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The Interrelation of Stock and Options Market Trading-Volume Data

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ABSTRACT

This research empirically investigates the relation between common stock and call option trading volumes. The paper hyothesizes and tests a sequential flow of information between the stock and option markets. If information trading for CBOE-listed firms is predominantly accomplished through option trading, then existing research methodologies may be biased against finding any significant economic consequences in those instances where option listing is an important variable. Results indicate that trading in call options leads trading in the underlying shares, with a one-day lag.

BLACK [2] SUGGESTS THAT INFORMATION traders may prefer trading in options rather than shares due to economic incentives provided by reduced transaction costs, capital requirements, and trading restrictions and due to the greater action afforded by option trading. Manaster and Rendleman [12] empirically support Black's [2] option-information trading preference, finding incremental information content in option prices up to twenty-four hours prior to its reflection in stock prices. Jennings and Starks [10] report that the stock price-adjustment process upon arrival of new information differs for those firms listed on the Chicago Board Option Exchange (CBOE), and they demonstrate that stock price adjustment to new information occurs more rapidly for firms with listed call options. The results in both papers appear to warrant consideration of an option-trading variable in the design of empirical tests. Both Manaster and Rendleman [12] and Jennings and Starks [10] investigate the price relation between shares and call options; this paper investigates trading volume.

Copeland [4] posits the use of trading volume as a proxy for the rate of information arrival. He concludes that the relation between absolute value of price changes and volume is positive and linear if one accepts a sequential-information-arrival hypothesis as valid. The present research hypothesizes and tests a sequential flow of information between the stock and option markets. Analyses presented are based on econometric tests for causality[1] derived from the works of Granger [6] and Sims [22]. If information trading takes place

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[1] The use of the term causality does not correspond well with traditional views of causation found in the philosophy and economics literatures. An alternative term such as "predictive ability" may be more appropriate. However, causality is retained here to maintain comparability to the referenced literature.

predominantly in options, one would expect to observe a lead-lag relation for the option/shares trading volumes. Conversely, in a world of symmetric-information arrival, one would expect to observe either instantaneous causality or feedback between the option and shares markets.

Section I reviews related literature on market information structures and the econometric literature on causality testing. Section II discusses selection of sample data. Sections III and IV summarize results of two alternative forms of causality tests employed to investigate relations between the transaction-volume series. The final section compares results obtained under the alternative methodologies and summarizes the research findings. The Appendix provides additional detail on the derivation of the empirical models employed.

I. Market Information Structure and Causality Testing

Copeland [4] and Jennings, Starks, and Fellingham [11] provide models of asset trading under conditions of informational asymmetry, viewing information arrival and dissemination in financial markets as a sequential process. In the simplest case, a trader receives new information while the market is in equilibrium. A temporary equilibrium is formed until information reaches the next investor, and so forth, until ultimately all investors have received the new data and the market attains a final equilibrium (at least until new information is generated). In this scenario, volume changes occur because some investors have access to information not generally available.

Others look at information in the context of the asymmetry presented by insider knowledge prior to public dissemination of financial reports. Morse [13, 14] develops an economic model that allows for asymmetric information, and he provides empirical approaches to investigate asymmetries through stock price and volume behavior.

The present paper assumes that individuals are motivated to prefer option-information trading. One should expect to observe an informational asymmetry between the option and share markets. Following a Jennings et al. [11] sequential-information flow model, option-volume increases should precede volume increases in the shares market, surrounding information releases. In this sense, option trading leads trading in common shares.

Tests performed are derived from econometric procedures developed by Granger [6] and Sims [22]. While most texts[2] caution that correlation cannot be interpreted as causation, Granger and Sims argue that causal interpretation is possible in many instances, given additional assumptions concerning the process under analysis.

The causal structure of Granger and Sims can be presented in terms of this paper's volume variables as follows. Let $P(X \mid Y)$ represent the conditional distribution of a random variable X, representing option trading volume, given a second random variable Y, representing stock volume. Further, let I_t represent

[2] See, for example, Neter and Wasserman [15], p. 27.

the universe of available information in period t. The causal test seeks to ascertain whether the series Y_t causes the series X_t.[3] Alternatively, one could test

$$P(X_{t+1} \mid I_t) = P(X_{t+1} \mid I_t - Y_t) \tag{1}$$

where $I_t - Y_t$ represents the universe of prior information at period t, excluding information about past stock volume. If the equality in (1) does not hold, then Y_t is said to cause X_t.

The causal test is essentially a test of the predictive ability of time-series models; i.e., if information about the series Y_t permits improved prediction of the series X_t, then Y_t causes X_t. An assumption of normality may not represent the true underlying distribution (Morse [13]). Inability properly to specify underlying conditional distributions is overcome using tests based on summary statistics the distribution of which can be more easily ascertained or for which the normality assumption is more appropriate. Granger [6] and Granger and Newbold [7] propose constructing tests of predictions of the conditional means of distributions. Causality tests are operationalized in a number of ways. Two different approaches are implemented here,[4] and the results are subsequently compared.

II. Sample Selection

A sample of twenty-five firms[5] is included in the study. The research investigates comparative behavior of listed call options and their underlying common shares

[3] The model further assumes that both X and Y are generated by stochastic processes. If X_t is a deterministic series, it makes no sense to state that Y_t causes X_t when it is known that X_t is caused by past X_t. This restriction is of little consequence in the present analyses as prior research, e.g., Morse [13] and Rogalski [19], indicates that transaction-volume series are not well modeled by simple deterministic processes. Instantaneous causality, defined by $P(X_t \mid I_t) = P(X_t \mid I_t - Y_t)$, is not testable using the methodology. Under assumptions of the model, observation of instantaneous causality is attributed to limitations in available data. For example, instantaneous causality in quarterly data is assumed to disappear if more frequent weekly or daily data are utilized.

[4] Tests were initially performed using the methodology described by Haugh [9] and employed by Rogalski [19] in an investigation of monthly price/volume dependencies in stock and warrant markets. Under this approach, univariate models are first fitted to individual volume series, and causality tests are accomplished through analyses of cross-correlation functions of the two residual series obtained from the univariate models. Although these results indicate dependence between stock- and option-volume series and are consistent with results obtained using the Granger-Newbold and multivariate methodologies, they do not clearly distinguish among competing causal interpretations. These results are, therefore, excluded from the presentation.

[5] Sample firms are randomly chosen after an additional restriction that option trading occurred on at least ninety percent of the test dates. The twenty-five sample firms represent approximately twenty percent of firms listed for CBOE trading. To the extent that these firms are viewed as not representative of the total CBOE population, test results should be interpreted as population, rather than sample, statistics. Verrecchia [23] notes that the relation between information and stock volume is unclear, due to noninformation-trading motivations. This problem may also exist in the options market, especially surrounding option maturity dates. Most traders reverse positions through offsetting trades immediately prior to expiration rather than exercising the options. (See Phillips and Smith [18].) Transactions occurring at option expiration dates have been eliminated to reduce this noninformation effect.

Table I

Summary of Time-Series Models Fitted to Stock and Option Volumes

		Stock Volume		Option Volume	
Firm	TKR	p, d, q[a]	Adjusted R^2	p, d, q[a]	Adjusted R^2
Atlantic Richfield	ARC	1, 0, 0	0.19	2, 0, 0	0.28
Bankamerica	BAC	1, 0, 0	0.18	1, 0, 0	0.30
Brunswick	BC	1, 0, 0	0.22	1, 0, 0	0.03
CBS, Inc.	CBS	1, 0, 0	0.12	1, 0, 0	0.02
Control Data	CDA	1, 0, 0	0.17	1, 0, 0	0.47
Delta Air Lines	DAL	1, 0, 0	0.10	1, 0, 0	0.16
Dow Chemical	DOW	1, 0, 0	0.26	1, 0, 0	0.12
Eastman Kodak	EK	1, 0, 0	0.14	1, 0, 0	0.37
Ford Motor Company	F	1, 0, 0	0.05	1, 0, 0	0.21
Federal Express	FDX	1, 1, 0	0.24	1, 0, 0	0.35
General Dynamics	GD	1, 0, 0	0.18	1, 0, 1	0.41
General Electric	GE	1, 0, 0	0.11	1, 0, 1	0.23
General Motors	GM	1, 0, 0	0.23	1, 0, 1	0.40
Honeywell	HON	1, 0, 0	0.10	1, 0, 0	0.33
Hewlett Packard	HWP	1, 0, 0	0.15	1, 0, 0	0.63
Litton Industries	LIT	1, 0, 0	0.13	1, 0, 0	0.09
NCR Corporation	NCR	1, 0, 0	0.35	1, 0, 1	0.27
Polaroid	PRD	1, 0, 0	0.10	1, 0, 0	0.28
RCA Corporation	RCA	2, 0, 0	0.11	1, 0, 0	0.22
R. J. Reynolds Industries	RJR	1, 0, 0	0.10	1, 0, 0	0.16
American Telephone and Telegraph	T	1, 0, 0	0.14	1, 0, 0	0.36
Texas Instruments	TXN	1, 0, 0	0.24	1, 0, 0	0.35
Warner Communications	WCI	1, 0, 0	0.38	1, 0, 1	0.24
Exxon	XON	2, 0, 2	0.50	1, 0, 0	0.23
Xerox	XRX	1, 0, 0	0.27	1, 0, 0	0.49

[a] p, d, q represent the autoregressive, degree-of-differencing, and moving-average parameters from the ARIMA (p, d, q) processes for the stock- and option-volume series.

for the period from January 1, 1982 through June 30, 1983.[6] Selection cri require that sample firms be listed for call option trading on the CBOE fo: entire period covered by the study. Additionally, sample firms must be listed on either the New York Stock Exchange (NYSE) or the American Stock Exchange (AMEX). A listing of the sample firms is provided in Table I.

Data collected include daily-volume information on the common shares. Volume data are also collected for all listed call options of sample firms that are

[6] Necessary data are obtained from Compuserv, Inc. Inclusion of eighteen months of daily trading data is sufficient to meet minimum observations required for Box and Jenkins' [3] time-series analyses (usually a minimum of sixty observations) and permits generalizations to longer term market behavior. Imposition of exchange-listing criteria and selection of actively traded firms reduce problems related to nonsynchronous trading as reported by Scholes and Williams [21]. Price data were collected to identify near-the-money options. Options included for further analyses are limited due to findings reported in Patell and Wolfson [16] and Whaley and Cheung [24]. Only those two option series with exercise prices that bracket the closing stock price are retained. This reduction eliminates unnecessary noise from the data since most option trading involves only the two bracketing series.

actively traded during the sampling period. The same sample is used for all of the tests described in Sections III and IV, and the results are subsequently compared in Section V.

The analyses in this paper are designed to detect firm-specific information flows. Therefore, raw volume data were first transformed to eliminate market effects by applying market-model volume regressions. Residual volume measures were derived as follows:

$$RV_{it} = a_i + b_i RV_{mt} + e_{it}, \tag{2}$$

where

RV_{it} = raw volume of security i trading in period t,
RV_{mt} = raw market volume of the NYSE (CBOE for the call options) in period t, and
e_{it} = volume residual for security i in period t.

The e_{it} give the residual option and stock volumes, X_t and Y_t, respectively, used in the remainder of the paper.

III. Granger-Newbold Tests

The first method employed is derived from Granger [6] and Granger and Newbold [7] and attempts to identify bivariate series directly through analyses of cross-correlograms or cross-covariances. However, as noted by Granger and Newbold [7], cross-correlations are generally large, even for two independent random-walk series, thereby causing possible problems of spurious correlations. Further, cross-correlograms are difficult, if not impossible, to interpret.

One method of avoiding spurious correlations, suggested in Granger [6], involves initial identification of the two univariate series. These are then combined into multiple-series models for implementation of causality tests.

A. Series Identifications and Estimations

Results of identification and estimation procedures are summarized in Table I for both the stock and option series.[7] Inspection of Table I indicates that most series are well fitted by simple first or second-order autoregressive models (ARIMA(1, 0, 0) or ARIMA(2, 0, 0)). Table I indicates that model fit appears good in all cases. Adjusted values of R^2 indicate the variation explained by the time-series models. Comparison of parameter estimates with standard errors (t-tests) indicates a high level of significance.

The models derived for the volume series are comparable to volume models obtained by Rogalski [19] in an investigation of monthly stock and warrant data.

[7] Time-series identifications are accomplished using procedures suggested in Grey, Kelley, and McIntire [8] (GKM hereafter). The GKM approach identifies series through mathematical analyses of the autocorrelation functions, relying less on the visual-inspection techniques of traditional Box and Jenkins [3] analysis. Once series are identified, parameter estimations are made following Box and Jenkins. Table I provides only summary data on the time-series regressions. A complete table of the coefficient estimates and t-statistics is available upon request.

The models generally conform to a simple, first-order, autoregressive scheme. Parameter estimates indicate a positive relation between adjacent daily volumes for both stocks and options, consistent with Rogalski's findings. Daily trading volume in both securities is positively correlated with the succeeding day's activity.

Table I also indicates considerable variability across firms, for both stocks and options, in the variation explained by the models (the adjusted R^2). This result is also similar to Rogalski's findings and justifies the firm-by-firm approach (versus a portfolio approach) adopted for the causality tests.

Only one stock-volume series (FDX) shows evidence of nonstationarity in levels of the volume variables, and nonstationarity is eliminated using a first-differences model.[8] All remaining models are either first or second-order ARIMA models. These prewhitened series provide data for the causality tests.

B. Implementation of the Causality Tests

This section presents pairwise causality tests for option and stock volumes. For each comparison, the simple causal model is represented by

$$X_t' = \textstyle\sum_{j=1}^{m} a_j X_{t-j}' + \sum_{j=1}^{m} b_j Y_{t-j}' + e_t \tag{3}$$

and

$$Y_t' = \textstyle\sum_{j=1}^{m} c_j X_{t-j}' + \sum_{j=1}^{m} d_j Y_{t-j}' + n_t. \tag{4}$$

X_t' and Y_t' are prewhitened stationary time series for option and stock residual volumes, respectively, having zero means, while e_t and n_t are uncorrelated white-noise series. The causality test is a standard t-test on regression parameters. Y_t' causes X_t' when some value of b_j is not equal to zero. If some value of c_j is not equal to zero, then X_t' causes Y_t'. If neither of these events occurs, then there is no causal relation between the two series. If b_0 and/or c_0 are not equal to zero, then instantaneous causality is being observed, and tests for causality require finer temporal partitioning of the data. Multiple-series regressions suggested by (3) and (4) are used to effect the causality tests.

Results of multiple-series tests are summarized in Tables II and III. Table II provides t-statistics for b_j from equation (3), with $m = 6$ (i.e., a six-day lag). Table III provides similar results for c_j from equation (4). Standard t-tests are used to test the hypotheses of b_j, $c_j = 0$.[9] Observation of a t-statistic greater than approximately 2.00 indicates rejection of the hypothesis (at a five percent significance level) and indicates a causal relation.

As indicated in Table II, at least one $b_j \neq 0$ for nine of twenty-five firms, suggesting that stock volume leads option volume. Alternatively, addition of past stock-volume information significantly affects option-volume predictions.

[8] The GKM methodology includes procedures for the identification of nonstationarities.

[9] X' and Y' are prewhitened residual amounts from the initial time-series identifications and estimations. The lagged dependent variables are retained in equations (3) and (4) to provide a more conservative test on the effectiveness of the prewhitening techniques. The results indicate that prewhitening was adequate. The t-statistics for a_j and d_j are not significant (at a five percent level), as expected. Therefore, values for a_j and d_j are omitted from Tables II and III for clarity.

Table II

t-Statistics for b_j in the Multiple-Series Granger Tests

Model:[a] $X_t' = \sum_{j=1}^{6} a_j X_{t-j}' + \sum_{j=1}^{6} b_j Y_{t-j}' + e_t$

	Coefficients						F-Tests[b]	
TKR	b_1	b_2	b_3	b_4	b_5	b_6	$F1$	$F2$
ARC	−0.70	−0.68	0.22	−0.02	−0.11	1.16	45.38[c]	27.77[c]
BAC	1.40	−0.04	0.53	−0.27	−0.64	0.59	48.69[c]	25.52[c]
BC	−0.78	−0.58	−0.98	−2.85[d]	−1.03	2.24[d,e]	4.08[f]	1.77
CBS	−0.42	0.39	0.37	−0.32	0.91	−1.14	88.60[c]	14.66[f]
CDA	0.46	−0.69	−1.75	0.06	0.78	−0.31	90.71[c]	19.88[c]
DAL	1.46	−1.45	−0.65	0.39	1.10	−0.08	25.21[c]	10.84[f]
DOW	1.26	−0.48	0.34	−1.25	−0.45	−0.93	23.77[c]	32.47[c]
EK	0.52	−0.79	0.25	−0.13	1.16	−1.35	75.05[c]	43.20[c]
F	−0.27	0.08	−1.20	−0.24	0.31	0.85	39.00[c]	24.38[c]
FDX	0.09	0.46	−1.18	−0.39	2.14[d,e]	−0.79	41.05[c]	24.26[c]
GD	0.64	0.89	−0.15	0.33	2.04[d,e]	0.57	74.64[c]	29.03[c]
GE	1.38	−0.83	−0.53	0.57	0.17	−1.79	44.53[c]	38.46[c]
GM	−0.61	−2.92[d]	0.88	0.24	−0.77	1.59	96.51[c]	18.08[c]
HON	−0.56	1.60	−1.49	1.11	−0.13	−1.69	46.48[c]	27.19[c]
HWP	1.24	−0.14	−2.27[d]	−1.50	−0.49	1.29	214.93[c]	14.98[f]
LIT	−0.54	−0.50	−0.51	−0.38	−0.21	−0.77	20.98[c]	14.83[f]
NCR	1.65[e]	−2.42[d]	−0.66	−0.74	−0.58	1.35	63.37[c]	29.75[c]
PRD	−0.67	−0.11	0.92	0.01	−0.79	1.10	68.22[c]	49.14[c]
RCA	1.15	−1.13	0.02	1.31	−0.63	−0.29	46.05[c]	16.31[c]
RJR	1.14	−0.15	−1.24	1.64	2.37[d,e]	−1.46	21.26[c]	21.37[c]
T	−0.52	1.73[e]	−0.10	−0.81	−0.46	−0.12	23.82[c]	19.49[c]
TXN	0.27	−0.24	−0.66	0.09	0.44	−1.67	64.87[c]	16.06[c]
WCI	0.60	0.51	−0.51	3.41[d,e]	−1.22	−0.91	64.03[c]	26.77[c]
XON	−0.08	−0.52	−0.26	−0.12	−1.70	1.06	34.74[c]	6.27[f]
XRX	2.27[d,e]	−1.19	1.35	−0.54	0.30	−0.73	121.35[c]	43.17[c]

[a] X_t' and Y_t' represent the prewhitened series for option and stock trading volumes, respectively, having zero means, while e_t is the uncorrelated white-noise series.

[b] $F1$ is a test to ascertain whether the coefficients b_1 to b_6 contribute significantly to the error sum of squares. $F2$ is a similar test for the restricted set b_2 to b_6.

[c] F-test indicates a significant contribution at the 0.001 level.

[d] Indicates that $b_j \neq 0$, at a five percent significance level (two-tailed test).

[e] Indicates that $b_j > 0$, at a five percent significance level (one-tailed test).

[f] F-test indicates a significant contribution at the 0.05 level.

In Table III, there are eighteen firms for which at least one $c_j \neq 0$, indicating that option volume is a causal variable for stock volume. Combining Tables II and III reveals that, for five firms, both some b_j and some c_j are not equal to zero, indicating feedback between the volume series for these firms. After consideration of both Tables II and III, option volume causes stock volume for thirteen firms, stock volume causes option volume for four firms, there is evidence of feedback for five firms, and no causal interpretation is possible for the remaining three sample firms.

Additional insight is provided by more careful inspection of the results. Underlying theories of sequential-information arrival and an option-information trading preference suggest an expectation of a significantly higher option volume. Hence, a one-tailed test may be more appropriate. Further, prior research

Table III

t-Statistics for c_j in the Multiple Series Granger Tests

Model:[a] $Y'_t = \sum_{j=1}^{6} c_j X'_{t-j} + \sum_{j=1}^{6} d_j Y'_{t-j} + n_t$

	Coefficients						F-Tests[b]	
TKR	c_1	c_2	c_3	c_4	c_5	c_6	$F1$	$F2$
ARC	1.63	0.02	−0.72	−1.04	1.24	−2.01	199.99[c]	99.98[c]
BAC	1.81[d]	0.67	−2.54[e]	0.32	0.20	2.26[d,e]	125.39[c]	123.19[c]
BC	1.88[d]	−2.44[e]	−2.16[e]	1.92[d]	0.57	−2.40[e]	77.69[c]	4.60[f]
CBS	−0.17	0.31	−1.14	1.04	0.04	3.08[d,e]	174.03[c]	59.55[c]
CDA	−0.12	−0.73	−0.63	2.18[d,e]	−0.23	1.45	99.69[c]	59.37[c]
DAL	−0.17	−1.76	2.01[d,e]	2.17[d,e]	−0.58	−0.25	127.41[c]	98.11[c]
DOW	1.74[d]	0.66	−0.72	0.33	0.69	−3.26[e]	277.95[c]	75.25[c]
EK	2.24[d,e]	−0.14	0.76	−0.36	−0.07	−0.02	95.29[c]	95.38[c]
F	2.73[d,e]	−2.27[e]	1.30	−0.32	1.06	−0.47	214.74[c]	104.02[c]
FDX	2.41[d,e]	−2.38[e]	1.19	−0.47	1.33	−0.85	401.81[c]	39.12[c]
GD	2.30[d,e]	0.39	0.05	1.15	0.30	−1.02	293.11[c]	131.32[c]
GE	1.92[d]	0.41	0.02	−2.86[e]	1.03	0.22	90.79[c]	19.13[c]
GM	−0.01	0.61	0.16	−0.50	0.92	−1.35	173.12[c]	86.16[c]
HON	1.27	−0.73	0.43	0.60	−0.18	−0.32	112.19[c]	49.54[c]
HWP	2.33[d,e]	0.01	−0.94	−0.28	0.48	0.27	79.10[c]	16.99[c]
LIT	2.58[d,e]	−0.17	0.67	0.03	3.30[d,e]	−1.86	68.31[c]	52.11[c]
NCR	0.33	0.88	0.34	0.39	−1.21	−1.12	179.09[c]	90.84[c]
PRD	0.43	0.35	−1.34	0.21	−0.59	−0.20	115.34[c]	91.14[c]
RCA	3.14[d,e]	−1.69	0.94	0.82	−0.74	0.76	114.11[c]	99.42[c]
RJR	1.87[d]	−1.63	−2.01[e]	−0.90	−0.21	−0.32	299.10[c]	141.51[c]
T	2.03[d,e]	0.95	0.63	−0.06	−0.12	0.72	166.18[c]	106.59[c]
TXN	−0.51	1.56	−2.80[e]	0.87	2.80[d,e]	−3.41[e]	132.68[c]	112.88[c]
WCI	−0.35	0.63	1.58	−0.89	0.57	−0.37	124.33[c]	80.69[c]
XON	0.25	−1.97[e]	2.38[d,e]	0.67	0.51	0.15	135.61[c]	13.79[f]
XRX	1.15	−1.58	−0.00	0.68	0.63	0.19	125.66[c]	60.75[c]

[a] X'_t and Y'_t represent the prewhitened series for option and stock trading volumes, respectively, having zero means, while n_t is the uncorrelated white-noise series.

[b] $F1$ is a test to ascertain whether the coefficients c_1 to c_6 contribute significantly to the error sum of squares. $F2$ is a similar test for the restricted set c_2 to c_6.

[c] F-test indicates a significant contribution at the 0.001 level.

[d] Indicates that $c_j > 0$, at a five percent significance level (one-tailed test).

[e] Indicates that $c_j \neq 0$, at a five percent significance level (two-tailed test).

[f] F-test indicates a significant contribution at the 0.05 level.

indicates that information travels very quickly in both stock and option markets.[10] If inspection of Tables II and III is concentrated on the one-day lagged results (columns b_1 and c_1 in Tables II and III), then additional conclusions are warranted. Based on the one-tailed test results, option trading leads share trading with a one-day lag in thirteen of the twenty-five cases presented (fifty-two percent), while stock trading leads in only two cases. These results are less mixed than results for lags two through six. Although significant observations occur at

[10] See, for example, Jennings and Starks [10], Manaster and Rendleman [12], Morse [14], and Patell and Wolfson [17].

lags two through six, on a cumulative basis, they do not appear particularly significant. Only twenty-nine of these coefficients (5.8 percent) are individually significant. These may represent random occurrences. This is clearly not the case for the one-day-lagged results. Further, the lag-one results suggest that even clearer evidence might be observed using intradaily data.

The last two columns of Tables II and III provide additional insight into the importance of the one-day-lagged results. $F1$ and $F2$ represent F ratios designed to test whether all coefficients significantly contribute to the error sum of squares. $F1$ tests all six coefficients b_1 through b_6 in Table II (c_1 through c_6 in Table III). $F2$ provides the same test for the restricted set b_2 through b_6 (c_2 through c_6). Observed F-ratios are highly significant. However, the importance of the one-day lag is clear in that $F2$ values are generally smaller than those observed for $F1$.

Additional explanation is also required for interpretation of the five feedback observations. Prewhitening implies that the series X_t' and Y_t' are each serially i.i.d. Specification of the test appears to rule out the existence of feedback. Feedback is, in fact, an observation of instantaneous causality. As Granger [6] notes, "··· a simple causal mechanism can appear to be a feedback mechanism if the sampling period for the data is so long that details of causality cannot be picked out" (p. 427).

IV. Multivariate Causality Tests

More recent work suggests that a multivariate approach to causal models provides more powerful hypothesis tests. This approach improves on the previously described methodology by modeling bivariate series directly, eliminating potential problems due to omitted variables and errors in the variables, and providing more precise parameter estimates. Empirical tests are performed using the seemingly unrelated regressions technique (SUR) presented in Zellner [25]. Causality is tested using a likelihood-ratio test (LRT) of the theoretically implied parameter restrictions. The section presents results of the multivariate causality tests. Detailed derivations of the multivariate tests are presented in the Appendix.

Tests for causality are effected using the following regression-system model:

$$
\begin{aligned}
X_t &= dZ_{t-1} + v_t, \\
a_t &= B(X_t - d^*Z_{t-1}) + e_t,
\end{aligned}
\tag{5}
$$

where

X_t represents residual option volume for period t,

Z_{t-1} is the set of past information about option and stock volumes available at the end of period $t-1$, including both X_t and Y_t,

a_t is the forecast error in predictions of X_t based on the restricted information set containing only past information about the options volume (X_t), and

v_t and e_t are disturbance terms assumed to have the property $\mathrm{E}(v_t \mid I_{t-1}) = 0$, $\mathrm{E}(e_t \mid I_{t-1}) = 0$.

If Y_t (which is included in Z_t) causes X_t, then $d = d^*$. The test of the cross-equation constraint implied by the causal model (i.e., $d = d^*$) is performed using the LRT. The system represented by (5) is solved using nonlinear least squares and Zellner's [25] SUR. Parameters are estimated first for the unrestricted system and then for the restricted system on a firm-by-firm basis. SUR provides estimates of covariance matrices for the restricted and unrestricted systems. As shown in the Appendix, the LRT is of the form:

$$-2 \ln L = N(\ln |S_a| - \ln |S_b|), \tag{6}$$

where $|S_a|$ and $|S_b|$ are determinants of variance-covariance matrices of residuals from the restricted and unrestricted systems, respectively.

The above procedures test the hypothesis that option volume causes stock volume (LRT(1) in Table IV). Procedures are repeated (reversing roles of X_t and

Table IV

LRT for the Multivariate Tests of Causality[a]

TKR	LRT(1)	LRT(2)
ARC	153.1[b]	45.2
BAC	161.8[b]	87.3
BC	175.4[b]	173.7[c,d]
CBS	152.8[b]	123.6
CDA	166.5[b]	61.1
DAL	148.2[b]	63.3
DOW	188.6[b]	119.1
EK	171.2[b]	38.5
F	180.8[b]	105.1
FDX	190.8[b]	175.7[c,d]
GD	178.0[b]	170.2[c,d]
GE	155.9[b]	66.4
GM	161.8[b]	160.3[c,d]
HON	68.6	73.7
HWP	179.3[b]	195.2[c,d]
LIT	159.5[b]	49.0
NCR	120.5	191.4[c]
PRD	159.4[b]	72.0
RCA	142.6	41.3
RJR	160.5[b]	145.1[c,d]
T	144.3[b]	115.4
TXN	186.1[b]	119.2
WCI	58.3	159.9[c]
XON	161.1[b]	90.8
XRX	104.4	158.9[c]

[a] LRT(1) and LRT(2) are the LRTs for the tests of X_t causes Y_t and Y_t causes X_t, respectively. Chi-squared at a five percent significance level is approximately 143.8

[b] Indicates that option volume causes stock volume.

[c] Indicates that stock volume causes option volume.

[d] Indicates feedback.

Y_t) to test whether stock volume causes option volume (LRT(2) in Table IV). Finally, results of unidirectional causality test are compared. If stock volume causes option volume and option volume also causes stock volume, then feedback is occurring.

Results of LRTs are summarized in Table IV. Inspection of Table IV reveals that stock volume causes option volume in three cases, option volume causes stock volume in fourteen cases, feedback is observed for six firms, and no causal inferences can be made for the remaining two firms. As in the previous tests, feedback is viewed as instantaneous causality. The following section compares these results with univariate results reported in Section III.

V. Summary and Conclusions

A. *Comparative-Results Summary*

This section compares results obtained from the two alternative causality-test procedures. "Test I" describes results obtained using the univariate multiple-series tests presented in Section III, and the multivariate tests described in Section IV are referred to as "Test II". Test I and Test II results are comparable, providing similar causal interpretations in eighty percent of the cases. Table V provides comparative summary results from the two approaches.

There are sixteen cases where either Test I, Test II, or both indicate that option volume cause stock volume, four cases where stock volume causes option volume, seven cases indicating feedback, and one case (HON) where neither test provides a causal interpretation. Most disagreement between the two tests relates to identification of feedback occurrences. There are two cases (BC and GM) where Test I observes unidirectional causality while Test II indicates feedback. In case BAC, Test II indicates causality and Test I indicates feedback. Test II provides no evidence of a causal relation for RCA, while Test I indicates that option volume causes stock volume. The opposite situation occurs for PRD.

If summarization is limited to instances where Test I and Test II results concur, then option volume causes stock volume in twelve cases (forty-eight percent), stock volume causes option volume in three cases (twelve percent), feedback is observed for four firms (sixteen percent), and no causal interpretation is possible for one firm (four percent). Results fail to concur for the remaining five firms (twenty percent) (BAC, BC, GM,PRD, and RCA).

The close correspondence of Test I and Test II results to the one-tailed results for one-day-lagged periods (in Tables II and III) is also notable. This indicates that results are driven by the one-day-lagged results. This might be expected as a priori knowledge suggests that both stock and option prices adjust quickly to new information.

B. *Conclusions and Research Extensions*

Results are clearly supportive of a dependence between the two series although the hypothesized leading role for option volume is less strongly supported. Option volume Granger-causes stock volume in a majority of cases considered (sixty-four percent), but this result is confirmed by both Test I and Test II for only

Table V

Comparison of Test Results[a]

TKR	Test I	Test II
ARC	A	A
BAC	C	A
BC	A	C
CBS	A	A
CDA	A	A
DAL	A	A
DOW	A	A
EK	A	A
F	A	A
FDX	C	C
GD	C	C
GE	A	A
GM	B	C
HON	D	D
HWP	C	C
LIT	A	A
NCR	B	B
PRD	D	A
RCA	A	D
RJR	C	C
T	A	A
TXN	A	A
WCI	B	B
XON	A	A
XRX	B	B

[a] A indicates that option volume causes stock volume (fifty-six percent occurrence rate in both Tests I and II). B indicates that stock volume causes option volume (sixteen percent occurrence rate in Test I and twelve percent in Test II). C indicates that feedback is occurring (twenty percent occurrence rate in Test I and twenty-four percent in Test II). D indicates that no dependence was detected between the two series (eight percent occurrence rate in both Tests I and II). Test I indicates the univariate tests, while Test II indicates the multivariate tests.

forty-eight percent of the firms. Concurrent results indicate unidirectional causality for sixty percent of the firms, but direction of the causal relation varies.

Test results must be carefully interpreted in light of the underlying information theories and the methodology employed. The results imply that option trading volume "leads" stock volume with a one-day lag. In this sense, results are consistent with Copeland's [4] sequential theory of information arrival, assuming that the use of trading volume as a proxy for the rate of information arrival is justified. Results are also consistent with Black's [2] hypothesized option-information trading preference. Observed volume relations are consistent with price-based findings offered by Manaster and Rendleman [12] and Jennings and Starks [10].

However, it should be noted that the observed phenomenon may be a technical one. Assume that all traders who so choose hold an equilibrium hedge position. The supply of a firm's stock is fixed, while the supply of options is not. If a new option is written, even for a random reason, then others may trade in the stock to return to their desired hedge positions. This could also account for the leading role observed for options.

Another technical restriction may account for the observations made here. CBOE trading closes ten minutes after the close of the NYSE. Daily data are employed here, and the leading role of options (especially the one-day-lagged results) could be attributed to options traded after the NYSE close.[11]

The results presented here cannot be interpreted as indicating any market inefficiency. A trader must be able to profitably exploit the information implied in the volume tests before such a claim could be advanced. This paper does not address the market-inefficiency issue. Tests of market efficiency would require the addition of market prices to the volume data employed here. The efficiency question would appear to present a useful area for future research.

Conclusions regarding appropriateness of the alternative methodologies employed are also warranted. Both methodologies provide satisfactory results in terms of ability to detect dependence between series and distinguish among alternative causal interpretations, and results are comparable in most instances. The multivariate approach is preferable for future applications as it overcomes problems of errors in variables and provides more precise parameter estimates.[12]

The results suggest several alternatives for future research. First, observations of feedback (instantaneous causality) indicate that additional insights might be obtained if intradaily transactions data were employed. Second, the causal relation may be better predicted by a subclassification of firms. For example, there may be an industry effect, or observed differences may be due to accounting or reporting characteristics of the firms. Sample-size limitations and results presented here do not permit such generalizations or conclusions. Subclassification variables should be considered in future research designs. The research might also be expanded to include both put and call option volume. An option trader who has information about "good" news may be motivated to trade in calls, whereas information about "bad" news might induce put option transactions.[13]

Finally, the hypothesized leading role for options may be more pronounced in periods surrounding important information events, e.g., earnings- or dividend-announcement dates. No attempt was made to test causal relations for these more limited periods in the present research, but future research could investigate this response.

[11] The author recognizes the contribution of these insights by the reviewer. Resolution of these alternatives can only be achieved using intradaily data. See, for example, Patell and Wolfson [17].

[12] See, for example, Abel and Mishkin [1] and Gibbons [5].

[13] See, for example, Patell and Wolfson [17].

Appendix: Derivation of the Multivariate Tests

The methodology described in Section III tests for causality by examining correlations between forecast errors and past information. Abel and Mishkin [1] and Sargent [20] demonstrate that such tests are equivalent to tests of theoretically implied restrictions in a linear system. The restrictions imply that the relation of forecast errors to past information is identical to the relation of realizations to past information. Abel and Mishkin [1] further demonstrate that the test of cross-equation restrictions holds regardless of what past information is used in the tests.

The Abel and Mishkin [1] framework can be directly adopted to provide a causality test as a test of implied cross-equation restrictions. Let I_{t-1} represent all information available at the end of period $t-1$, relevant for forecasting X_t. Then $E(X_t \mid I_{t-1})$ represents the expectation of X_t, conditional on I_{t-1} and $E(X_t \mid R_{t-1})$ represents the expectation conditional on the restricted information set R_{t-1}, restricted in the sense that it excludes information about Y_t.

A causal model implies that, if Y_t causes X_t, then Y_t is useful in predicting X_t. Availability of information about past observations of Y_t changes the conditional expectation of X_t, as compared with expectations made without knowledge of past Y_t. The causal relation can be formulated as

$$E(X_t \mid I_{t-1}) = E(X_t \mid R_{t-1}). \tag{A1}$$

(A1) implies that Y_t does not cause X_t. (A1) can be modified to test the causal hypothesis as

$$E(X_t - E(X_t \mid R_{t-1}) \mid I_{t-1}) = 0. \tag{A2}$$

Substituting

$$f(w_t) = E(X_t \mid R_{t-1}) \tag{A3}$$

into (A2), where w_t is some subset of I_t, results in

$$E(X_t - f(w_t) \mid I_{t-1}) = 0. \tag{A4}$$

If $a_t = X_t - f(w_t)$, then (A4) becomes

$$E(a_t \mid I_{t-1}) = 0. \tag{A5}$$

It is possible to test (A5) in a regression of the form:

$$a_t = bZ_{t-1} + u_t, \tag{A6}$$

where

Z_{t-1} is a vector of past information contained in I_{t-1},
b is a vector of coefficients, and
u_t is a disturbance where $E(u_t \mid I_{t-1}) = 0$.

(A5) can be alternatively modeled as

$$a_t = (X_t - X_t^e)B + e_t, \tag{A7}$$

where

e_t is a scalar disturbance term such that $E(e_t \mid I_{t-1}) = 0$,

X_t is a vector of past information about the security's trading volume relevant to predicting the volume at period t,
X_t^e is a vector of forecasts of X_t based on past information about X_t, and
B is a vector of coefficients.

Model (A7) is similar to the efficient-market model presented in Abel and Mishkin [1]. In (A7), a_t differs from zero only if information about past Y_t is useful in improving predictions of X_t. In other words, a_t differs from zero if and only if Y_t causes X_t. If Y_t causes X_t, then a linear model for X is of the form:

$$X_t = dZ_{t-1} + v_t, \tag{A8}$$

where d is a matrix of coefficients and v_t is a vector of disturbances. If it is assumed that $E(v_t \mid I_{t-1}) = 0$, then X_t^e provides an unbiased linear forecast of X when

$$X_t^e = dZ_{t-1}. \tag{A9}$$

If (A9) is substituted into (A7), one obtains

$$a_t = B(X_t - d^*Z_{t-1}) + e_t, \tag{A10}$$

where $d = d^*$.

(A8) and (A10) can be stacked into a single regression system and estimated using least squares. The causal model implies $d = d^*$. The implied cross-equations constraint of $d = d^*$ can be tested with a likelihood-ratio test (LRT). Abel and Mishkin [1] further demonstrate that the LRT provides a test of causality, even if other variables (other than past observations of X_t and Y_t) are relevant for forecasting X_t but have been omitted from Z_{t-1}.

The form of LRT needed can be shown to follow that presented in Gibbons [5]. The stacked regression represented by (A8) and (A10) can be solved applying Zellner's [25] SUR technique, where the Z_{t-1} are equal to right-hand-side variables. The LRT takes the form:

$$-2 \ln L = N(\ln |S_a| - \ln |S_b|), \tag{A11}$$

where $|S_a|$ and $|S_b|$ are determinants of variance-covariance matrices of residuals from the restricted and unrestricted systems, respectively. (The restriction is $d = d^*$.)

The asymptotic distribution of $-2 \ln L$ is approximately chi-squared with $N-1$ degrees of freedom. (A11) can be compared with the appropriate level of chi-square to effect the causality test.

Causality tests are accomplished by testing the system represented by (A8) and (A10) separately to test predictions of stock and options volumes, providing tests of unidirectional causality. Comparison of unidirectional-test results indicates feedback in cases where X_t causes Y_t and Y_t also causes X_t.

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