 is less than zero, the filter rule follows the reversal model described above on day T. However, if the previous day's serial correlation coefficient is positive, then for the current day's trading, the adaptive model takes and liquidates positions exactly opposite to the rule outlined above.[4]

Thus, if positive serial correlation is detected on day T-1, the adaptive model uses a trading rule on day T which is successful if there is also positive serial correlation on day T. Similarly, the adaptive model uses the inverse trading rule on day T if a reversal tendency is detected the previous day.

Results from the inverse and the adaptive filter models are generated using filter sizes of \$.005, \$.01, \$.015, \$.03, and \$.05 cents per bushel. The results using the inverse rule are shown in Table II. The smallest filter size (half a cent) is the most successful in all tests. This result is not unexpected because in active markets, a floor trader is often ready to buy at slightly below the last price or sell at slightly above the last price, where slightly is defined as, "...the minimum price change commonly occurring at that time

[3]See Praetz (1976) for a discussion.

[4]For a more complete discussion of the use of adaptive filter models, see Martell and Philippatos (1974).

Table II
INVERSE FILTER RULE
DIFFERENCE BETWEEN PROFITS FROM ACTUAL PRICES VERSUS RANDOMIZED PRICES

	Filter Size				
Contract	**.005**	**.010**	**.015**	**.030**	**.050**
WMAR77	17.3380	−11.9679	−42.8009	−27.9167	20.3472
	(.69)	(−.62)	(−2.26)*	(−2.17)*	(2.07)*
WMAY77	−6.6946	−35.9903	4.2271	−15.2778	6.4915
	(−.29)	(−2.11)*	(.30)	(−1.41)	(.91)
WJUL77	26.7669	−6.1445	−5.0633	−12.7373	−.8439
	(1.30)	(−.37)	(−.37)	(−1.36)	(−.15)
WSEP77	11.5818	−8.0273	−14.1588	1.8661	4.2062
	(.87)	(−.85)	(−1.89)	(.37)	(1.43)
WDEC77	80.5429	6.5922	−17.5639	−11.2454	−4.6305
	(3.35)**	(.64)	(−1.92)	(−1.99)	(−1.52)
WDEC76	877.9076	319.0489	37.2283	10.3967	3.4239
	(8.53)**	(5.66)**	(1.45)	(.53)	(.19)
WMAR78	88.2102	14.2045	−3.3617	−11.7187	−3.3826
	(6.32)**	(1.57)	(−.44)	(−2.41)*	(−1.36)
WMAY78	65.2059	4.2146	−25.2155	−9.1475	13.6734
	(3.86)**	(.29)	(−1.36)	(−.96)	(1.94)
CMAR77	145.8266	4.5766	−22.0968	−18.3468	−5.4839
	(9.25)*	(.38)	(−2.10)*	(−2.61)**	(−1.05)
CMAY77	71.9392	15.0043	−10.9803	−13.1207	−.8776
	(5.58)**	(1.28)	(−1.20)	(−2.45)**	(.21)
CJUL77	139.7469	23.2955	2.0919	−15.6250	−6.8182
	(9.90)**	(2.22)*	(.25)	(−2.53)**	(−1.98)*
CSEP77	54.2542	−2.5998	−15.4937	.7616	.2363
	(5.59)**	(−.32)	(−1.90)	(.19)	(.12)
CDEC77	253.6953	13.8002	−29.6007	−25.7984	−21.8294
	(4.41)**	(1.35)	(−3.01)**	(−4.19)**	(−5.47)**
CSEP76	153.1741	19.0118	−1.2107	−5.2683	.0327
	(6.58)**	(1.30)	(−.09)	(−.53)	(.00)
CDEC75	410.4002	76.4081	4.1502	−37.5247	−28.4832
	(13.26)**	(3.32)**	(.27)	(−3.42)**	(−3.74)**
CMAR78	117.5926	5.6944	−17.1528	−14.6528	−6.7824
	(8.58)**	(.65)	(−2.20)*	(−3.18)**	(−2.79)**
CMAY78	100.9728	−3.3424	−16.7315	−9.6304	−2.0425
	(7.97)**	(−.48)	(−2.18)*	(−1.98)*	(−1.11)
SMAR77	504.4476	206.2734	−114.7472	−5.9457	10.7912
	(4.36)**	(2.77)**	(−2.32)*	(−.16)	(.30)
SMAY77	164.0676	113.5790	−3.3998	10.6270	−9.3648
	(1.50)	(1.23)	(−.05)	(.24)	(−.21)
SJUL77	864.0746	964.4380	741.0853	241.9574	77.8828
	(4.87)**	(5.56)**	(5.39)**	(3.35)**	(1.37)

*$p \leq .05$.
**$p \leq .01$.

Table II
INVERSE FILTER RULE
DIFFERENCE BETWEEN PROFITS FROM ACTUAL PRICES VERSUS RANDOMIZED PRICES continued

	Filter Size				
Contract	**.005**	**.010**	**.015**	**.030**	**.050**
SAUG77	−197.9712	−119.5026	19.1754	−170.2225	−36.6492
	(−2.09)*	(−1.33)	(.22)	(−2.32)*	(−.59)
SSEP77	68.7808	−40.3941	−33.4360	−78.7562	36.3227
	(−.96)	(−.57)	(−.53)	(−1.28)	(.77)
SNOV77	2223.4123	1444.5312	644.7329	233.4425	49.4960
	(16.05)**	(13.70)**	(9.56)**	(4.76)**	(1.09)
SNOV76	1873.0686	1557.6717	811.1356	183.1813	28.9700
	(11.12)**	(10.00)**	(7.11)**	(2.94)**	(.61)
SJAN78	533.9500	243.7000	90.2500	−4.6251	18.7750
	(4.67)**	(3.17)**	(1.35)	(−.11)	(.47)
SMAR78	418.6141	76.3134	14.2210	−8.8089	−44.9728
	(4.16)**	(1.29)	(.38)	(−.27)	(−1.62)

*$p \leq .05$.
**$p \leq .01$.

in the market." [Working (1977), p. 209] Thus, the price concessions that investors have to make for liquidity usually are relatively small in active markets.

Table II shows that with the smallest filter size, 20 of the 26 contracts produce significant means of profit differences at the .05 level. That is, in 77% of the contracts there is a significant difference between the profits of the inverse rule when applied to actual commodity price series and those obtained when the rule is applied to the random rearrangement of those series. Because the inverse filter rule is designed to perform well in the presence of a reversal, its success is consistent with the tendency towards reversals found in the other tests.

The results using the adaptive model are presented in Table III. For the smallest filter size, all contracts have significant means of profit differences at the .01 level. The adaptive model produce much better results than the inverse rule. Except for 5 of the 26 contracts, the adaptive model has higher means of profit differences. The conclusion from filter analysis is that the systematic patterns detected with serial correlation and runs analysis can be translated into gross profits by a floor trader.[5]

V. THE BEHAVIOR OF INTRADAY PRICES AND THE ACTIVITY OF THE MARKET

Transaction-to-transaction price movements are dominated by temporary imbalances between supply and demand and by the way the floor traders absorb these imbalances. It is argued below that the behavior of the floor trader is in turn affected by the volume of trading in the market. Thus, the level of activity in the market affects the movement in transaction-to-transaction prices.

[5] To determine whether the filter profits obtained constitute a market inefficiency, transaction costs, the cost of capital, and the appropriate opportunity cost of the time needed by a floor trader to follow these strategies would have to be included.

Table III
ADAPTIVE FILTER RULE
DIFFERENCE BETWEEN PROFITS FROM ACTUAL PRICES VERSUS RANDOMIZED PRICES

	Filter Size				
Contract	**.005**	**.010**	**.015**	**.030**	**.050**
WMAR77	186.5046	13.4954	2.6620	−.6019	9.5139
	(8.17)	(.67)	(.13)	(−.04)	(.81)
WMAY77	161.3225	−12.1377	−25.7246	−2.8382	18.0857
	(7.39)**	(−.64)	(−1.63)	(−.18)	(1.78)
WJUL77	162.4209	7.1466	4.9051	−6.7774	11.1814
	(7.33)**	(.40)	(.32)	(−.53)	(1.28)
WSEP77	43.3945	7.4941	.5924	4.1765	1.1256
	(3.27)**	(.71)	(.06)	(.65)	(.27)
WDEC77	112.7053	−4.4024	6.0219	6.5009	−5.8622
	(7.46)**	(−.38)	(.06)	(.85)	(−1.56)
WDEC76	899.6467	−182.8533	11.7935	29.3207	2.1739
	(8.87)**	(−3.32)**	(.38)	(1.21)	(.10)
WMAR78	101.4678	−30.6818	−1.6098	−.3078	−3.6932
	(7.02)**	(−2.85)**	(−.16)	(−.04)	(−1.00)
WMAY78	101.5086	1.2931	−17.6964	−11.1590	−1.3649
	(5.26)**	(.07)	(−1.26)	(−1.05)	(−.18)
CMAR77	134.7782	−11.9960	−11.5323	−1.8952	9.6774
	(9.32)**	(−1.00)	(−1.04)*	(−.25)	(1.87)
CMAY77	80.8861	−13.4632	−1.4341	9.7817	2.2902
	(6.01)**	(−1.16)	(−.14)	(1.48)	(.50)
CJUL77	138.4556	8.1095	.3874	.3357	−1.7045
	(9.14)**	(.72)	(.04)	(.05)	(−.46)
CSEP77	45.0105	−20.4044	2.2059	.9716	5.0683
	(3.51)**	(2.32)*	(.25)	(.18)	(2.11)*
CDEC77	245.7117	−4.4480	3.6953	5.7710	−8.3714
	(13.95)**	(.42)	(.35)	(.82)	(−2.05)*
CSEP76	143.5537	4.1558	−2.3233	−18.2264	−.7526
	(5.68)**	(.23)	(−.16)	(−1.51)	(−.08)
CDEC76	421.1709	−23.7895	−19.9111	19.4911	4.5208
	(13.43)**	(−1.17)	(−1.27)	(−1.51)	(.49)
CMAR78	130.2315	−15.4167	17.9861	−2.4306	−.3935
	(9.45)**	(−1.89)	(2.40)*	(−.45)	(−.16)
CMAY78	131.0798	−15.3156	17.3152	1.9455	.2918
	(9.86)**	(−1.80)	(1.94)	(.31)	(.11)
SMAR77	1032.3970	287.9682	12.0318	62.0787	41.4560
	(10.16)**	(3.89)**	(.24)	(1.48)	(1.07)
SMAY77	1032.4324	421.4780	−44.3607	−14.9837	12.5814
	(11.02)**	(4.67)**	(−.62)	(−.30)	(.26)
SJUL77	1815.9157	1342.8294	197.5775	−96.8023	−47.8924
	(12.18)**	(8.49)**	(1.30)	(−1.24)	(−.78)

*$p \leq .05$.
**$p \leq .01$.

Table III
ADAPTIVE FILTER RULE
DIFFERENCE BETWEEN PROFITS FROM ACTUAL PRICES VERSUS RANDOMIZED PRICES continued

	Filter Size				
Contract	**.005**	**.010**	**.015**	**.030**	**.050**
SAUG77	348.3639	153.3377	30.6283	−47.6440	77.0942
	(4.10)**	(1.98)*	(.34)	(−.70)	(1.01)
SSEP77	150.7389	−6.6502	−47.9064	41.9335	−83.6207
	(2.15)*	(−.10)	(−.75)	(.70)	(−1.39)
SNOV77	2283.5937	244.00272	−64.2389	141.1542	−4.8387
	(16.73)**	(1.76)	(−.82)	(2.49)*	(−.10)
SNOV76	1692.2747	1214.1094	−66.7650	−117.0333	−44.2060
	(9.73)**	(6.94)**	(−.54)	(−1.79)**	(−.31)
SJAN79	967.2500	305.8000	35.1500	19.8750	−91.6250
	(9.63)**	(3.79)**	(.68)	(.46)	(−2.39)*
SMAR78	871.8297	−1.7210	30.2989	5.3216	−14.7645
	(9.90)**	(−.03)	(.70)	(.15)	(−.44)

*$p \leq .05$.
**$p \leq .01$.

Because orders to sell tend to be filled at the bid price and orders to buy tend to be filled at the offer price; transaction prices tend to jump between the bid and ask prices. Such a pattern of trading produces the negative serial correlation reported in this study. This suggests that futures contracts cannot be sold quickly except at a small discount and cannot be bought quickly except at a small premium from their true equilibrium price. The discount and premium are a liquidity cost to the investor and are the source of profits that compensate the floor trader for the services provided and the risks taken.

Floor traders adjust the size of the bid-ask spread and, therefore, their compensation as the risks change. Assuming a constant rate of arrival of unanticipated information, the risks to a floor trader increase with the length of time he holds a position. This time is longer in inactive markets and shorter in active markets. Therefore, active markets reduce the risk to a floor trader and, therefore, the size of the bid-ask spread is smaller. Thus, in active markets, the large number of transactions causes prices to frequently jump between a narrow bid-ask spread resulting in the "jiggles" (negative serial correlation) found in empirical studies.

However, in inactive markets, the tendency for prices to jump between a wider spread is not as easily observed. The longer the time between two transactions, the higher the probability that the equilibrium price will have changed and, therefore, the location of the bid-ask price will have moved. The longer the elapsed time between two transactions, the more important the "information" effect (i.e., the change in equilibrium price) becomes and the less important the "scalping" effect in determining the behavior of prices.

The previous discussion argues for less negative serial correlation when a market is less active but does not explain the positive serial correlation found at the beginning of a contract's life. A possible explanation of this positive serial correlation is that, when markets are relatively inactive, large orders to buy or to sell are broken into smaller orders and executed one at a time (with the hope of obtaining a better price). This can result in the price being driven gradually up (if orders to buy) or gradually down (if orders to sell). These arguements lead to the hypothesize that the negative serial correlation of prices increases as the market moves from inactive to active.[6] To test this relation empirically, this study correlates the degree of dependency (as measured by the serial correlation, runs and filter profits) with two measures of market activity: open interest and trading volume. The results are shown in Table IV.

The results indicate that as the volume of trading activity increases, the incidence of reversals increases. The correlation coefficients tend to be high. For example, correlating serial correlation and trading volume, the coefficients range from .2943 to .7757. Similarly, using runs and trading volume, the correlation coefficients range from .5007 to .9177. Using filter profits, the correlation coefficients are smaller but still significant. Thus, both the behavior of prices and the filter profitability are affected by the level of activity of the market.

Trading volume tends to be a better explanatory variable than open interest. This is not surprising since, as a rule, floor traders do not carry large open positions overnight. The frequency of transactions and the consequent risks to the floor trader do not depend on the positions outstanding, but rather on the trading activity.

VI. SUMMARY AND CONCLUSION

Previous studies find the presence of negative serial correlation in transaction-to-transaction price changes. This study finds, however, that by breaking a contract price history into days the behavior of intraday prices for a given contract is not homogenous over time. This study shows that in every contract the intraday serial correlation gradually changes during the life of a contract from small but significantly positive, to not significantly different from zero, to strongly negative. Using filter analysis, it is shown that the intraday patterns detected with serial correlation and runs analysis can be translated into gross profits by a floor trader. Finally, strong relationship is found between intraday behavior and the activity of the market. Specifically, the intraday serial correlation moves from significantly positive correlation in inactive days to very strong and negative in the more active days of a contract's life. This relationship between price behavior and the activity of the market is due to the behavior of the floor trader, the nature of spreads in agricultural commodities, and the market clearing process in organized futures markets.

These results should not be taken as evidence that the market is inefficient. To determine whether the filter profits obtained constitute a market inefficiently transaction cost, the cost of capital and the appropriate opportunity cost of the time used by a floor trader need to be included. Finally, it should be noted that while the results of this study are not necessarily incompatible with the serially uncorrelated day-to-day price changes found in other studies, they demonstrate that important patterns can be overlooked when price series are artificially aggregated.

[6]This study uses agricultural commodities as its data base. One reason for using agricultural commodities is that the calendar spreads are relatively less stable due to the old crop, new crop issue. The deferred months, that is the newly listed contracts, in agricultural commodities are less directly tied to the active nearby contract than in a contract such as gold (Williams (1986)). Thus, anyone trading the deferred months of an agricultural contract may act very much like traders in a new futures contract. One of the author's experiences with new contracts suggests that large orders are broken up and executed a piece at a time. Similar behavior on the part of both locals and trade firms may explain the pattern of positive serial correlation found in the deferred months of the agricultural contracts used in this study.

Table IV
CORRELATION COEFFICIENTS AMONG ALTERNATIVE MEASURES OF DEPENDENCY AND OPEN INTEREST AND TRADING VOLUME*

Contract	Serial Correlation		Runs		Inverse Rule[1]		Adaptive Rule[1]	
	OI	TV	OI	TV	OI	TV	OI	TV
WMAR77	−.5183	−.6140	.6772	.7609	.5826	.5422	.2753	.2302
WMAY77	−.4931	−.7422	.5850	.7817	.4428	.6161	.0674*	.0102*
WJUL77	−.5143	−.7052	.6549	.7539	.5428	.6637	.2708	.1658
WSEP77	−.3755	−.4832	.5508	.6182	.4130	.4336	.2368	.1747
WDEC77	−.5646	−.6838	.7757	.8524	.6525	.6712	.5488	.5169
WDEC76	−.6364	−.6371	.8309	.7688	.7718	.4874	.7631	.4697
WMAR78	−.4430	−.5323	.7638	.8319	.6855	.6853	.6398	.6185
WMAY78	−.2597	−.5651	.2936	.6497	.1072	.5077	−.0252*	.2495
CMAR77	−.6285	−.6184	.8456	.8308	.5968	.6090	.6005	.6024
CMAY77	−.5944	−.6529	.7822	.8182	.4864	.5347	.4495	.4776
CJUL77	−.5587	−.7445	.7783	.9007	.5406	.5745	.5195	.5356
CSEP77	−.5423	−.5273	.8427	.8142	.3930	.4378	.3693	.3749
CDEC77	−.6188	−.7757	.8404	.9177	.6980	.6491	.7110	.6795
CSEP76	−.3734	−.4455	.6911	.7583	.7371	.6759	.7504	.6883
CDEC76	−.3531	−.5428	.7178	.8404	.6384	.5411	.6468	.5556
CMAR76	−.6122	−.7082	.8328	.8948	.7039	.6570	.7082	.6593
CMAY78	−.3743	−.6682	.6671	.8681	.7094	.6719	.6714	.6046
SMAR77	−.6039	−.4755	.7916	.5425	.8364	.5061	.7936	.5503
SMAY77	−.4223	−.3546	.6726	.5582	.7735	.5689	.6192	.5729
SJUL77	−.6004	−.7455	.7108	.7967	.8668	.8294	.7582	.6490
SAUG77	−.4221	−.4800	.4317	.5007	.4001	.3576	.1806	.0110*
SSEP77	−.2281	−.2943	.4197	.5196	.2810	.4083	.2850	.2611
SNOV77	−.5989	−.7275	.7707	.7790	.8691	.7982	.8588	.7579
SNOV76	−.5238	−.5948	.6569	.8598	.8610	.7765	.5660	.5909
SJAN78	−.5781	−.6652	.7647	.7768	.8608	.7728	.8254	.7584
SMAR78	−.6121	−.6096	.8523	.7657	.8035	.7255	.7123	.6680

[1]Profits from the .005 filter size were used in each case.

*Note = All coefficients except the ones marked are significant at the .05 level.

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