Supplementary Information and Markov Processes in Soybean Futures Trading

Steven C. Turner
Jack E. Houston
Tommie L. Shepherd

INTRODUCTION

Forecasting futures prices is an integral part of profitable commodity futures trading. Various technical analysis techniques exist to assist traders in detecting profitable opportunities. 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. For example, in a vertical line price (bar) chart, volume and open interest changes are used to reinforce expectations from the price signal formation, and then, not on a day-to-day basis [e.g., Jiler (1962, 1965, 1975); Belveal (1985); Stewart (1986)]. Cornell (1981) finds a highly significant contemporaneous relationship between volume and price variability in futures markets, though day-to-day lead and lag relationships are not significantly correlated.

One indicator that directly incorporates volume is the on-balance volume (OBV) index developed by Granville for the stock market (Aspray, 1989). The OBV index is used to confirm or discount expected price movements. Another indicator that combines price, volume, and open interest is the Herrick Payoff Index (HPI), developed by John Herrick. The HPI is used to calculate the money flow in or out of a commodity. When the HPI is positive, money flow is positive, and a bullish market is indicated. A negative HPI indicates money is leaving the commodity, which indicates a bearish market (Aspray, 1989).

Markov-chain analysis provides another possible method of integrating information on price, open interest, and volume of futures contract trading into one unit.

Appreciation is expressed to Dr. Jeffrey H. Dorfman for suggesting the use of the Henriksson-Merton test.

Steven C. Turner is an Assistant Professor in the Department of Agricultural Economics at the University of Georgia.

Jack E. Houston is an Associate Professor in the Department of Agricultural Economics at the University of Georgia.

Tommie L. Shepherd is a former Graduate Student at the University of Georgia.

The Journal of Futures Markets, Vol. 12, No. 1, 61–74 (1992)

CCC 0270-7314/92/010061-14$04.00

Markov processes can be used to study the nature of sequences of events ranging from purely random to purely deterministic (Davis, 1973). 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 essentially 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, 1986). Lane's application is based on the observation that, as prices increase, closing prices tend to be nearer the upper end of the price range. Conversely, in downtrends, the closing price tends to be near the lower end of the range. The intent of Lane's trading system is to determine where the closing price lies in relation to the price range for a given time period. That is, Lane's stochastic process measures where the closing price is in relationship to the total price range on a scale of 0–100.

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 is published in the area of applying Markov analysis to futures price forecasting. McKallip (1986) presents a general format for applying such an analysis and testing its results. He examines weekly price charts for 19 commodities from 1970–1979 for obvious pattern formations. These formations or states, varying in both duration and magnitude, are assigned subjectively, and a transitions matrix (i.e., a tabulation of transitions between states) is created to represent the historical number of transitions between each state and various other states. A probability matrix is then calculated to describe the initial transitions matrix. This calculated transitions matrix is compared by means of a chi-square test to an expected-value matrix representing transitions which are expected due to random chance. Reported results for the 1970–1979 period indicate that transitions among states are not due to random chance at the 0.05 significance level. Presence of systematic elements in futures behavior is a necessary condition if a Markov process is to offer any predictability.

A Markov approach to three stock market states was developed by Pariseau (1980) using quarterly Dow Jones Industrial Averages from 1928–1979. The states of nature are defined as increasing, decreasing, or stagnant, with an 8% change being the criterion. The transitions between market states are modeled as a Markov process and, when used in conjuction with parametric decision models and a Bayesian probability updating model, yield profitable results.

While Markov processes may be used to describe random systems (Davis, 1973), the description of a random system offers no information as to the development of the system, but only its composition. For example, if market conditions behave according to the Random Walk Theory (Samuelson, 1965), 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 produce varying results depending upon the use of different time periods, research techniques, and other study-specific features (Garcia, Hudson, and Waller, 1988). Hudson, Leuthold, and Sarassoro (1987) perform turning point and phase length tests on futures price changes, rejecting the randomness hypothesis in only 13% and 14% of the observed cases, respectively. The results of their study also indicate that price changes are more likely to be characterized by trends than reversals, that futures prices adjust efficiently to new information, and that futures prices adjust more efficiently since the 1973–1975 period. Hudson et al. (1987) assert, "If futures price changes follow a random walk,...one can not consistently use past prices to predict future price changes accurately. Technical analysis schemes based on price trends and periodic price behavior will therefore become less effective for trading" (p. 295). Taylor (1985) rejects the random walk hypothesis as applied to futures prices. On the other hand, Tomek and Querin (1984) demonstrate, through simulations, that a price series generated by a random walk process could have "systematic components" over a finite period. The implication is that technical analysis applied to such a series can be profitable.

Evaluation of forecasting techniques generally includes out-of-sample profits. For example, Lukac, Brorsen, and Irwin (1988) evaluate the simulated trading of 12 technical systems for a portfolio of 12 commodities from 1978–1984 to test for market disequilibrium. They prefer the moniker "disequilibrium," rather than the more ubiquitous "efficiency." The differentiation between terms relates to information. Market efficiency, as defined by Fama (1970), implies that current prices reflect all available information. Short-run market disequilibrium, on the other hand, implies that prices do not adjust quickly to information shocks. Lukac et al. find evidence of disequilibrium and positive net returns. Many other studies [see Lukac et al. (1988) for an extensive list] also simulate trading with a specified decision rule and find that profits do exist. The convenient framework utilized by Lukac et al. to evaluate technical trading systems is used here to evaluate a Markov indicator.

The premise of this article is that there is a systematic relationship between states composed of price, volume, and open interest changes for futures contracts. This study examines the feasibility of using a Markov indicator to improve trader profitability. The specific objectives are to develop a Markov technical indicator for soybean futures that incorporates price, volume, and open interest information, and to evaluate the Markov indicator under the Lukac et al. (1988) criteria.

3A MARKOV INDICATOR

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 in this application, is referred to as a discrete-time Markov-chain.

In general, a Markov-chain $X_1, X_2, \ldots$, with m states numbered $1, 2, 3, \ldots, m$, is specified by a transition probability matrix, P:

$$P = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1m} \\ P_{21} & P_{22} & \cdots & P_{2m} \\ \cdot & & \cdot & \cdot \\ \cdot & & \cdot & \cdot \\ \cdot & & \cdot & \cdot \\ P_{m1} & P_{m2} & \cdots & P_{mm} \end{bmatrix}$$

where 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, 1987).

The potential for using a Markov process to describe behavior of futures prices is evident once a set of discrete states describing possible market conditions is defined. McKallip (1986) defines 12 market states based upon commonly observed price patterns, such as flags, trends, triangles, and wedges. These states vary in both duration and magnitude and are subject to multiple interpretations. The determining factor when a pattern encloses other patterns is to pick the one that is "best formed."

For purposes of this study, market states are defined not only as a function of price changes, but of volume and open interest changes as well. Volume is used by technicians as a "measure of intensity of buying and selling pressure.... Changes in this volume pattern often warn of a reversal in trend before it actually happens" [Jiler (1962), p. 33]. Open interest is used as a "measurement of conflicting opinions... the willingness of longs and shorts to maintain opposing positions in the market" [Belveal (1985), pp. 75, 76]. Changes in open interest quantify differences of opinion among market participants as to continuation of trends or changes in direction of price movements.

First differences in closing price, volume, and open interest are assigned either a positive or negative value indicative of an increase or decrease in that variable. Table I depicts the definitions of the eight states used to describe market conditions for this analysis. Sensitivity analysis is performed by examining market states which exist over several different time periods to gain insights into which length of time is the most relevant for forecasting. Tests are performed on changes in market conditions over four-, nine-, and 18-day intervals. These are the most commonly used intervals by charting services. Three-, five-, ten-, and 20-day intervals are used also, but those results are not presented here. No attempt is made to optimize the interval parameters. For purposes of comparison with other indicators used by professionals (e.g., moving averages), only the four-, nine-, and 18-day interval indicators are presented.

After states are defined and assigned, a transitions matrix is constructed which gives the historical number of transitions from each state of the market to every

Table I
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.

other state. Defining states as uniform-interval, discrete time periods rather than as pattern formation periods is more useful in decision criteria for entering and exiting a market because timing is critically important and states of widely varying duration are of little use.

The initial transitions matrix is 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, because it gives the probability of going from each state to every other state in one step. From the transition probability matrix, a forecast may be generated using the transition state with the greatest probability. Of course, returns result from price changes, not from volume and open interest changes. Nevertheless, the Markov indicator incorporates this extra information in a concise and consistent format. The decision rule for the indicator used in this analysis is simple and straightforward. If the forecasted state includes an increasing (decreasing) price component, then a buy (sell) position is taken or held.

PROCEDURE

An in-sample Markov indicator is used to forecast out-of-sample November soybean price movements. For example, data from 1970–1977, on the November soybean contract, are used to develop the 1978 forecast. Successive forecasts incorporate the preceding year data to regenerate a forecast for the following year. Thus, the forecasts are adaptive.

The procedure used to evaluate the Markov indicator (MI) follows that of Lukac et al. (1988). The hypothesis that gross returns from using the MI are positive is tested using a one-tailed t-test. Furthermore, the same hypothesis for returns, which takes into account transactions costs, is also tested using a one-tailed t-test. Using a t-statistic assumes a normal and independent distribution of monthly returns. Previous research shows that daily futures price changes are not normally distributed (Mandelebrot, 1963, 1966). But Lukac et al. (1988) use a Kolmogorov–Smirnov (KS) test to test the distribution of monthly returns from technical analysis for normality. Their tests do not reject normality at a 0.1 significance level. An additional potential problem with the t-test is positive autocorrelation of returns (Gardner, 1982). If it exists, the strength of significance may be overstated using the t-statistic. Again, Lukac et al. (1988) calculate first-order autocorrelation coefficients to detect overstated significance levels. Both the KS test and the calculation of first-order autocorrelation coefficients are performed in this analysis.

To adjust returns for risk, the Jensen (1968) approach is used. The model (Lukac et al., 1988) is:

$$E(R_i) = a_i + B_i R_m^* + e_i \tag{1}$$

where $E(R_i)$ is the monthly return of the Markov indicator; R_m^* equals $E(R_m - R_f)$, where R_m is represented by the returns to the Standard and Poor's 500 Stock Index as computed by Ibbotson Associates (1989), and R_f is Ibbotson Associates' reported 30-day U.S. Treasury bill returns. Since capital invested and held for margin calls could be invested in 30-day U.S. Treasury bills, a risk-free rate is not subtracted from $E(R_i)$ in this study, and R_m^* in eq. (1) is represented by R_m. To determine if returns exist above returns to risk, the intercept term a_i is tested to determine if it is significantly greater than zero. Data used in this study are from the Dunn and Hargitt Commodity Data Bank, a computerized history of daily market conditions for over 30 commonly traded commodities futures contracts. Daily closing prices, volumes, and open interest for the November Soybean futures contract are used for the years 1970–1989.

MARKOV RESULTS

A chi-square test is performed to test for independence of transitions between states. Chi-square tests are performed on the four-, nine- and 18-day time-lag transitions series. As described by Ott (1984), chi-square tests are basically of two types. The first type, a chi-square goodness-of-fit test, compares the distribution of data to some assumed distribution, e.g., normal,Poisson, etc. The second, a chi-square test of independence, tests whether 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 seems more 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.

Expected and observed values for the four-day time lag for the 1989 forecast, which uses 1970–1988 data, as well as each cell's contribution to the overall chi-square and *P*-values, are shown in Table II. The hypothesis of independence is rejected, as indicated by an overall chi-square value of 1000.3 for the 1989 four-day interval test, 1029 for the 1989 nine-day interval, and 876.3 for the 1989 18-day interval. 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 critical 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 0.0. This result is consistent for all the years used in the analysis.

Tables III, IV, and V present the forecasted states, given a particular state, for four-, nine-, and 18-day period time lags, respectively. For example, given that the November soybean contract is in state 1, with price up and volume and open interest down, the Markov-forecasted state four days in the future for 1978 is state 4, with continuing upward price movement. With these forecasts, out-of-sample accuracy is evaluated. Using the adaptive Markov indicator, the 1978–1989 November contracts are used for out-of-sample testing (Tables III, IV, and V).

Correct forecast rates are presented from two perspectives. The first perspective is strict in the sense that the exact future state must be correctly forecast. The second perspective is more pragmatic and tracts whether the forecasted state is correct with respect to the direction of the price change. For instance, if the market is in state 1, the forecast is state 4, and the next actual state is 2, then in a strict sense the forecast is incorrect. Yet the forecast of the important outcome is correct in that the correct price change direction is forecast (an increase). For the four-day Markov indicator, state-to-state forecast rate averages 0.22, while the state-to-price forecast rate averages 0.51. In 1979 and 1988, the state-to-price forecast rate is 0.59 and 0.62, respectively, while it is 0.43 in 1981 and 1986.

When a simplified trading rule is enacted based on the four-day Markov indicator, the results are impressively supportive of the hypothesis that incorporating market activity (volume) and participation (open interest) information can improve price movement forecasts. The rule specifies taking and holding a one-contract

Table II
TRANSITIONS, EXPECTED TRANSITIONS, AND CHI-SQUARE RESULTS FOR NOVEMBER SOYBEAN FUTURES USING FOUR-PERIOD TIME-LAG RESULTS, (1970–1988)

State (t)	State (t + 4) 1	2	3	4	5	6	7	8
	No. of Transitions							
1 Observed	35	34	50	62	29	28	48	55
Expected	24.85	52.75	22.89	76.22	34.51	47.96	25.58	56.24
Cell chi-sq.	4.15	6.67	32.11	2.65	0.88	8.30	19.66	0.03
2 Observed	18	93	37	262	28	79	46	163
Expected	52.91	112.31	48.73	162.28	73.48	102.10	54.45	119.74
Cell chi-sq.	23.03	3.32	2.82	61.28	28.15	5.23	1.31	15.63
3 Observed	47	29	38	28	79	34	35	25
Expected	22.96	48.73	21.14	70.41	31.88	44.30	23.63	51.95
Cell chi-sq.	25.19	7.99	13.44	25.54	69.63	2.39	5.47	13.98
4 Observed	57	216	37	235	100	216	39	149
Expected	76.45	162.28	70.41	234.48	106.17	147.53	78.68	173.01
Cell chi-sq.	4.95	17.78	15.85	0.00	0.36	31.78	20.01	3.33
5 Observed	48	36	64	89	54	31	80	71
Expected	34.47	73.17	31.75	105.73	47.87	66.52	35.48	78.01
Cell chi-sq.	5.31	18.88	32.76	2.65	0.78	18.97	55.87	0.63
6 Observed	24	79	45	197	27	78	44	167
Expected	48.17	102.26	44.37	147.75	66.90	92.96	49.58	109.02
Cell chi-sq.	12.13	5.29	0.01	16.42	23.80	2.41	0.63	30.84
7 Observed	65	45	25	28	89	44	32	23
Expected	25.58	54.30	23.56	78.46	35.53	49.36	26.33	57.89
Cell chi-sq.	60.75	1.59	0.09	32.45	80.49	0.58	1.22	21.03
8 Observed	48	194	19	148	69	150	28	121
Expected	56.62	120.20	52.15	173.68	78.64	109.27	58.28	128.15
Cell chi-sq.	1.31	45.31	21.08	3.80	1.18	15.18	15.73	0.40

Overall chi-square, 1000.3; P-value, 0.0; degrees of freedom, 49.

market position based on the Markov indicator at the beginning of a time-based period. That position is closed out when the MI signals a reversal and a new one-contract market position, based on the new time period state and Markov indicator, is opened. This process repeats itself from November–November of the contract. For example, trading begins on November 1, 1988 for the 1989 November contract and ends on October 31, 1989. The gross monetary trading results of this strategy for the four-day MI totals $40,736.50 over the 12 years of the study, while the annual average is $3,394.70. Representative transaction costs of $100 and $50 per roundturn are used to calculate net returns. For the four-day MI, these net returns average $1,753.04 and $2,573.87 annually for the $100 and $50 roundturns, respectively.

Table III
FORECASTED STATES, FORECAST RATES, GROSS RETURNS, NET RATES OF RETURNS, AND NUMBER OF ROUNDTURNS FOR FOUR-DAY MARKOV INDICATOR (1978–1989)

Item	Year												
	1978	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	Average
	Forecasted State												
Initial state													
1	4	8	4	4	4	4	3	3	3	4	4	4	
2	4	4	4	4	4	4	4	4	4	4	4	4	
3	5	5	5	5	5	5	5	5	5	5	5	5	
4	2	2	2	4	4	4	4	4	4	4	4	4	
5	7	7	7	7	7	7	7	7	4	4	4	4	
6	4	4	4	4	4	4	4	4	4	4	4	4	
7	5	5	5	5	5	5	5	5	5	5	5	5	
8	2	2	2	2	2	2	2	2	2	2	2	2	
Forecast rates													
State-to-state	0.18	0.27	0.23	0.20	0.23	0.22	0.23	0.18	0.24	0.21	0.25	0.26	0.22
State to price change	0.55	0.59	0.48	0.43	0.50	0.49	0.50	0.45	0.43	0.52	0.62	0.55	0.51
Returns ($)													
Gross	1487	11025	1800	−1350	−2275	−1300	5087.5	−3612.5	−6025	3512.5	30337	2050	3394.7
Net (100)	287	9425	−200	−3350	−3875	−3900	2987.5	−5212.5	−7125	2512.5	28737	750	1753.0
Net (50)	887	10225	800	−2350	−3075	−2600	4037.5	−4412.5	−6575	3012.5	29537	1400	2573.8
Rates (%)													
Gross	48	304	45	−39	−70	−8	142	−140	−235	114	753	30	78
Net rate % ($100)	10	259	−9	−93	−121	−83	79	−196	−279	75	710	−10	28
Net rate % ($50)	29	281	18	−66	−96	−45	110	−168	−257	95	731	10	53
Roundturns													
Number	12	16	20	20	16	26	21	16	11	10	16	13	16.41

Table IV
FORECASTED STATES, FORECAST RATES, GROSS RETURNS, NET RATES OF RETURNS, AND NUMBER OF ROUNDTURNS FOR NINE-DAY MARKOV INDICATOR (1978–1989)

Item	Year												
	1978	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	Average
	Forecasted State												
Initial state													
1	5	5	7	5	5	5	5	5	5	5	8	8	
2	4	4	4	4	4	4	4	4	4	4	4	4	
3	5	5	5	5	5	5	5	5	5	5	5	5	
4	4	4	4	4	4	4	4	4	4	4	4	4	
5	3	3	3	3	3	3	1	3	3	3	4	4	
6	4	4	4	4	4	4	4	4	4	4	4	4	
7	5	5	5	5	5	5	5	5	5	5	5	5	
8	4	2	4	4	4	2	2	2	4	4	4	4	
Forecast rates													
State-to-state	0.19	0.34	0.28	0.19	0.26	0.36	0.12	0.14	0.18	0.26	0.48	0.23	0.25
State to price change	0.42	0.65	0.60	0.42	0.53	0.64	0.36	0.29	0.44	0.42	0.62	0.53	0.49
Returns ($)													
Gross	−50	9350	7100	−8450	−675	20050	−10112	−5825	−325	−650	20037	−1450	2416.66
Net (100)	−450	8750	6600	−9450	−1575	19850	−10812	−6125	−925	−1150	19237	−1950	1833.33
Net (50)	−250	9050	6850	−8950	−1125	19950	−10462	−5975	−625	−900	19637	−1700	2125.00
Rates (%)													
Gross	−38	257	165	−220	−19	495	−329	−203	−22	−40	457	−46	38
Net rate % ($100)	−50	240	151	−246	−49	489	−349	−214	−46	−59	436	−62	20
Net rate % ($50)	−44	249	158	−233	−34	492	−339	−208	−34	−49	447	−54	29
Roundturns													
Number	4	6	5	10	9	2	7	3	6	5	8	5	5.83

Table V
FORECASTED STATES, FORECAST RATES, GROSS RETURNS, NET RATES OF RETURNS, AND NUMBER OF ROUNDTURNS FOR 18 DAY MARKOV INDICATOR (1978–1989)

Item	1978	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	Average
	Forecasted State												
Initial state													
1	7	7	4	8	4	8	8	8	8	8	8	8	
2	4	4	4	4	4	4	4	4	4	4	4	4	
3	5	5	5	5	5	5	5	5	5	5	5	5	
4	4	4	4	4	4	4	4	4	4	4	4	4	
5	4	4	4	4	4	4	4	4	4	4	4	4	
6	4	4	4	4	4	4	4	4	4	4	4	4	
7	5	3	3	3	3	3	5	5	5	5	5	5	
8	8	4	4	4	8	8	8	8	8	8	8	8	
Forecast rates													
State-to-state	0.25	0.41	0.33	0.25	0.25	0.25	0.33	0.23	0.23	0.50	0.38	0.16	0.29
State to price change	0.50	0.66	0.41	0.33	0.41	0.58	0.58	0.53	0.23	0.83	0.46	0.33	0.48
Returns ($)													
Gross	−4700	3175	4100	−11525	−6862.5	12150	−3887.5	2900	−7925	6112.5	3225	−7987.5	−935.41
Net (100)	−5200	3075	4000	−11625	−7462.5	11650	−4187.5	2000	−8625	5612.5	2525	−8787.5	−1418.75
Net (50)	−4950	3125	4050	−11575	−7162.5	11900	−4037.5	2450	−8257	5862.5	2875	−8387.5	−1177.08
Rates (%)													
Gross	−181	80	87	−315	−235	260	−142	102	−308	240	47	−238	−50
Net rate % ($100)	−198	77	84	−318	−253	246	−451	70	−336	220	28	−262	−90
Net rate % ($50)	−190	78	86	−316	−244	253	−146	86	−322	230	38	−250	−58
Roundturns													
Number	5	1	1	1	6	5	3	9	7	5	7	8	4.83

A better perspective from which to evaluate the MI is gained by using rates of returns. In this analysis, a 0.1 margin is considered the representative investment in the contract. This 0.1 margin is maintained throughout trading and is used to calculate rates of return. As in the case of returns, both gross and net rates are calculated. The gross rate of return for the four-day MI over the 12-year study period averages 78%, while the net rate for the $100 and $50 roundturns average 28% and 53%. It should be noted that an extremely profitable year in 1988 contributes greatly to these returns and rates for the four-day MI.

The nine-day MI also appears to be a profitable technical trading tool from 1978–1989. The average gross rate of return is 38%, while the average net $100 and $50 roundturn rates are 20% and 29%, respectively. On the other hand, results from the 18-day MI are unprofitable, with average rates of return of −50% (gross), −90% ($100 roundturn), and −58% ($50 roundturn).

To further evaluate the Markov indicators, tests are performed for normality and autocorrelation of monthly returns. Both tests are important when using *t*-statistics to test for statistical significance. Table VI presents results from the above test along with the monthly means and *t*-statistics for the three Markov indicators examined. The normality assumption for gross and net rates of return cannot be re-

Table VI

MEANS AND TEST FOR NORMALITY AND AUTOCORRELATION OF MONTHLY RETURNS FROM FOUR-, NINE-, AND 18-DAY MARKOV INDICATOR (1978–1989)

	Markov Indicator		
Item	**4-day**	**9-day**	**18-day**
Normality[a]			
Kolmogorov test statistic			
Gross return (%)	0.084	0.093	0.089
Net return % ($100)	0.067	0.093	0.092
Net return % ($50)	0.073	0.091	0.093
Autocorrelation[a]			
Coefficient (*t*-value)			
Gross return (%)	−0.0381	0.1571[d]	−0.02208
	(−0.4527)	(1.89)	(−0.2610)
Net return % ($100)	−0.0376	0.1576[d]	−0.02166
	(−0.4464)	(1.89)	(−0.2559)
Net return % ($50)	−0.0380	0.1574[d]	−0.021907
	(−0.4508)	(1.89)	(−0.2589)
Means[b]			
t-statistic			
Gross return (%)	6.55[c]	3.16	−4.24
	(1.41)	(.62)	(−0.82)
Net return % ($100)	2.37	1.65	−5.58
	(0.51)	(0.32)	(−1.08)
Net return % ($50)	4.46	2.41	−4.91
	(0.96)	(0.47)	(−0.95)

[a]Two-tailed test.
[b]One-tailed test.
[c]Significant at 0.10 level.
[d]Significant at 0.05 level.

jected for any of the indicators at the 0.1 level. While all the rates of return for the four- and 18-day MI exhibit no significant autocorrelation, the rates for the nine-day MI exhibit significant autocorrelation. Thus, the significance levels of the statistical test for the nine-day MI may be overstated. Except for the mean monthly gross rate of return for the four-day MI, none of the means are statistically significant at the 0.1 level.

Perhaps the *t*-statistic is not the most appropriate barometer of the success of a trading tool such as a MI. A Henriksson–Merton (1981) test for the information value of the four-day MI results in a confidence level of 0.82771 (a significance level of 0.17229). Thus, the Henriksson–Merton test would fail to reject the null hypothesis of no information value at the 0.17 level.

A simple four- to nine-day moving average (MA) forecast is used for comparison purposes. The same trading rule was applied, in that a position is taken and maintained based on the MA forecast until a reversal is indicated. Then the one-contract position is closed, and a new one-contract position is opened based on the new forecast. Thus, the simulated trader is always in the market and encounters more roundturns under the MA regime. Table VII presents the above cumulative comparison. It is evident that both the four- and nine-day MI outperform the MA.

Performing the Jensen test on the four- and nine-day MI results in a significant (0.1 level) intercept using a one-tailed test for the four-day MI (Table VIII). Thus, for the four-day MI, monthly net returns (using $50 roundturns) are significantly above a return to risk. The beta coefficient for the four-day MI is negative but insignificant. This indicates that the rates of return from the four-day MI are negatively correlated with stock market returns.

CONCLUSIONS

The Markov indicator used in this analysis of November soybean futures is based on the historical probabilities of moving from one market state or condition to all

Table VII
COMPARISON OF RETURNS FROM MARKOV INDICATORS WITH FOUR- TO NINE-DAY MOVING AVERAGE (1978–1989)

Item	Moving Average	Markov Indicator		
		4-day	9-day	18-day
Monthly average (*t*-statistic)				
Gross return (%)	−2.58	6.55[a]	3.16	−4.24
	(−0.46)	(1.41)	(0.62)	(−0.82)
Net return % ($100)	−10.51	2.37	1.65	−5.58
	(−1.81)	(0.51)	(0.32)	(−1.08)
Net return % ($50)	−6.55	4.46	2.41	−4.91
	(−1.14)	(0.96)	(0.47)	(−0.95)
Cumulative ($)				
Gross return	−12,075	40,736.50	29,000	−11,225
Net return ($100)	−48,375	21,036	22,000	−17,025
Net return ($50)	−30,225	30,886	25,550	−14,125

[a]Significant at the 0.10 level.

Table VIII
REGRESSION COEFFICIENTS FOR TEST OF EXCESS RETURNS BASED ON CAPITAL ASSET PRICING MODEL (1978–1988)

	Independent Variable		
	Intercept	S&P 500 Returns	
Markov Indicator	Coefficient (t-value)	Coefficient (t-value)	R^2
4-day	0.0701[a]	−0.9907	0.006
	(1.33)	(−0.92)	
9-day	0.0420	0.1337	0.0001
	(0.75)	(0.12)	

[a]Significant at 0.10 level.

other possible states. States are defined as combinations of directional changes in price, volume, and open interest during a given interval of time. Previous studies concentrate primarily on price levels or price changes alone, without directly considering underlying market conditions, participant behavior, and other supplementary information which may influence these changes.

The integration of volume and open interest into predicting price trend and major turning point 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. The implication here, for trading purposes, is that certain market conditions are strong indicators of reversals. For instance, if price and volume are increasing and open interest is decreasing (state 3), a reversal is forecast by the four-day MI. This forecast is consistent with basic technical chart analysis. Thus, the MI simply incorporates the three components of price, volume, and open interest rates into one state, and observes the state changes over time.

The analysis offers support for the work by Hudson et al. (1987) and Tomek and Querin (1984), who find trends to be more likely than reversals. It is inappropriate to infer, from this analysis, conclusions about serial correlation of prices or price changes such as those made by Hudson et al. (1987). 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.

Bibliography

Aspray, T. E. (1989): "Using Volume and Open Interest to Confirm Price Trend Directions," *Futures Magazine,* 18:38–40.

Belveal, L. D. (1985): *Charting Commodity Market Price Behavior* (2 ed.). Homewood, IL: Dow Jones–Irwin.

Cornell, B. (1981): "The Relationship between Volume and Price Variability in Futures Markets," *The Journal of Futures Markets,* 3:303–316.

Davis, J. C. (1973): *Statistic and Data Analysis in Geology.* New York: John Wiley & Sons.

Fama, E. F. (1970): "Efficient Capital Markets: A Review of Theory and Empirical Work," *Journal of Business,* 25:383–417.

Garcia, P., Hudson, M. A., and Waller, M. L. (1988): "The Pricing Efficiency of Agricultural Futures Markets: An Analysis of Previous Research Results," *Southern Journal of Agricultural Economics,* 20(1):119–130.

Gardner, B. (1982): "Commentary," *Review of Research in Futures Markets,* 1:105–108.

Henriksson, R. D., and Merton, R. C. (1981): "On Market Timing and Investment Performance. II. Statistical Procedures for Evaluating Forecasting Skills," *Journal of Business,* 54(4):513–533.

Hudson, M. A., Leuthold, R. M., and Sarassoro, G. F. (1987): "Commodity Futures Price Changes: Recent Evidence for Wheat, Soybeans and Live Cattle," *The Journal of Futures Markets,* 7:287–301.

Ibbotson Associates (1989): *Stocks, Bonds, Bills, and Inflation: 1989 Yearbook.* Chicago: Capital Market Research Center.

Jensen, M. L. (1968): "The Performance of Mutual Funds in the Period 1945–64," *Journal of Finance,* 23:389–416.

Jiler, W. L. (1962): *How Charts Can Help You in the Stock Market.* New York: Trendlines Division of Standard and Poor's Corp.

Jiler, W. L. (1965): "'Volume and Open Interest' Analysis as an Aid to Price Forecasting." In *Guide to Commodity Price Forecasting,* Jiler, H., and Parker, G. B. (eds.). New York: Commodity Research Bureau, pp. 61–72.

Jiler, W. L. (1975): *Volume and Open Interest: A Key to Commodity Price Forecasting.* New York: Commodity Research Bureau.

Lukac, L. P., Brorsen, B.W., and Irwin, S. H. (1988): "A Test of Futures Market Disequilibrium Using Twelve Different Technical Trading Systems," *Applied Economics,* 20:623–639.

Mandlebrot, B. (1963): "The Variation of Certain Speculative Prices," *Journal of Business,* 36:394–419.

Mandelbrot, B. (1966): "Forecasts of Futures Prices, Unbiased Markets, and Martingale Models," *Journal of Business,* 39:242–255.

McKallip, C. Jr. (1986): "Investigating Chart Patterns Using Markov Analysis," *Technical Analysis of Stocks and Commodities,* 12:25–28.

Murphy, J. J. (1986): *Technical Analysis of the Futures Markets.* New York: Institute of Finance.

Ott, L. (1984): *An Introduction to Statistical Methods and Data Analysis.* Boston, MA: Prindle, Weber and Schmidt Publishers.

Pariseau, R. R. (1980): "Stock Markets: A New Approach to Investment Timing for the Average Investor," Washington DC: George Washington University.

Samuelson, P. A. (1965): "Proof That Properly Anticipated Prices Fluctuate Randomly," *Industrial Management Review,* 6:41–49.

Seila, A. (1987): "Working Papers," University of Georgia, Department of Management Science, Athens, GA.

Stewart, T. H. (1986): *How Charts Can Make Your Money: Technical Analysis for Investors.* New York: Nichols Publishing.

Taylor, S. J. (1985): "The Behavior of Futures Prices Over Time." *Applied Economics,* 17:713–734.

Tomek, W. G., and Querin, S. F. (1984): "Random Processes in Prices and Technical Analysis," *Journal of Futures,* 4(1):15–23.