Another Tool in the Technical Analyst's Toolbox: A Markov Indicator for Soybean Futures

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Another Tool in the Technical Analyst's Toolbox:

A Markov Indicator for Soybean Futures

Steven C. Turner, Jack E. Houston, and Tommie L. Shepherd*

Forecasting futures prices is an integral part of profitable commodity futures trading. Various fundamental and technical techniques have been developed to assist traders in detecting profitable opportunities. Two technical devices that are commonly used are the relative strength index and moving average. For each of these techniques, there are certain signals that trigger trader decision responses. For example, with a 4- and 9-day moving average approach, a buy signal occurs when the 4-day intersects the 9-day from below. This technique is useful in trending markets.

Many technical indicators rely solely on price, price changes, or some variation in the price component. Few indicators or techniques incorporate other valuable trading information, such as volume and open interest, except in a peripheral way. That is, in a bar chart, volume and open interest changes are used to reinforce anticipation of the price signal formation.

Little has been done to incorporate price, open interest, and volume of futures contract trading into one unit to better forecast price movement. One possible method of integrating these three factors is to use Markov-chain analysis. Markov processes can be used to study the nature of sequences of events ranging from purely random to purely deterministic (Davis). In this procedure, expectations about future market conditions can be based on historically determined probabilities of moving from one state or condition of the market to another when these conditions exhibit serial correlation.

A stochastic process is basically a series of random variables which represents the behavior of a system over time. Unlike deterministic models, stochastic models take into consideration the fact that the system or process being described cannot be predicted with absolute certainty. Application of stochastic processes to the technical analysis of futures trading was introduced by George Lane (Murphy). Lane's application was based on the observation that as prices increase, closing prices tended to be nearer the upper end of the price range. Conversely, in downtrends, the closing price tended to be near the lower end of the range. The intent of Lane's trading system was to determine where the closing price lies in relation to the price range for a given time period. To summarize, Lane's stochastic process measured where the closing price was in relationship to the total price range on a basis of 0 to 100.

A Markov process is a type of stochastic or probability process in which only the current random variable is used to describe the behavior of a system over time. Little has been published in the area of applying Markov analysis to futures price forecasting. McKallip presented a general format for

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applying such an analysis and testing its results. He examined weekly price charts for 19 commodities from 1970 to 1979 for obvious pattern formations. These formations, varying in both duration and magnitude, were assigned subjectively and a transitions matrix (i.e., a tabulation of transitions between states) was created representing the historical number of transitions between each state and various other states. A probability matrix was then calculated to describe the initial transitions matrix. This calculated transitions matrix was compared by means of a chi-square test to an expected-value matrix representing transitions which would be expected due to random chance. Reported results for the 1970 to 1979 period indicated that transitions among states were not due to random chance at the .05 significance level. This presence of systematic elements in futures price behavior is a necessary condition if a Markov process is to offer any predictability.

While Markov processes may be used to describe random systems (Davis), the description of a random system could offer no information as to the development of the system but only its composition. For example, if market conditions were to behave according to the Random Walk Theory (Samuelson), a Markov process could evaluate the amount of time the market is likely to spend in various conditions but not the probability of correlation between conditions.

Tests for the presence of systematic elements in futures prices have produced contradictory results. Mann and Heifner tested the hypothesis that price changes are serially independent by using two non-parametric methods: the turning point test and the phase length test, as outlined by Kendall and Stuart. Using 1959 to 1971 data for a variety of agricultural commodities, they found both tests to reject the notion of serial independence in favor of significant correlation in futures prices. Mann and Heifner went on to suggest two possible reasons for the presence of this correlation--deliberate price manipulation by certain traders and the tendency for groups of traders to unintentionally follow similar patterns in their trades. These findings refuted Working's theory of anticipatory prices which argued that prices fluctuate randomly due to the actions of many diverse traders with differing information and expectations acting independently in an efficient market.

Recent work by Hudson et al. performed turning point and phase length tests on futures price changes rather than on the price levels themselves, as was done by Mann and Heifner. Results for the turning point and phase length tests rejected the randomness hypothesis in only 13% and 14% of the observed cases, respectively. These results also indicated that price changes were more likely to be characterized by trends than reversals, that futures prices adjust efficiently to new information, and have adjusted more efficiently since the 1973-75 period (p. 293). Previously, Mann and Heifner had rejected the hypothesis of randomness in more than 97 percent of observed contracts using the turning point test and 90 percent using the phase length test in their study of actual futures prices (p. 15).

Hudson et al. asserted, "If futures price changes follow a random walk, ... one can not consistently use past prices to predict future price changes accurately. Technical analysis schemes bases on price trends and periodic price behavior will therefore become less effective for trading."

While the above assertion might be true for price changes, the premise of this paper is that there is a systematic relationship between states composed of price, volume, and open interest changes for futures contracts. This study will examine the feasibility of using a Markov indicator to improve trader profitability. The specific objectives are:

1. To develop a Markov technical indicator for soybean futures that incorporates price, volume, and open interest.
2. To evaluate the Markov indicator under alternative criteria.

MARKOV PROCESSES AND AN APPLICATION TO PRICE FORECASTING

Stochastic processes, including Markov processes, are made up of a parameter space and a state space. The parameter space consists of all the possible values of the indexing variable, time. If the indexing variable is reported in discrete time units, then the process is said to have a discrete parameter space. If the indexing variable is continuous time, then the parameter space is said to be continuous, as the value of the parameter space may cover a range of possible values. The state space describes all the possible values the random variable may assume. It also may be discrete or continuous, depending upon the characteristics of the variable. A process defined by both a discrete parameter space and a discrete state space, as is this application, is referred to as a discrete-time Markov Chain.

In general, a Markov chain X_1, X_2, ..., with m states numbered 1, 2, 3, ..., m, is specified by a transition probability martix, P:

$$P = \begin{matrix} P_{11} & P_{12} & \cdots & P_{m} \\ P_{21} & P_{22} & \cdots & P_{2m} \\ . & . & & . \\ . & . & & . \\ . & . & & . \\ P_{m1} & P_{m2} & \cdots & P_{mm} \end{matrix}$$

where P_{ij} is the probability that $x_{n+1=j}$, given that $X_{n=i}$. That is, P_{ij} is the probability of going from state i to state j in one transition. Since the Markov chain has the Markov property, the future development of the process depends only upon the current state. Therefore, the transition probability matrix, P, is sufficient to completely describe the future development of the process (Seila, p. 10).

The potential for using a Markov process to describe behavior of futures price is evident once a set of discrete states describing possible market conditions is defined. McKallip defined 12 market states based upon commonly observed patterns, such as flags, trends, triangles, and wedges. These states varied in both duration and magnitude and were subject to multiple interpretation. The determining factor when a pattern enclosed other patterns was to pick the one that was "best formed" (McKallip, p. 25).

For purposes of this study, market states were defined not only as a function of price, but of volume and open interest as well. First differences in closing price, volume, and open interest were assigned either a positive or negative value indicative of an increase or decrease in that variable. To take into consideration the magnitude of such changes would severely complicate the analysis, since the number of states required would grow geometrically with each degree of change considered. Table 1 depicts the definitions of the 8 states used to describe market conditions for this analysis.

Sensitivity analysis was performed by examining market states which exist over several different time periods in order to offer insights into what length of time is most relevant in forecasting. Tests were performed on changes in market conditions over four, nine, and eighteen-day intervals. Another set of time periods used was five, ten, and twenty-day but those results are not presented. This ability to vary the time period over which observations are made introduces memory capabilities into an otherwise memoryless process. Observations taken over longer periods of time allow more prior information to be considered or remembered in determining the current state of the system.

After states were defined and assigned, a transitions matrix was constructed which gave the historical number of transitions from each state of the market to every other state. Defining states as discrete time periods rather than pattern formations is more useful in decision criteria for entering and exiting a market. Since timing is of critical importance, states of widely varying duration would be of little use.

The initial transitions matrix was converted into a probability matrix by dividing each element in the matrix by its row total. This probability matrix is referred to as a one-step probability matrix, since it gives the probability of going from each state to every other state in one step. From this one-step probability matrix, an N-step probability matrix can be calculated which gives the probability of going from each state to every other state in N-steps.

Markov states are defined as being either transient or recurrent. A transient state is one from which the process will leave and never return if it is allowed to proceed for a sufficiently long time. A recurrent state is not transient; i.e., there is always a probability that the process will return to this state. Given the ongoing and cyclical nature of futures markets, this analysis will assume a set of recurrent states, meaning that the Markov chain is irreducible, or that the market may cycle indefinitely through any of the 8 states without end. A chi-square test was used to determine the presence of correlation in the transition matrices by comparing the historical number of transitions with the number expected if transitions are random.

In addition, Markov analysis of recurrent states can be used to answer several questions. First, given that the process is in a particular state, what is the mean or expected length of time (number of transitions) until the process enters this state again? Second, starting from an arbitrary state, what is the probability that, after many transitions, the process is in each of the possible states (Seila).

The application of this type of analysis to futures price behavior could be helpful to a trader. For instance, if a certain market condition indicates a reversal or a trend, the probable number of transitions until the next such reversal or trend can be calculated.

Table 1. Market States as Defined by Changes in Price, Volume and Open Interest Variables

State	Price	Volume	Open Interest
	------------------Direction of Change---------------		
1	>	<	<
2	>	<	>
3	>	>	<
4	>	>	>
5	<	<	<
6	<	<	>
7	<	>	<
8	<	>	>

Note: > indicates an increase in the level of a variable
      < indicates a decrease in the level of a variable

DATA, PROCEDURES, AND RESULTS

Data used in this study is from the Dunn and Hargitt Commodity Data Bank, a computerized history of daily market conditions which began in 1959 and compiles data for over thirty commonly traded commodities futures contracts. Daily closing prices, volumes, and open interest for the November Soybean futures contract were used for the years 1968 to 1988.

The procedure used here in applying Markov analysis to forecast soybean futures price behavior involved several steps. The first step was to define the market conditions which constituted each state. States were defined based on changes in price, volume, and open interest over distinct time periods of 4, 9, and 18 days. Eight possible market conditions or "states" were defined. An increase or decrease was defined as a positive or negative change respectively, in the value of a variable. Observations were deleted if some variable remained unchanged over the observation period so as ensure that all states were mutually exclusive.

Once states were defined, the changes in price, volume, and open interest were calculated over each successive time interval and a new variable, "state", was created and assigned a value of 1 through 8 based on the criterion shown in Table 1. For example, if the change in price was positive, the change in volume negative, and the change in open interest positive, the market was said to be in state 2 during this time. Through this procedure, a Markov chain was created which described the behavior of the November Soybean contract over time based on the market conditions of price, volume, and open interest.

Using matrix notation the number of transitions from each state to every other state was recorded in an eight by eight matrix, providing the form necessary for application of statistical tests and Markov analysis. Table 2 illustrates the end result of these procedures for November contracts from 1968 to 1986 using a four time-period lag. Each cell within the matrix gives the number of transitions from the state indicated by the column index to the state indicated by the row index. For example, there were 15 transitions observed from state 5 to state 1. This procedure was repeated over intervals of 9 and 18 days, respectively, resulting in tables 3 and 4.

Chi-Square Tests

A Chi-square test of independence was performed to test for independence of transitions between states. Chi-square tests were performed only on the 4 day time lag transitions series so as to conform as closely as possible to the requirements for Chi-square tests set forth by Ott; that is, that no expected cell values should be less than 1 and no more than 20 percent should be less than 5 in order to obtain valid results. This condition was strictly met only by the 4-period lag and not by the 9-period or 18-period series, due to the relatively small occurrences of certain states over these longer observation intervals. This shortcoming appears to be only partly due to the lack of observations, as there were 489 and 247 observations for the 9-period and 18-period series, respectively. What is indicated is the relative infrequency

Table 2. Transition Matrix for November Soybean Futures Using a Four Period Time Lag, 1968 to 1986.

State	State							
	1	2	3	4	5	6	7	8
	number of transitions							
1	6	14	9	9	8	7	8	13
2	2	16	7	54	6	25	13	38
3	14	8	6	8	15	5	7	7
4	15	38	10	57	21	54	13	33
5	15	3	13	23	11	11	19	11
6	3	23	15	48	7	18	9	51
7	12	10	4	7	25	16	11	2
8	8	49	6	35	13	38	7	27

Table 3. Transition Matrix for November Soybean Futures Using a Nine Period Time Lag, 1968 to 1986

State	State							
	1	2	3	4	5	6	7	8
	number of transitions							
1	3	2	3	8	7	3	3	6
2	0	8	6	19	4	8	4	22
3	4	2	6	2	11	5	5	0
4	9	24	3	27	10	22	2	15
5	7	8	9	4	5	3	6	9
6	1	6	4	23	1	9	5	21
7	5	5	3	2	8	3	2	1
8	6	16	2	27	5	16	2	13

Table 4. Transition Matrix for November Soybean Futures Using an Eighteen Period Time Lag, 1968 to 1986

State	State							
	1	2	3	4	5	6	7	8
	number of transitions							
1	2	3	1	1	3	1	0	5
2	0	0	3	11	5	1	2	5
3	4	0	2	1	3	2	1	1
4	3	17	2	15	4	15	2	6
5	3	2	3	8	7	3	3	3
6	2	1	1	12	3	4	1	13
7	1	0	1	0	6	1	1	1
8	1	4	2	16	1	9	1	12

with which some of these states tended to occur over longer periods of time, an important factor in Markov analysis.

As described by Ott, Chi-square tests are basically of two types. A Chi-square goodness of fit test compares the distribution of data to some assumed distribution, e.g. normal, poison, etc. A chi-square test of independence tests whether or not the row-classifying variables act independently of the column-classifying variables. Since the states used to classify market conditions are each separate and distinct and do not form a continuous scale for which a distribution may be assumed, the test of independence was most appropriate. The Chi-square test of independence tests the null hypothesis that row and column classifying variables act independently of one another against the alternative hypothesis that dependence exists. For the 4-day time lag, the large differences in observed and expected values indicates independence is not a reasonable assumption. Expected and observed values, as well as each cell's contribution to the overall Chi-square and P-values are shown in table 5.

The hypothesis of independence is rejected in favor of dependence as indicated by a Chi-square value of 265.7 for the 4-day interval test. The overall Chi-square value is the sum of the individual Chi-square values for each cell. The P-value is the probability of observing a Chi-square statistic with 49 degrees of freedom that is as great or greater than the chi-square value. One would reject the hypotheses of independence any time the desired significance level is larger than the P-value. Thus, the hypothesis of independence can be clearly rejected and one can accept dependence in transitions between market states based on P-values of 0.0000.

Recurrent Analysis

Markov analysis of the transitions matrix is performed using recurrent analysis procedures. These procedures are based on the assumption that the market states are indeed recurrent, or that the chain may possibly move from any one state to any other state and will cycle indefinitely through the eight possible states without ever leaving the system. Application of this analysis requires that the transitions matrix be converted into a probability matrix, which gives the historical probability of moving from each state to every other state. Dividing each cell value in the transition matrix by its row total, the resulting probability matrices are shown in Tables 6-8. The probability matrix Table 6 indicates, that given the market is currently in state 1, the probability of remaining in state 1 at the end of the current period is .081, while the probability of being in state 2 is .189, and so on. Viewing this probability matrix in the context of the market conditions which actually defined those states, one can see that if over the past four days price increased while volume and open interest decreased (state 1), there is a .512 probability that price will increase over the next four days. That is, the sum of the probabilities of going from state 1 to states 1 through 4 is .512. Results of the recurrent analysis for the November contracts are given in Table 9.

The limiting distribution, or stationary probability, is the percentage of time which the market will spend in each state if allowed to proceed for a sufficiently long period of time. Thus, the product of each state's limiting

Table 5. Chi-Square Results for November Soybean Futures Using Four Period Time Lag Results, 1968 to 1986

State		State 1	2	3	4	5	6	7	8
		---number of transitions---							
1	observed	6	14	9	9	8	7	8	13
	expected	5.06	10.87	4.73	16.27	7.16	11.75	5.87	12.29
	cell CHI SQ	0.17	0.90	3.86	3.25	0.10	1.92	0.77	0.04
2	observed	2	16	7	54	6	25	13	38
	expected	11.02	23.65	10.28	35.40	15.57	25.56	12.78	26.74
	cell CHI SQ	7.38	2.47	1.05	9.77	5.88	0.01	0.00	4.75
3	observed	14	8	6	8	15	5	7	7
	expected	4.79	10.28	4.47	15.39	6.77	11.11	5.56	11.62
	cell CHI SQ	17.71	0.51	0.52	3.55	10.00	3.36	0.37	1.84
4	observed	15	38	10	57	21	54	13	33
	expected	16.49	35.40	15.39	52.99	23.31	38.26	19.13	40.02
	cell CHI SQ	0.13	0.19	1.86	0.30	0.23	6.47	1.96	1.23
5	observed	15	3	13	23	11	11	19	11
	expected	7.25	15.57	6.77	23.31	10.25	16.83	8.41	17.60
	cell CHI SQ	8.27	10.15	5.73	0.00	0.05	2.02	13.32	2.48
6	observed	3	23	15	48	7	18	9	51
	expected	11.91	25.56	11.11	38.26	16.83	27.62	13.81	28.89
	cell CHI SQ	6.66	0.26	1.36	2.48	5.74	3.35	1.68	16.91
7	observed	12	10	4	7	25	16	11	2
	expected	5.95	12.78	5.56	19.13	8.41	13.81	6.91	14.45
	cell CHI SQ	6.14	0.60	0.44	7.69	32.69	0.35	2.43	10.72
8	observed	8	49	6	35	13	38	7	27
	expected	12.52	26.88	11.69	40.24	17.70	29.05	14.53	30.39
	cell CHI SQ	1.63	18.20	2.77	0.68	1.25	2.76	3.90	0.38

Overall Chi Square 265.7
P Value 0.0000
Degrees of Freedom 49

Table 6. Probability Matrix for November Soybean Futures Using a Four Period Time Lag, 1968 to 1986

State	State							
	1	2	3	4	5	6	7	8
	---probability---							
1	.081	.189	.121	.121	.108	.094	.108	.175
2	.012	.099	.043	.335	.037	.155	.080	.236
3	.200	.114	.085	.114	.214	.071	.100	.100
4	.062	.157	.041	.236	.087	.224	.053	.136
5	.141	.028	.122	.216	.103	.103	.179	.103
6	.017	.132	.086	.275	.040	.103	.051	.293
7	.137	.114	.045	.080	.287	.183	.126	.022
8	.043	.267	.032	.191	.071	.207	.038	.147

Table 7. Probability Matrix for November Soybean Futures Using a Nine Period Time Lag, 1969 to 1986

State	State							
	1	2	3	4	5	6	7	8
	---probability---							
1	.085	.057	.085	.228	.200	.085	.085	.171
2	.000	.112	.084	.267	.056	.112	.056	.309
3	.114	.054	.171	.057	.314	.142	.142	.000
4	.080	.214	.026	.241	.089	.196	.017	.133
5	.137	.156	.176	.078	.098	.058	.117	.176
6	.014	.085	.057	.328	.014	.128	.071	.300
7	.172	.172	.103	.068	.275	.103	.068	.034
8	.068	.183	.022	.310	.057	.183	.022	.149

Table 8. Probability Matrix for November Soybean Futures Using an Eighteen Period Time Lag, 1968 to 1986

State	State							
	1	2	3	4	5	6	7	8
	---probability---							
1	.125	.187	.062	.062	.187	.062	.000	.312
2	.000	.000	.111	.407	.185	.037	.074	.185
3	.285	.000	.142	.071	.214	.142	.071	.071
4	.046	.265	.031	.234	.062	.234	.031	.093
5	.093	.062	.093	.250	.218	.093	.093	.093
6	.054	.027	.027	.324	.081	.108	.027	.351
7	.090	.000	.090	.000	.545	.090	.090	.090
8	.021	.086	.043	.347	.021	.195	.021	.260

distribution and the number of specified time periods in the contract's life will yield the number of days which the market is expected to spend in each state. This information, along with the mean recurrence time, is expected to be very useful in predicting trend lengths and reversals. The mean recurrence time is the reciprocal of the limiting distribution and represents the expected time intervals between recurrences of each market state or condition.

In Table 9, for example, if state 1, in which price is increasing with decreasing volume and open interest, is interpreted as indicating a particular type of market condition, a similar condition is expected in 14.706 four-day periods, or approximately 59 days. Given that the market is currently in state 1 and is expected to return to state 1 in approximately 59 days, probable patterns may be predicted over this time interval. For example, the most likely transition from state 1 is to state 2 in which price and open interest were increasing and volume was decreasing. From state 2, the process is most likely to move to state 4 in which all variables are increasing.

Should the process not move to state 4 but continue in state 2, the next prediction may be updated based on the fact that the market has been in state 2 for two periods, or approximately nine days, using the 9-period lag results. This would indicate the most likely transition is now to state 8 (note that one would then expect to be in state 8 over the next 9 days, not the next 4). Should it become evident that the market is not meeting the criterion for state 8, a new prediction could be made using conditions over the past 4 days. In this manner, predictions about future market behavior may be continually updated based on new market information as it is reflected in price, volume, and open interest.

Markov Forecasts

From the transition probability matrix, a forecast may be generated using the transition state with the greatest probability. Table 10 presents the forecasted states given a particular state for each time period lag. For example, given that the November soybean contract is in state 1, the Markov forecasted state four days in the future is state 2. With these forecasts, out-of-sample accuracy may be evaluated. This was done using the 1987 and 1988 November contracts from November 1986 to August 1988. Table 11 presents correct prediction percentages from two different perspectives. The first is academic and strict in the sense that the exact future state must be correctly forecast. The other perspective is more pragmatic and simply tracts whether the forecasted state is correct with respect to the direction of the price change. For instance, if the market was in state 1, the forecast was state 4, and the next actual state was 2, then in a strict sense the forecast was incorrect. Yet the forecast of the importnat outcome was correct in that the correct price change direction was forecast (an increase). As is clear, the nine-day time interval forecast is superior is a strict sense. But when viewed from a trader's perspective the performance of each of the time interval Markov indicators was equivalent. They correctly forecast price change direction about 57 percent of the time.

This might not seem significant, but when a simple trading rule is enacted based on the Markov indicator the results were impressive. The rule was to take a one-contract market position based on the Markov indicator at the beginning of a time-based period, and close out that position at the next

Table 9. Recurrent Analysis of November Soybean Futures Contact Using a 4, 9, and 18 day Time Period, 1968-1986

State	Limiting Distribution			Mean Recurrence Time		
	Time Periods					
	4	9	18	4	9	18
1	0.068	0.072	0.066	14.706	13.889	15.152
2	0.147	0.145	0.109	6.803	6.897	9.174
3	0.064	0.74	0.061	15.625	13.514	16.393
4	0.220	0.228	0.258	4.545	4.386	3.876
5	0.097	0.105	0.131	10.309	9.524	7.634
6	0.159	0.141	0.146	6.289	7.092	6.849
7	0.079	0.059	0.045	12.658	16.949	22.222
8	0.166	0.177	0.185	6.024	5.650	5.405

Table 10. Markov Forecasts for November Soybean Futures Using Four, Nine, and Eighteen Period Time lags, 1968-1986

State	Forecasted State		
	Time Period		
	4	9	18
1	2	4	8
2	4	8	4
3	5	5	1
4	4	4	2
5	4	3	4
6	8	4	8
7	5	5	5
8	2	4	4

Table 11. Correct Percent Forecast Rate of Markov Indicator for November Soybean Futures Using Four, Nine, and Eighteen Time Period for 1987 and 1988 November Contracts.

Degree of Exactness	Time Period		
	4	9	18
	Percent Correct Rate		
State to State	.222	.404	.304
State to Price Change	.574	.574	.565

Table 12. Monetary Results of Trading Strategy Using Markov Indicators (4,9, and 18 day) for 1987 and 1988 November Soybean Futures, November 1986-July 1988.

Contracts	Time Periods		
	4	9	18
	$ Profit (1 5000 bu contract)		
1987 November	+ 5762.5	- 2687.5	- 1,687.5
1988 November	+23,875.0	+24,000.0	+15,650.0
Total	+29,637.5	+21,312.5	+13,962.5

time period, and open a new one-contract market position based on the new time period state and Markov indicator. Table 12 presents the monetary trading results of this strategy for the November 1987 and 1988 soybean contracts starting in November 1986 and ending on July 30, 1988. No transaction costs were included. The strategy would have involved 108, 47, and 23 roundturns for the 4, 9, and 18-day periods, respectively. Even with this mechanical and large transaction cost strategy, the overall total profits are encouraging. As would be expected, the four-day Markov indicator generates greater profits. It appears to generate more than enough profits to handle the 108 roundturns. If each roundturn cost was $50, the total transaction cost would be $5400, which results in a $24,237.50 gain for the year and a half of trading.

CONCLUSIONS

The Markov technique used in this analysis of November Soybean Futures is based on the historical probabilities of moving from one market state or condition to all other possible states where states are defined as a combination of directional changes in price, volume, and open interest during a given interval of time. Previous studies in this area have concentrated primarily on prices or price changes alone, without considering underlying market conditions and information which may influence these changes.

This integration of volume and open interest into predicting price behavior offers advantages over analysis of price alone by allowing traders to observe market reaction to various levels of price. For example, changes in volume may help to confirm or reject market acceptance of some price level as above or below perceived value. Analysis of this type also offers insights into the time frame in which changes in price level may be accepted or rejected. For instance, note that limiting distributions do not remain constant as the observation time interval increases. Limiting distributions tend to decrease for some states, such as 2 and 7, while increasing for others, such as 4 and 5. This may indicate that over longer intervals of time, the market spends less time in some states and more in others.

The implication here for trading purposes is that certain market conditions occur only over short periods of time before giving way to conditions which occur for longer periods of time. Thus, these short time-frame conditions may serve as indicators of the longer time-frame conditions which will follow.

The analysis offers support for the work cited earlier by Hudson et al., which found trends to be more likely than reversals. It would be inappropriate to infer from this analysis conclusions about serial correlation of prices or price changes such as were made by Mann and Heifner and Hudson et al. But this study does offer evidence which strongly supports correlation in the market conditions defined herein; i.e., directional price changes qualified by accompanying directional volume and open interest changes. Information concerning this correlation of market conditions may assist traders in evaluating market positions, improving timing decisions, and making risk/reward decisions concerning place-and-lift, or selective, hedging.

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