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The Cross-Sectional Relationship Between Trading Costs and Lead/Lag Effects in Stock & Option Markets

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Abstract

Prior empirical research has failed to settle the question of lead/lag effects between stock and option markets. This study investigates the relation between cross-sectional differences in trading costs and intraday lead/lag effects in stock and option markets. The data for the study comprise 19 firms sampled at five-minute intervals over a two-month period. Consistent with a trading cost hypothesis, results indicate overall stock market leading behavior. However, the lead appears to be related to option market trading costs. This study uses an error correction model framework to investigate the lead/lag effects. This approach provides information on both the long run equilibrating process as well as the short term interactions between stock and option markets. Information regarding the long run equilibrating process is important to the overall understanding of lead/lag effects and cannot be determined from time series models of differenced data. Specific criteria for assessing lead/lag effects in cointegrated series are also proposed. One advantage of these new criteria is their ability to identify leading behavior in the presence of feedback. All models are estimated with quote data and are constructed to eliminate overnight effects. Hence, the results are robust to previously identified distortions due to closing, overnight, and potential non-trading effects. However, caution should be employed in generalizing the results as the study covers a two-month trading period for a limited number of firms.

Keywords: parallel markets, market microstructure, options, cointegration, granger causality

JEL Classifications: C32/G13/G14

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1. Introduction

Fleming, Ostdiek, and Whaley (1996) propose a trading cost hypothesis to explain lead/lag effects in related markets. This hypothesis suggests that markets with lower trading costs have more rapid price discovery and hence exhibit leading effects. On the other hand, Amin and Lee (1994) and Easley, O'Hara, and Srinvas (1998) argue that the option market is primarily a market for informational trading. Their hypothesis implies option market leading behavior. Empirical research into lead/lag relations between stock indexes and index derivatives generally supports both hypotheses. In particular, index derivative products have lower trading costs and appear to reflect information more rapidly than the underlying index. However, evidence from the stock and option markets has been inconclusive. Several researchers find stock market leads. Others find option market leads, and at least one study suggests that lead/lag effects between stock and option markets are spurious. Hence, additional research into lead/lag effects in stock and option markets appears justified. This study investigates lead/lag behavior as it relates to cross-sectional differences in trading costs. Results are consistent with a trading cost hypothesis, as stock market trading appears to reflect information more rapidly. However, leading effects appear to be related to option market trading costs. This suggests that the trading cost hypothesis needs to be modified. It may not be average market level trading costs but rather firm level trading costs that drive lead/lag effects.

2. Literature review

Fleming, Ostdiek, and Whaley (1996) suggest that on average, trading costs are lower in the stock market than in the option market. If their trading cost hypothesis is correct, then stock market leading behavior should be evident. However, empirical evidence regarding lead/lag effects in stock and option markets has been decidedly mixed. For example, using closing stock and option market prices, Manaster and Rendleman (1982) find that option markets reflect information up to one day ahead of stock markets. Kumar and Shastri (1990) suggest that Manaster and Rendleman fail to properly control for dividend effects. Using a sub-sample of non-dividend paying stocks, they find no evidence of option market leading effects in closing data. Bhattacharya (1987) finds option market leading effects in overnight trading, but finds no such lead in intraday trading. However, as noted by Stephan and Whaley (1990), neither Bhattacharya (1987) nor Manaster and Rendleman (1982) test for the possibility that the stock market leads the option market.

To capture the potential for either stock or option market leading behavior, Stephan and Whaley (1990) utilize Sims (1972) style causality tests of observed and implied stock prices. They generate the implied stock values by inverting Roll's (1977) American call option pricing formula, which allows up to two discrete dividends per option. Given both an observed and implied stock series, they regress current observed (implied) stock price changes on lead, contemporaneous, and lagged implied (observed) stock price changes. Using intraday data sampled at five-minute intervals, they find up to a fifteen-minute stock market lead. Chan, Chung, and Johnson (1993) suggest that the Stephan and Whaley (1990) results are distorted by the structure of trading ticks in stock and option markets. They note that on a percentage basis, the minimum tick size for option trading is generally larger than that for stock trading. Hence, small stock price movements may not be reflected in option prices. Chan, Chung, and Johnson (1993) suggest that quote data do not suffer from this non-trading effect. Using a time series specification similar to Stephan and Whaley (1990), they confirm a stock market lead in trade data but find no leading effects in quote data. Based on these results, they conclude that the stock market lead in intraday data is spurious.

Finucane and Van Inwegen (1995) criticize all of the preceding intraday time series models for sampling the data at fixed time intervals. They note that trading frequencies vary throughout the day. Hence, any fixed sampling interval may be too short for heavy trading periods and/or too long for light trading periods. Using real time sampling of quote data that is sensitive to the frequency of trading, they find that the stock market leads the option market by a minimum of a few seconds to a maximum of six minutes. They also note feedback effects from the option market to the stock market.

One problem with the Sims (1972) style causality models used by Stephan and Whaley (1990), Chan, Chung, and Johnson (1993), and Finucane and van Inwegen (1995) is that parameterization of the regression model requires arbitrary selection of the dependent variable. Should stock market data be regressed on option market data, or vice versa? In practice, researchers typically model both possibilities. Nevertheless, regression results may be sensitive to the choice of dependent variable. One potential solution to this problem, especially if feedback effects are present, is the multivariate Vector Autoregression (VAR) model advocated by Sims (1980). The advantage to VAR modeling is that both the stock and option data series can be potentially endogenous. Hence, the VAR model captures feedback effects and avoids the problems associated with arbitrary selection of a single dependent variable. Using volume as a proxy for the rate of information arrival, Anthony (1988) employs a VAR model to test the timing and direction of information flows between the stock and option market. Based on daily data from 25 firms, he finds option volume leads stock volume in 13 cases, stock volume leads option volume in four cases, and feedback effects dominate the remaining eight cases. One problem with this approach is that volume may not be the best proxy for information, especially when price change data are also available. In addition, the Stephan and Whaley (1990), Chan, Chung, and Johnson (1993), and Finucane and van Inwegen (1995) results suggest that lead/lag dynamics may be very short-lived. Hence, daily volume may not fully capture all relevant information flows between stock and option markets.

A problem with the preceding tests is a failure to control for potential cointegration effects between stock and option market data. In particular, the previously mentioned univariate time series causality models are all estimated with differenced data. In cointegrated series, models based exclusively on differenced data may be misspecified, as the impact of the long run equilibrating process on current price changes is omitted. Properly specified, error correction models capture the effects of both the long run equilibrating dynamic as well as the short term price change interactions. Diltz and Kim (1996) implement an error correction model to investigate lead/lag relationships in daily stock and option market data. They find up to a two-day option market lead. As with Anthony (1988), the Diltz and Kim (1996) model omits the intraday informational flows between stock and option markets. Therefore, an intraday error correction model of lead/lag effects in stock and option markets seems particularly appropriate. Finally, none of the previous studies examine the relation between firm level trading costs and lead/lag effects. This study also begins to address this gap in the empirical literature.

3. Data

The primary data sources for this study are the Berkeley Option Data Base (BODB) and the TORQ Database. The BODB is constructed from the Chicago Board Option Exchange's (CBOE) Market Data Retrieval tapes and contains time stamped trades and quotes as recorded on the floor of the exchange.[1] The TORQ Database contains trades, quotes, order processing, and audit trail information for a sample of 144 NYSE listed stocks for the period November 1, 1990–January 31, 1991.[2] Of the 144 stocks in the TORQ database, 19 have CBOE listed options. At the time of the study, the January 1991 BODB was not available to the author. Also, the first trading day of the sample is lost as prior implied volatility information is required to transform the option data. Hence, the study comprises data from the 40 trading days between November 2, 1990–December 31, 1990, for each of the 19 firms listed on both the BODB and TORQ databases.

For each firm, the observed stock series, $\{S\}$, is constructed from bid/ask quote midpoints sampled at five-minute intervals, as recorded in the TORQ database. The last quote from each five-minute interval is used in the sample. If no quote is recorded in an interval, the quote midpoint from the previous interval is used. Each firm's option market series is constructed in a similar manner. However, the relation between stock and option values is non-linear.

Hence, to facilitate analysis, option values are transformed into implied stock values, $\{I\}$, by inverting a known option pricing formula. This study inverts a dividend adjusted binomial option pricing model to generate each implied stock value. Both Stephan and Whaley (1990) and Diltz and Kim (1996) generate implied stock prices by inverting Roll's (1977) compound option pricing formula. One drawback to the compound option pricing formula is that it does not correctly value

[1] See *The Berkeley Options Data Base User's Guide* (1995) for details.

[2] See Hasbrouck, J., *Using the TORQ Database* (1992) for details.

the early exercise provision in American style put options. The advantage to the binomial model is that it incorporates the value of the early exercise option in American style put options.

In addition to the option value, the time to maturity, and the strike price, inversion of the binomial option pricing model requires estimates for the risk free rate, expected dividends, and expected stock volatility. This study uses maturity matched Treasury bills, recorded from *The Wall Street Journal*, to generate the estimated risk free rates. Actual dividends proxy for expected dividends and are also from *The Wall Street Journal*. Expected stock volatility is not directly observable. This study uses the previous day's closing option quotes to generate implied volatilities. The observed option values are drawn from the near-term, at-the-money series. The near-term, at-the-money series trade most frequently, and hence, are expected to contain the most information. To avoid known volatility spikes and price distortions, observed option values are required to have at least one week to maturity. Following Chan, Chung, and Johnson (1993), observed option values are from bid/ask quote midpoints, which helps to eliminate potential non-trading effects in option data. To test whether lead/lag effects vary between call and put option series, separate implied stock series are constructed from both the near-term, at-the-money call and put option series. Finally, to avoid non-synchronous closing observations, the observed and implied stock series are constructed from the 6.5 hours in which both the NYSE and CBOE are open for trading. This produces 78 observations per day or a total of 3,120 observations per series.

4. Error correction testing and modeling

4.1. The error correction model

In order to exclude overnight effects, the model is designed so that opening observations are not regressed on observations from the previous day. Let each day contain j = 1,…,J intervals with J being the last interval of the day. Also, let the study contain t = 1,…,T days with T being the last day of the study. Then, S_{tj} is the jth observed stock value on day t, and $\Delta S_{tj} = S_{tj} - S_{t,j-1}$. I_{tj} and ΔI_{tj} are defined analogously. Note that if the model includes p lagged difference variables plus one lagged levels variable, the total number of lags in the model is defined as k = p + 1 lags. Therefore, each day contains J-k useable observations. Hence the total number of observations is N = T x (J-k). Finally, let $\mathbf{Z}_{tj}$ and $\Delta\mathbf{Z}_{tj}$ be defined as:

$$\mathbf{Z}_{tj} = \begin{bmatrix} S_{tj} \\ I_{tj} \end{bmatrix} \tag{1}$$

$$\Delta \mathbf{Z}_{tj} = \begin{bmatrix} \Delta S_{tj} \\ \Delta I_{tj} \end{bmatrix} \tag{2}$$

For k lags, a VAR model can be written as:

$$\mathbf{Z}_{tj} = \mathbf{A}_1 \mathbf{Z}_{t,j-1} + \cdots + \mathbf{A}_k \mathbf{Z}_{t,j-k} + \varepsilon_{tj} \tag{3}$$

where each $\mathbf{A}_i$ is a (2 × 2) matrix of parameters and $\varepsilon_{tj} \sim N(0, \Omega)$. Note that Equation (3) is in reduced form as each dependent variable is regressed on a predetermined set of regressors. Following Harris (1995), Equation (3) can be rewritten in error correction form as:

$$\Delta \mathbf{Z}_{tj} = \boldsymbol{\pi} \mathbf{Z}_{t,j-k} + \sum_{i=1}^{k-1} \Gamma_i \Delta \mathbf{Z}_{t,j-1} + \varepsilon_{tj} \tag{4}$$

with $\boldsymbol{\Gamma}_i = -(\mathbf{I} - \mathbf{A}_1 - \cdots - \mathbf{A}_i)$, i = 1, 2, ..., k-1, and $\boldsymbol{\pi} = -(\mathbf{I} - \mathbf{A}_1 - \cdots - \mathbf{A}_k)$. In Equation (4), the $\boldsymbol{\pi}$ matrix contains information on the long run equilibrium relation between $\{S_t\}$ and $\{I_t\}$,[3] and the $\boldsymbol{\Gamma}_i$ matrices contain information on the short term interactions between $\{\Delta S_t\}$ and $\{\Delta I_t\}$. Hence, both the π and the Γ_i matrices contain important information regarding lead/lag effects. The long run equilibrium relation between $\{S_t\}$ and $\{I_t\}$ may also include an intercept. For example, Johansen (1995) shows that without loss of generality, an intercept can be included in the cointegration space by letting $\mathbf{Z}_{t,j-k}$ be defined as $[S_{t,j-k}\ I_{t,j-k}\ 1]'$. Dummy intervention variables can also be included in the model. For example let $\mathbf{D}_{tj}$ be a (d × 1) vector of ones and zeroes, and let $\boldsymbol{\Psi}$ be (2 × d) vectors of parameters. With these adjustments the error correction model can be written as:

$$\Delta \mathbf{Z}_{tj} = \boldsymbol{\pi} \mathbf{Z}_{t,j-k} + \sum_{i=1}^{k-1} \boldsymbol{\Gamma}_i \Delta \mathbf{Z}_{t,j-i} + \boldsymbol{\Psi} \mathbf{D}_{tj} + \varepsilon_{tj} \tag{5}$$

4.2. Testing for cointegration

Johansen (1988) proposes a one-step Maximum Likelihood Estimination (MLE) technique to both test for cointegration between $\{S_t\}$ and $\{I_t\}$ and to estimate the cointegrating vector. Hence this technique may be more efficient than the two step Engle-Granger (1987) approach used by Diltz and Kim (1996). Rewriting Equation (5) as:

$$\Delta \mathbf{Z}_{tj} + \boldsymbol{\pi} \mathbf{Z}_{t,j-k} = \sum_{i=1}^{k-1} \boldsymbol{\Gamma}_i \Delta \mathbf{Z}_{t,j-1} + \boldsymbol{\Psi} \mathbf{D}_{tj} + \varepsilon_{tj} \tag{6}$$

[3] Where no confusion arises, the second subscript on $\{S_{tj}\}$ and $\{I_{tj}\}$ is dropped for expositional simplicity.

the MLE begins as a reduced rank regression.[4] In particular, the short run effects are removed from the model by separately regressing $\Delta\mathbf{Z}_{tj}$ and $\mathbf{Z}_{t,j-k}$ on the right hand side of Equation (6) and saving the residuals from these regressions in residual matrices $\mathbf{R}_{0n}$ and $\mathbf{R}_{1n}$, respectively.

For a system with two endogenous series, the residual matrices are used to form four product moment matrices:

$$\mathbf{V}_{ab} = \mathbf{N}^{-1} \sum_{n=1}^{N} \mathbf{R}_{an}\mathbf{R}'_{bn} \qquad a,b = 0,1 \tag{7}$$

Letting $\pi = \alpha\beta'$, Johansen (1988) shows that the MLE of the cointegrating vector(s) in β is obtained by solving:

$$\left|\lambda V_{11} - V_{10}V_{00}^{-1}V_{01}\right| = 0 \tag{8}$$

to find the two eigenvalues (λ_1 and λ_2) and corresponding eigenvectors ($\hat{h}_1$ and $\hat{h}_2$) where $\hat{H} = (\hat{h}_1, \hat{h}_2)$. The cointegrating vectors in β are the first r elements in $\hat{H}$ that produce stationary relations in the levels series. In this case, r is the rank of the π matrix from Equation (6) and is determined by the number of non-zero elements in $\hat{H}$. Harris (1995) notes that the eigenvalues are the squared canonical correlations between the levels residuals $\mathbf{R}_{1n}$ and the differenced residuals $\mathbf{R}_{0n}$. Since, the difference residuals $\mathbf{R}_{0n}$ are stationary, only those $\mathbf{R}_{1n}$ that are highly correlated with $\mathbf{R}_{0n}$ are also likely to be stationary. Hence, the r statistically significant eigenvectors in $\hat{H}$ indicate linear combinations of $\{S_t\}$ and $\{I_t\}$ that are likely to be stationary.

Johansen provides two Likelihood Ratio (LR) tests to determine the rank(π). The null hypothesis of at most r cointegrating vectors is:

$$H_0 : \lambda_i = 0 \qquad i = r + 1,2 \tag{9}$$

The Trace statistic tests H_0 against the general alternative hypothesis that rank(π) $\neq$ r. The Trace statistic is defined as:

$$\lambda_{trace} = -N \sum_{i=r+1}^{2} \ln(1-\hat{\lambda}_i) \tag{10}$$

The λ-max statistic tests the hypothesis of r cointegrating vectors against the specific alternative of r + 1 cointegrating vectors. The λ-max statistic is:

$$\lambda\text{-max }(r,r+1) = -N \ln(1 - \hat{\lambda}_i) \tag{11}$$

Critical values for both test statistics are given in Osterwald-Lenum (1992).[5]

[4] See Anderson (1950) for details on reduced rank regression.

[5] It should be noted that inclusion of dummy intervention variables may affect the asymptotic properties of the LR test statistics. Therefore in models that contain dummy intervention variables, published critical values may only be indicative of the true rank(π).

These test results are easily interpreted. If r = rank(π) = 0, then no linear combinations of $\{S_t\}$ and $\{I_t\}$ are stationary, and the VAR model should be estimated in differences. If rank(π) = 2, then both $\{S_t\}$ and $\{I_t\}$ are stationary, and the VAR model can be safely estimated in levels. However if rank(π) = 1, then the linear combination $\mathbf{h}'_i\mathbf{Z}_{tj}$ is stationary and a vector error correction model (VECM) can be estimated. For a model with r = rank(π) = 1, $\{S_t\}$ and $\{I_t\}$ as the endogenous variables, and an intercept in the cointegration space, $\hat{\beta} = \hat{h}_i = (\hat{\beta}_S\ \hat{\beta}_I\ \hat{\mu})$, where by convention, $\hat{\beta}$ is normalized so that $\hat{\beta}_S$ bequals one.

4.3. Estimating the error correction model

Once $\hat{\beta}$ is estimated, it can be inserted into Equation (5). The remaining parameters can be estimated using Ordinary Least Squares (OLS) techniques. Note that since the model contains a common set of regressors, each equation can be separately estimated without loss of efficiency. Rewriting (5) for easier interpretation gives:

$$\begin{bmatrix} \Delta S_{tj} \\ \Delta I_{tj} \end{bmatrix} = \begin{bmatrix} \alpha_S \\ \alpha_I \end{bmatrix} [\hat{\beta}_S\ \hat{\beta}_I\ \hat{\mu}] \begin{bmatrix} S_{t,j-1} \\ I_{t,j-1} \\ 1 \end{bmatrix} + \sum_{i=1}^{k-1} \begin{bmatrix} \gamma 11_i & \gamma 12_i \\ \gamma 21_i & \gamma 22_i \end{bmatrix} \begin{bmatrix} \Delta S_{t,j-i} \\ \Delta I_{t,j-i} \end{bmatrix} + \begin{bmatrix} \Psi_S \\ \Psi_I \end{bmatrix} D_{tj} + \begin{bmatrix} \varepsilon_{S_{tj}} \\ \varepsilon_{I_{tj}} \end{bmatrix} \tag{12}$$

The α_S and α_I speed of adjustment parameters indicate how vigorously each market responds to shocks to the long run equilibrating process. In particular, the leading market should exhibit the smaller (in magnitude) α parameter. An α parameter equal to zero indicates a market that has no response to shocks. For example, if $\alpha_S = 0$, then all response to shocks occurs in the option market, which is a strong indication of stock market leading behavior. The lagged cross-coefficients $\gamma 12_1, \ldots, \gamma 12_{k-1}$ and $\gamma 21_1, \ldots, \gamma 21_{k-1}$ are also important to assessing lead/lag effects. Significant values for the $\gamma 12_i$ parameters suggest that lagged ΔI observations affect current ΔS values. Likewise, significant $\gamma 21_i$ values indicate that that lagged ΔS observations influence current ΔI values.

4.4. Evaluating lead/lag effects in vector error correction models

Stephen and Whaley (1990), Chan, Chun, and Johnson (1993), Finucane and van Inwegen (1995), and Diltz and Kim (1996) rely on the significance of individual regression coefficients to investigate lead/lag behavior. In addition, none of these authors conduct formal causality tests of lead/lag behavior. Instead, they rely on economic interpretation of the estimated coefficients. However, formal Granger causality tests may provide insights into the nature of lead/lag behavior in stock and option markets. For example, suppose the hypothesis that stock market data do not Granger cause option market data is rejected. Then, current stock market information is relevant to forecasting future option market prices. At the same time, suppose the hypothesis that option market data do not Granger cause stock market data fails to reject. Then, option market data do not help forecast stock market prices. In this hypothetical case, stock market data appear to forecast option market values while option market data cannot forecast stock market values. Hence, the stock market may be considered the informational leading market, as it appears to reflect information more rapidly. Naturally, the alternative scenario of option market leading behavior is also possible.

Feedback effects occur if each market appears to Granger cause the other. In this case detection of the leading market is more difficult as interpretations rest on determining the relative strength and duration of the feedback effects. For example, suppose that stock market data help forecast option market prices several periods into the future. At the same time, suppose that option market prices help forecast stock market prices only one or two periods into the future. In this case, stock market data retain forecasting value for a longer period of time than option market data. This may be indicative of weaker, but still measurable stock market leading behavior. Again, weak but measurable option market leading behavior is also possible.

Enders (1995, p. 371) discusses proper formulation of the hypothesis of no Granger causality in error correction models. He suggests that an endogenous variable's response to prior deviations from long-run equilibrium is relevant to the issue of Granger causality. In particular deviations from long run equilibrium contain prior information from both markets. If that prior information is relevant to forecasting future prices then it is relevant to hypothesis tests regarding Granger causality. Therefore, hypothesis tests of Granger causality should include significance tests of the speed of adjustment coefficients as well as the lagged cross-coefficients. To construct formal hypothesis tests of no Granger causality first define H_{0S} and H_{0I} as:

$$H_{0S} : \gamma 21_1 = \gamma 21_2 = \cdots = \gamma 21_{k-1} = 0 \tag{13}$$

$$H_{0I} : \gamma 12_1 = \gamma 12_2 = \cdots = \gamma 12_{k-1} = 0 \tag{14}$$

Thus, H_{0S} (H_{0I}) hypothesizes that the lagged ΔS (ΔI) cross-coefficients are jointly zero. Also define $H\alpha_S$ and $H\alpha_I$ as:

$$H\alpha_S : \alpha_S = 0 \text{ and } H\alpha_I : \alpha_I = 0 \tag{15}$$

Then with respect to Equation (12),

$$\{S_t\} \text{ does not Granger cause } \{I_t\} \text{ if neither } H_{0S} \text{ nor } H\alpha_I \text{ rejects, and} \tag{16}$$

$$\{I_t\} \text{ does not Granger cause } \{S_t\} \text{ if neither } H_{0I} \text{ nor } H\alpha_S \text{ rejects} \tag{17}$$

Rejecting either H_{0S} or $H\alpha_I$ implies that $\{S_t\}$ Granger causes $\{I_t\}$. Likewise rejecting either H_{0I} or $H\alpha_S$ implies that $\{I_t\}$ Granger causes $\{S_t\}$.

If both hypotheses of no Granger causality are rejected then feedback exists. However, feedback effects do not necessarily preclude a reasonable interpretation of leading behavior. In cases with feedback, the relative length of time it takes for each market to reflect information from the corresponding market provides insight into lead/lag effects. This study proposes the following approach to identifying lead/lag behavior in the presence of feedback. Suppose that Granger causality tests find feedback between a firm's observed and implied stock series. In this case, consider two new hypotheses regarding lagged cross-coefficients for lags two through k-1.

$$H_{0S_2} : \gamma 21_2 = \gamma 21_2 = \cdots \gamma 21_{k-1} = 0 \tag{18}$$

$$H_{0I_2} : \gamma 12_2 = \gamma 12_3 = \cdots \gamma 12_{k-1} = 0 \tag{19}$$

H_{0S_2} tests whether ΔS cross-lags two through k-1 enter the ΔI equation while H_{0I_2} tests whether ΔI cross-lags two through k-1 enter the ΔS equation. Suppose that H_{0S_2} rejects while H_{0I_2} fails to reject. Rejecting H_{0S_2} suggests a relation between ΔI_t and the subset of observations, $\{\Delta S_{t-2}$ to $\Delta S_{t-(k-1)}\}$ indicating that ΔI_t takes at least two periods to fully reflect information from ΔS. Acceptance of H_{0I_2} suggests that ΔS_t takes at most one period to fully reflect option market information. Therefore in this hypothetical example, feedback from the option market to the stock market dies out more quickly than information flows from the stock market to the option market. An equivalent interpretation is that option market prices take longer to fully reflect information. Hence despite feedback effects, the hypothetical example suggests stock market leading behavior. However, the lead is of a weaker nature due to the detection of mild feedback from the option to the stock market.

In principal, the joint significance of any subset of lagged cross-coefficients may be examined. Thus, given feedback effects, any the following hypotheses may be constructed:

$$H_{0S_j} : \gamma 12_j = \gamma 12_{j+1} = \cdots \gamma 12_{k-1} = 0 \quad \text{for } j > 1 \tag{20}$$

$$H_{0I_j} : \gamma 21_j = \gamma 21_{j+1} = \cdots \gamma 21_{k-1} = 0 \quad \text{for } j > 1 \tag{21}$$

For any $j > 1$, H_{0S_j} tests whether ΔS cross-lags j through k–1 enter the ΔI equation while H_{0I_j} tests whether ΔI cross-lags j thorough enter the ΔS equation.

If feedback exists, both speed of adjustment coefficients may be significant. Recall that the lagging market will tend to have the stronger response to shocks. Hence, a result in which $|\alpha_I| > |\alpha_S| > 0$ is also consistent with weaker stock market leading behavior. Alternatively, $|\alpha_S| > |\alpha_I| > 0$ is consistent with weak option market leading behavior. These conditions reflect the idea that the leading market may respond to disequilibria in the levels data. However, its response is dominated by adjustments in the lagging market.

Table 1 below summarizes the proposed conditions for strong and weak leading behavior based on the tests of coefficient restrictions discussed above.

Table 1

Classification of informationally leading behavior

Strong Stock Market Lead	**Strong Option Market Lead**
Either H_{0S} or $H\alpha_I$ Rejects, and Neither H_{0I} or $H\alpha_S$ Reject	Either H_{0I} or $H\alpha_S$ Rejects, and Neither H_{0S} or $H\alpha_I$ Reject
Weak Stock Market Lead	**Weak Option Market Lead**
$\lvert\alpha_S\rvert < \lvert\alpha_I\rvert$ H_{0S_j} Rejects and H_{0I_j} Fails to Reject (for some j > 1)	$\lvert\alpha_I\rvert < \lvert\alpha_S\rvert$ H_{0I_j} Rejects and H_{0S_j} Fails to Reject (for some j > 1)

5. Results

5.1. Descriptive trading cost statistics

This study examines the relation between trading costs and lead/lag effects. Trading costs can be measured by a number of variables. Fleming, Ostdiek, and Whaley (1996) consider two components of trading costs: market liquidity and bid/ask spreads. In particular they measure market liquidity based on volume and trading frequency. They measure direct compensation to market makers with quoted bid/ask spreads. Since this study analyzes time series constructed from quote midpoints, quote frequencies are also presented for informational completeness. This study also adds effective spreads as an additional proxy measure of direct compensation, as actual trade prices can fall within the quoted spreads. Following Vijh (1990) and Lee and Ready (1991) effective spreads are measured as two times the absolute value of the difference between the transaction price and the existing bid/ask midpoint.

Table 2, Panel A presents descriptive statistics of the five proxies for stock market trading costs for each of the 19 sample firms. Note that daily volume is measured in lots traded. In terms of volume and trading frequencies, the sample represents a good cross-section of firms. On the high side of liquidity, American Telephone & Telegraph averages 14,946 lots and 654 trades per day. In contrast, the least liquid firm Diebold averages only 345 lots and 18 trades per day. As expected, the average daily trade and quote frequencies move in tandem with volume. Also as expected, average percentage effective spreads are smaller than average percentage quoted spreads, but effective and quoted spreads move directly with each other. Finally, both average percentage effective and quoted spreads appear to increase as volume falls. The correlation matrix in Panel B supports these observations.

Table 3 presents the descriptive statistics and correlation matrix for the corresponding measures of option market trading costs. These statistics are culled from all live call and put option series. Based on the sample, the range of option market liquidity appears to be much more extreme. For example in the option market, International Business Machines averages roughly 7,821 times as much volume and 6,615 times as many trades as Safeway, the least liquid firm. Even when compared to General Electric and Boeing, the next two most liquid firms, International Business Machines' option trading averages approximately five to seven times as much volume and six to seven times as much trading. Nevertheless, the correlation matrix reveals relations similar to those found in the stock market. In particular, the liquidity measures are positively correlated among themselves. Likewise, the spread measures are also positively correlated. Finally, the liquidity measures are negatively correlated with the spread measures. However, the correlations between the option market liquidity and spread measures do not appear significant.

Table 2

Stock market trading costs

Measured over the 40 trading days from November 2, 1990–December 31, 1990. Average daily volumes are in round lots traded. Effective spreads equal two times the absolute value of the trade price less the existing quote midpoint. The p-values are reported in the parentheses.

Panel A: Descriptive Statistics of Stock Market Trading Costs

Firm	Average Daily Volume	Average Trades Per Day	Average Quotes Per Day	Average % Effective Spreads	Average % Quoted Spreads
International Business Machines	12,940	503	509	0.08%	0.11%
General Electric	11,496	582	320	0.20%	0.31%
Boeing	8,995	285	199	0.21%	0.39%
American Telephone & Telegraph	14,946	654	96	0.33%	0.53%
Exxon	8,298	250	148	0.19%	0.33%
Federal Express	2,015	74	53	0.31%	0.67%
Waban	1,907	86	129	0.97%	1.79%
Schlumberger	4,666	167	157	0.22%	0.44%
Colgate-Palmolive	1,571	90	98	0.17%	0.32%
Tektronix	753	39	26	0.68%	1.29%
Hansen	3,860	84	83	0.60%	0.83%
Promus Companies	747	45	39	0.77%	1.59%
First Fidelity	909	48	42	0.54%	1.21%
Northern Telecom	1,916	44	80	0.39%	0.65%
Cyprus Minerals	815	48	35	0.60%	1.17%
Diebold	345	18	28	0.62%	0.89%
Readers' Digest	807	26	32	0.43%	0.92%
Premark International	464	33	32	0.79%	1.43%
Safeway	358	21	19	0.97%	1.82%

(continued)

Table 2 *(continued)*

Stock market trading costs

Panel B: Correlation Matrix for Descriptive Stock Market Trading Costs

	Volume	Trades	Quotes	% Effective Spread	% Quoted Spread
Volume	1.0000 (0.0000)				
Trades	0.9732 (0.0000)	1.0000 (0.0000)			
Quotes	0.7530 (0.0024)	0.7276 (0.0055)	1.0000 (0.0000)		
% Effective Spreads	−0.6469 (0.0370)	−0.5922 (0.0905)	−0.6073 (0.0726)	1.0000 (0.0000)	
% Quoted Spreads	−0.6785 (0.0193)	−0.6145 (0.0649)	−0.6204 (0.0590)	0.9740 (0.0000)	1.0000 (0.0000)

Compared with the stock market measures, option market percentage quoted and effective spreads are uniformly higher. These results are generally consistent with both Fleming, Ostdiek, and Whaley (1996) and Vijh (1990), and suggest that on the basis of spreads, option market trading costs appear higher. Comparison of liquidity measures across the stock and option market is slightly more difficult. However, it is worth noting that in terms of volume, International Business Machines averages more option contracts traded than round lots of stock traded. For all the other firms in the study, average round lots of stock traded exceed average option contracts traded. Likewise, the average number of option trades for International Business Machines exceeds the average number of stock trades. However, for all other firms, the average number of stock trades exceeds the average number of option trades. In many cases, the stock market liquidity measures are several multiples higher than their option market counterparts. While it appears that for most firms the stock market has greater liquidity, the relative levels of stock and option market liquidity are not consistent across all firms. This observation has important implications for the trading cost hypothesis. Recall that Fleming, Ostdiek, and Whaley (1996) argue for stock market leads based on the observation that average stock market trading costs exceed average option market trading costs. However at the firm level, the descriptive statistics suggest option market liquidity may not be uniformly lower. This suggests that lead/lag behavior may vary cross-sectionally, depending on the firm's option market liquidity. Hence, a firm such as International Business Machines with extremely high option market liquidity and firms such as General Electric and Boeing with moderately higher option market liquidity, may exhibit different lead/lag behaviors than firms with lower levels of option market liquidity.

Table 3

Option market trading costs

Measured over the 40 trading days from November 2, 1990–December 31, 1990. Option market volume is measured in contracts traded. Effective spreads equal two times the absolute value of the trade price less the existing quote midpoint. The p-values are reported in the parentheses.

Panel A: Descriptive Trading Cost Statistics for all Live Call and Put Option Series

Firm	Average Daily Volume	Average Trades Per Day	Average Quotes Per Day	Average % Effective Spreads	Average % Quoted Spreads
International Business Machines	15,643	1,323.0	3,071	5.52%	6.09%
General Electric	3,047	258.6	855	10.07%	11.14%
Boeing	2,068	211.9	435	11.24%	11.72%
American Telephone & Telegraph	1,910	110.0	247	12.93%	13.41%
Exxon	868	59.1	357	11.98%	13.73%
Federal Express	603	58.9	247	13.93%	19.42%
Waban	158	14.5	118	17.00%	24.49%
Schlumberger	263	22.3	355	16.96%	11.97%
Colgate-Palmolive	152	11.2	330	15.90%	20.16%
Tektronix	62	5.6	138	14.57%	31.61%
Hansen	41	3.3	197	18.05%	18.14%
Promus Companies	18	2.6	239	19.06%	34.97%
First Fidelity	43	3.3	214	20.71%	41.46%
Northern Telecom	25	2.8	196	19.35%	38.43%
Cyprus Minerals	22	2.1	277	22.00%	20.91%
Diebold	19	1.8	84	20.32%	18.26%
Readers' Digest	17	0.6	131	15.75%	19.42%
Premark International	13	1.0	195	24.38%	32.80%
Safeway	2	0.2	131	49.42%	26.62%

Panel B: Correlation Matrix for Descriptive Option Market Trading Costs

	Volume	Trades	Quotes	% Effective Spread	% Quoted Spread
Volume	1.0000				
	(0.0000)				
Trades	0.9987	1.0000			
	(0.0000)	(0.0000)			
Quotes	0.9887	0.9899	1.0000		
	(0.0000)	(0.0000)	(0.0000)		
% Effective	–0.5181	–0.5162	–0.5062	1.0000	
Spreads	(0.2130)	(0.2168)	(0.2373)	(0.0000)	
% Quoted Spreads	–0.5057	–0.5016	–0.4877	0.5787	1.0000
	(0.2383)	(0.2469)	(0.2769)	(0.1087)	(0.0000)

5.2. Cointegration and lead/lag test results

To save space, the λ-max and Trace test statistics for the eigenvalues of the reduced rank regressions of observed and call implied stock values are not presented.[6] However, 17 of the 19 firms reject the null hypothesis H_0: rank(π) = 0 at a 0.05 or lower level for both the λ-max and Trace statistics. The remaining two firms reject H_0: rank(π) = 0 at a 0.05 or lower level for the Trace statistic only. These results provide strong evidence that for all 19 firms, the $\{S_t\}$ and $\{I_t\}$ series contain at least one cointegrating vector. Eighteen firms fail to reject H_0: rank(π) = 1 at a even the 0.10 level. This suggests at most one cointegrating vector for these firms and indicates that the error correction model should be estimated with β restricted to a single (normalized) cointegrating vector. One firm does reject H_0: rank(π) = 1, in favor of the hypothesis that rank(π) equals two. For this individual firm, a VAR model in levels may be acceptable. However, no nonstationary elements are introduced into an error correction model for the case in which rank(π) equals two. Hence for consistency, all 19 firms are estimated using the error correction model given by Equation (12).

Error correction models produce a large number of coefficient estimates. However, the α_S and α_I speed of adjustment coefficients and the $\gamma 21_i$ and $\gamma 12_i$ lagged cross-coefficients are most important to assessing lead/lag effects. Table 4 presents each firm's estimated speed of adjustment and lagged cross-coefficient estimates for the error correction models estimated with observed and call option implied stock values sampled at five-minute intervals. The coefficient estimates are in bold with corresponding *p*-values presented below each coefficient. For consistency, each model is estimated with k = 7 total lags (k – 1 = 6 lagged interaction variables), which produces residuals that are generally free of measurable serial correlation. Although not presented, the R-square statistics are all above 0.05, indicating acceptable fits. Note that the degrees of freedom vary across firms, as some models require dummy interaction variables. The table also presents F-tests of hypotheses H_{0S} nor H_{0I} and hypotheses H_{0S_j} and H_{0I_j} for j = 2, 3. The F-test statistics are in bold with the corresponding significance below each statistic. For example, in the ΔI equations, F(6,•) tests $H_{0S} : \gamma 12_1 = \cdots = \gamma 12_6 = 0$. Likewise, F(5,•) tests $H_{0S_2} : \gamma 12_2 = \cdots = \gamma 12_6 = 0$ and F(4,•) tests $H_{0S_3} : \gamma 12_3 = \cdots = \gamma 12_6 = 0$. In some cases, the lagged cross-coefficients may be statistically significant but not economically meaningful. Hence, to help assess the economic value of each equation's lagged cross-coefficients, the table also presents the sum of the magnitudes of each equation's lagged cross-coefficients. These sums appear under the heading $\sum \gamma_i$.

Consider the results for International Business Machines. In the ΔS equation, $H\alpha_S$ clearly rejects as the α_S estimate of 0.016 has a *p*-value of 0.022. This suggests that its stock market prices do respond to prior shocks in the levels data. For the

[6] Full results for all tests mentioned in the paper are available from the author.

Table 4

Annotated error correction model results for observed and call implied stock observations

The estimated model is: $\begin{bmatrix}\Delta S_{tj}\\ \Delta I_{tj}\end{bmatrix} = \begin{bmatrix}\alpha_S\\ \alpha_I\end{bmatrix}[\hat{\beta}_S\ \hat{\beta}_I\ \hat{\mu}]\begin{bmatrix}S_{t,j-1}\\ I_{t,j-1}\\ 1\end{bmatrix} + \sum_{i=1}^{k-1}\begin{bmatrix}\gamma 11_i & \gamma 12_i\\ \gamma 21_i & \gamma 22_i\end{bmatrix}\begin{bmatrix}\Delta S_{t,j-i}\\ \Delta I_{t,j-i}\end{bmatrix} + \begin{bmatrix}\Psi_S\\ \Psi_I\end{bmatrix}D_{tj} + \begin{bmatrix}\varepsilon_{S_{tj}}\\ \varepsilon_{I_{tj}}\end{bmatrix}$ where the $\hat{\beta}$ vector is estimated from the reduced rank regression. Since the model contains a common set of regressors, each equation can be separately estimated with OLS, without loss of efficiency. The α_S and α_I speed of adjustment parameters indicate how vigorously each market responds to shocks to the long run equilibrating process. The leading market is expected to exhibit the smaller (in magnitude) α parameter. Significant values for the $\gamma 12_i$ parameters suggest that lagged ΔI observations affect current ΔS values. Likewise, significant $\gamma 21_i$ values indicate that lagged ΔS observations influence current ΔI values.

The α speed of adjustment and γ cross-coefficient estimates are in bold with *p*-values given below each coefficient estimate. F-test statistics are also in bold with the corresponding significance below each F-test statistic.

Firm	Dep Var	df	Cross-Coefficient and Significance at Lag: α_i	1	2	3	4	5	6	$\Sigma\gamma_i$	F(6,*)	F(5,*)	F(4,*)
International Business Machines	ΔS	2820	**0.016**	**0.248**	**0.147**	**0.130**	**0.100**	**0.065**	**0.025**	0.715	**16.834**	**6.751**	**5.718**
			0.022	0.000	0.000	0.000	0.000	0.011	0.218		0.000	0.000	0.000
	δI	2820	**0.038**	**0.256**	**0.179**	**0.095**	**0.057**	**0.033**	**0.018**	0.638	**12.283**	**5.715**	**2.314**
			0.000	0.000	0.000	0.006	0.095	0.294	0.491		0.000	0.000	0.055
General Electric	ΔS	2826	**0.018**	**0.131**	**0.033**	**−0.025**	**0.033**	**0.006**	**0.047**	0.275	**6.523**	**1.914**	**1.627**
			0.062	0.000	0.200	0.335	0.884	0.784	0.052		0.000	0.088	0.165
	ΔI	2826	**0.047**	**0.330**	**0.235**	**0.154**	**0.144**	**0.077**	**0.072**	1.012	**30.611**	**16.204**	**10.168**
			0.000	0.000	0.000	0.000	0.000	0.005	0.004		0.000	0.000	0.000
Boeing	ΔS	2827	**0.005**	**0.154**	**0.047**	**0.004**	**−0.029**	**0.024**	**−0.008**	0.266	**7.887**	**1.658**	**0.952**
			0.378	0.000	0.060	0.872	0.736	0.281	0.651		0.000	0.141	0.432
	ΔI	2827	**0.026**	**0.285**	**0.136**	**0.096**	**0.029**	**0.002**	**−0.011**	0.559	**32.320**	**9.191**	**4.851**
			0.000	0.000	0.000	0.000	0.189	0.899	0.542		0.000	0.000	0.001
American Telephone & Telegraph	ΔS	2827	**−0.006**	**0.009**	**0.024**	**−0.033**	**−0.039**	**−0.026**	**−0.013**	0.144	**1.757**	**1.511**	**1.912**
			0.36	0.592	0.163	0.059	0.051	0.119	0.403		0.104	0.183	0.106
	ΔI	2827	**0.048**	**0.254**	**0.084**	**0.070**	**0.043**	**0.016**	**0.017**	0.484	**21.583**	**4.308**	**2.929**
			0.000	0.000	0.000	0.002	0.059	0.474	0.434		0.000	0.001	0.020

(continued)

Table 4 *(continued)*

Annotated error correction model results for observed and call implied stock observations

Firm	Dep Var	df	Cross-Coefficient and Significance at Lag: α_i	1	2	3	4	5	6	$\Sigma\gamma_i$	F(6,*)	F(5,*)	F(4,*)
Exxon	ΔS	2827	**−0.005**	**0.052**	**0.003**	**0.009**	**−0.004**	**0.017**	**−0.020**	0.105	**1.620**	**0.649**	**0.807**
			0.475	0.010	0.861	0.620	0.826	0.356	0.221		0.137	0.662	0.520
	ΔI	2827	**0.040**	**0.238**	**0.126**	**0.093**	**0.084**	**0.079**	**0.048**	0.668	**24.545**	**10.745**	**8.751**
			0.000	0.000	0.000	0.000	0.000	0.000	0.016		0.000	0.000	0.000
Federal Express	ΔS	2814	**−0.003**	**0.016**	**0.013**	**0.015**	**0.014**	**0.022**	**0.014**	0.094	**1.553**	**1.801**	**1.701**
			0.528	0.212	0.302	0.231	0.252	0.064	0.189		0.157	0.109	0.147
	ΔI	2814	**0.026**	**0.303**	**0.034**	**0.039**	**0.041**	**−0.063**	**−0.053**	0.533	**22.090**	**3.982**	**4.507**
			0.000	0.000	0.240	0.169	0.106	0.007	0.020		0.000	0.001	0.001
Waban	ΔS	2825	**−0.013**	**0.045**	**0.018**	**0.014**	**0.026**	**0.017**	**0.011**	0.131	**1.787**	**0.799**	**0.652**
			0.100	0.033	0.403	0.510	0.201	0.423	0.536		0.098	0.549	0.625
	ΔI	2825	**0.041**	**0.232**	**0.099**	**0.102**	**−0.001**	**−0.031**	**−0.023**	0.488	**28.120**	**10.306**	**8.235**
			0.000	0.000	0.000	0.000	0.973	0.122	0.225		0.000	0.000	0.000
Schlumberger	ΔS	2816	**0.001**	**0.029**	**0.005**	**−0.007**	**−0.009**	**−0.014**	**0.004**	0.068	**0.642**	**0.232**	**0.231**
			0.866	0.121	0.792	0.717	0.620	0.455	0.798		0.697	0.949	0.922
	ΔI	2816	**0.026**	**0.294**	**0.111**	**0.075**	**0.028**	**0.053**	**0.054**	0.615	**23.578**	**5.730**	**3.578**
			0.000	0.000	0.000	0.004	0.288	0.039	0.028		0.000	0.000	0.000
Colgate-Palmolive	ΔS	2812	**0.004**	**0.024**	**0.039**	**−0.002**	**0.007**	**0.000**	**−0.010**	0.082	**1.622**	**1.672**	**0.250**
			0.269	0.127	0.009	0.895	0.641	0.999	0.418		0.137	0.138	0.910
	ΔI	2812	**0.019**	**0.267**	**0.123**	**0.097**	**0.039**	**0.033**	**0.063**	0.622	**26.919**	**8.774**	**6.254**
			0.000	0.000	0.000	0.000	0.083	0.131	0.003		0.000	0.000	0.000

(continued)

Table 4 *(continued)*

Annotated error correction model results for observed and call implied stock observations

Firm	Dep Var	df	Cross-Coefficient and Significance at Lag:							$\Sigma\gamma_i$	F(6,*)	F(5,*)	F(4,*)
			α_i	1	2	3	4	5	6				
Tektronix	ΔS	2826	**−0.007**	**0.031**	**0.028**	**−0.005**	**0.006**	**−0.006**	**−0.024**	0.100	**1.451**	**1.146**	**0.855**
			0.228	0.075	0.106	0.776	0.729	0.693	0.122		0.191	0.334	0.490
	ΔI	2826	**0.051**	**0.119**	**0.012**	**0.094**	**0.037**	**0.047**	**0.013**	0.322	**6.031**	**3.560**	**4.434**
			0.000	0.000	0.638	0.000	0.131	0.045	0.538		0.000	0.003	0.001
Hansen	ΔS	2826	**0.004**	**0.044**	**0.026**	**0.029**	**0.035**	**0.023**	**0.010**	0.167	**2.222**	**1.385**	**1.596**
			0.033	0.002	0.102	0.054	0.023	0.125	0.441		0.038	0.227	0.173
	ΔI	2826	**0.008**	**0.171**	**0.108**	**0.064**	**0.033**	**0.009**	**−0.007**	0.392	**10.407**	**4.709**	**2.060**
			0.001	0.000	0.000	0.008	0.165	0.706	0.742		0.000	0.000	0.083
Promus Companies	ΔS	2827	**−0.006**	**0.036**	**0.021**	**0.011**	**0.007**	**0.012**	**0.015**	0.102	**1.422**	**0.849**	**0.623**
			0.244	0.017	0.115	0.431	0.565	0.358	0.216		0.202	0.514	0.646
	ΔI	2827	**0.011**	**0.160**	**0.067**	**−0.008**	**0.035**	**0.019**	**−0.011**	0.300	**5.403**	**1.323**	**0.493**
			0.050	0.000	0.029	0.789	0.248	0.537	0.704		0.000	0.251	0.741
First Fidelity	ΔS	2825	**−0.011**	**0.025**	**−0.023**	**−0.033**	**0.003**	**0.002**	**0.005**	0.091	**1.185**	**1.263**	**1.072**
			0.033	0.139	0.182	0.052	0.845	0.883	0.735		0.311	0.277	0.369
	ΔI	2825	**0.112**	**0.117**	**0.067**	**0.056**	**0.004**	**0.019**	**0.001**	0.264	**5.082**	**2.016**	**1.063**
			0.001	0.000	0.018	0.041	0.839	0.916	0.946		0.000	0.073	0.373
Northern Telecom	ΔS	2826	**0.001**	**−0.018**	**−0.021**	**0.009**	**−0.010**	**−0.025**	**0.010**	0.093	**1.231**	**1.284**	**1.150**
			0.793	0.241	0.192	0.543	0.511	0.095	0.506		0.287	0.268	0.331
	ΔI	2826	**0.022**	**0.183**	**0.074**	**0.006**	**0.042**	**0.037**	**−0.008**	0.350	**7.338**	**1.909**	**1.051**
			0.000	0.000	0.016	0.835	0.128	0.170	0.758		0.000	0.089	0.379

(continued)

Table 4 *(continued)*

Annotated error correction model results for observed and call implied stock observations

Firm	Dep Var	df	Cross-Coefficient and Significance at Lag: α_i	1	2	3	4	5	6	$\Sigma\gamma_i$	F(6,*)	F(5,*)	F(4,*)
Cyprus Minerals	ΔS	2826	**0.000**	**0.012**	**0.007**	**0.005**	**0.006**	**0.014**	**0.003**	0.047	**1.552**	**1.375**	**0.988**
			0.972	0.374	0.617	0.694	0.660	0.027	0.813		0.157	0.230	0.413
	ΔI	2826	**0.025**	**0.130**	**0.104**	**0.020**	**0.412**	**0.041**	**0.076**	0.783	**7.551**	**5.278**	**3.327**
			0.000	0.000	0.000	0.450	0.120	0.117	0.002		0.000	0.000	0.010
Diebold	ΔS	2827	**0.002**	**0.002**	**0.000**	**0.007**	**0.003**	**0.004**	**0.014**	0.030	**1.433**	**1.671**	**1.293**
			0.259	0.884	0.999	0.570	0.571	0.704	0.174		0.198	0.138	0.270
	ΔI	2827	**0.017**	**0.039**	**0.038**	**0.032**	**−0.002**	**0.004**	**0.002**	0.117	**13.482**	**10.538**	**6.252**
			0.008	0.000	0.000	0.000	0.792	0.507	0.756		0.000	0.000	0.000
Readers' Digest	ΔS	2827	**−0.002**	**0.007**	**0.056**	**0.035**	**0.014**	**0.022**	**0.010**	0.144	**1.064**	**1.244**	**0.068**
			0.783	0.792	0.024	0.158	0.560	0.366	0.656		0.382	0.286	0.629
	ΔI	2827	**0.029**	**0.258**	**0.050**	**0.008**	**0.030**	**0.013**	**−0.060**	0.419	**10.012**	**1.320**	**1.199**
			0.000	0.000	0.155	0.819	0.379	0.708	0.065		0.000	0.252	0.309
Premark International	ΔS	2827	**−0.006**	**0.036**	**0.021**	**0.011**	**0.007**	**0.012**	**0.015**	0.102	**1.422**	**0.849**	**0.623**
			0.244	0.017	0.115	0.431	0.565	0.358	0.216		0.202	0.514	0.646
	ΔI	2827	**0.032**	**0.128**	**0.041**	**0.119**	**0.036**	**0.044**	**0.041**	0.409	**5.298**	**3.555**	**4.346**
			0.000	0.000	0.179	0.000	0.229	0.116	0.129		0.000	0.003	0.002
Safeway	ΔS	2827	**−0.003**	**−0.049**	**0.019**	**0.038**	**0.005**	**−0.004**	**−0.060**	0.175	**1.248**	**0.713**	**0.643**
			0.616	0.050	0.436	0.134	0.828	0.851	0.700		0.279	0.614	0.632
	ΔI	2827	**0.012**	**0.088**	**0.097**	**0.012**	**0.031**	**0.042**	**0.004**	0.274	**1.967**	**1.571**	**0.472**
			0.093	0.020	0.010	0.746	0.411	0.250	0.841		0.067	0.165	0.756

same equation F(6, 2820) = 16.834 which rejects $H_{0I} : \gamma 21_1 = \cdots = \gamma 21_6 = 0$ at a significance level of 0.00. From Table 1, these results rule out a strong stock market lead. Note that for the same equation, F(5, 2820) and F(4, 2820) clearly reject H_{0I_2} and H_{0I_3}. Hence, International Business Machines' data provide no evidence of even weak stock market leading behavior. The ΔI equation produces similar results. In particular, the α_I estimate of 0.038 is highly significant and F-tests clearly reject H_{0S}, H_{0S_2}, and H_{0S_3}. Hence, no evidence of even weak option market leading behavior exists. For the time period covered, International Business Machines' stock and near-term, at-the-money call option trading appears to be dominated by feedback. This suggests that its stock and call option trading reflect new information at approximately the same rate.

Boeing and General Electric also provide evidence of feedback between the stock and option markets. However, the strength and duration of information flows from the stock to the option market indicate weak stock market leading behavior. Looking first at General Electric, both the ΔS and ΔI equations have significant F(6, 2826) statistics, indicating that both H_{0I} and H_{0S} can be rejected. Hence, neither market exhibits strong leading behavior. However in the ΔS equation, the F(5, 2826) and F(4, 2826) statistics fail to reject hypotheses H_{0I_2}, and H_{0I_3} at the 0.05 and 0.10 levels, respectively. This provides evidence that the influence of ΔI cross-lags on current ΔS values begins to diminish after one period and disappears altogether after two periods. Conversely, the F(5, 2826) and F(4, 2826) statistics in the ΔI equation easily reject both H_{0S_2}, and H_{0S_3}. This suggests that lagged ΔS values influence current ΔI values for at least three periods. Note also that the estimated α_S coefficient is much smaller in magnitude than the corresponding α_I estimate. This suggests that the option market has a stronger response to deviations from the long run equilibrium. Based on the criteria in Table 1, these results suggest a weak stock market lead for General Electric over the sample period. Note that magnitudes of the estimated cross-coefficient are consistent with this interpretation. Boeing's results are similar. The F(6, 2827) statistics for both the ΔS and ΔI equations are significant, indicating no strong informational leads. However as with General Electric, the F(5, 2827) and F(4, 2827) tests indicate that information flows from the option market to the stock market die out rather quickly. However, information flows from the stock to the option market appear significant for at least three periods. Finally, the α estimates indicate stronger option market responses to disequilibrating shocks. Hence, by the criteria in Table 1, Boeing also exhibits a weak stock market lead. Note that the magnitudes of the lagged cross-coefficients are consistent with this interpretation as well.

Examining American Telephone & Telegraph next, note that in the ΔS equation both $H\alpha_S$ and H_{0I} fail to reject at conventional significance levels. On the contrary, in the ΔI equation $H\alpha_I$ and H_{0S} easily reject. In this case, the option market responds to long run equilibrating shocks while the stock market does not. In addition, the F-tests detect strong information flows from the stock to the option market but no information flows from the option to the stock market. By the criteria in Table 1, these results indicate strong stock market leading behavior. In fact, all of the remaining firms except Hansen can be classified as exhibiting strong stock market leading behavior. The lone holdout, Hansen, exhibits weak stock market leading behavior.

Although not presented here, similar results obtain when the error correction models are estimated with implied stock data generated from near-term, at-the-money put option data. In particular, the eigenvalues from the reduced rank regressions indicate the observed and implied stock series are cointegrated and can be modeled within an error correction framework. The F-tests from the error correction models indicate no leading behavior for International Business Machines and weak stock market leading behavior for Boeing and General Electric. Of the remaining 16 firms, 13 exhibit strong stock market leading behavior and three exhibit weak stock market leading behavior.

Overall, the error correction models suggest the following. First, no evidence of option market leading behavior exists. This result contrasts with Diltz and Kim (1996) who find option market leads using error correction models estimated with daily data. The most likely explanation is different informational dynamics in intraday as opposed to daily time series observations. The results also contrast with Chan, Chung, and Johnson (1993) who find no stock market leading behavior in time series constructed from quote midpoints. Recall that the Chan, Chung, and Johnson (1993) estimate pooled regressions while this study examines lead/lag effects at the firm level. A second differentiating factor may be that the error correction models in this study specifically capture the long run equilibrating mechanism between the stock and option market. Finally, the results are consistent with Fleming, Ostdiek, and Whaley (1996) as this study finds stock market leading behavior generally dominates. Also consistent with the Fleming, Ostdiek, and Whaley (1996) notion of a trading cost effect, the results suggest that lead/lag relationships may be affected by cross-sectional variation in option market trading costs. Although the study does not statistically test the relation between option market trading costs and lead/lag effects, it is interesting to note that International Business Machines has the lowest option market trading costs and the highest degree of feedback. General Electric and Boeing have the next lowest option market trading costs and while feedback is detected, weak stock market leads are measurable. The remaining firms all have higher option market trading costs and strong stock market leads in at least one of the error correction models.

6. Summary

This study examines lead/lag behavior between the stock and option markets using error correction models that are robust to distortions due to non-synchronous closing, overnight, and non-trading effects. Error correction models are utilized as they control for cointegration effects between stock and option market data and provide a Granger causality framework that allows formal classification of lead/lag behavior. The data for the study comprise 19 firms sampled at five-minute intervals over a two-month period. Hence, some caution should be employed in generalizing the results. Nevertheless, the findings are consistent with the Fleming, Ostdiek, and Whaley (1996) trading costs hypothesis, as stock market leading behavior generally dominates. In addition, the results also suggest cross-sectional variation in lead/lag behavior that appears to be related to option market trading costs. These results are consistent regardless of whether models are estimated with implied stock values generated from call or put option data. Overall, the results contrast with Diltz and Kim (1996), who find option market leads using error correction models estimated with daily data. This suggests different informational dynamics in daily versus intraday trading. The results also contrast with the Amin and Lee (1994) and Easley, O'Hara, and Srinvas (1998) proposition that option markets are primarily used for informational trading. Finally, the results do not support the Chan, Chung, and Johnson (1993) finding of a spurious stock market lead.

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