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Option Volume and Stock Prices: Evidence on Where Informed Traders Trade

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ABSTRACT

This paper investigates the informational role of transactions volume in options markets. We develop an asymmetric information model in which informed traders may trade in option or equity markets. We show conditions under which informed traders trade options, and we investigate the implications of this for the linkage between markets. Our model predicts an important informational role for the volume of particular types of option trades. We empirically test our model's hypotheses with intraday option data. Our main empirical result is that negative and positive option volumes contain information about future stock prices.

THE INFORMATION CONTENT of trading activity is a subject of widespread interest. If trades are correlated with private information, then the outcome of the transaction process may portend future movements in price. The extension of trading to different venues or to derivative instruments, however, means that this link between transactions and information need not be easily discernible. If there are alternative markets in which informed traders can profit from their information, then where informed traders choose to trade may have important implications not only for security price movements, but for the behavior of related prices as well. This suggests that transactions in derivative markets may be an important predictor of future security price movements.

In this paper we investigate the informational role of transactions volume in options markets. For some readers, this focus may seem puzzling; an option is a derivative security so its price should be dictated unilaterally by the behavior of the stock price. This unidirectional linkage is only true, however, in complete markets; if information is impounded into prices by trading, then the ability of informed traders to transact in options markets means

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that the *option trading process* is not redundant.[1] If the options market is more attractive to informed traders, then option trades (rather than option prices) may first reflect information due to the fact that option pricing models need the stock price and volatility to determine the option price, but the new information would not yet have been incorporated into stock prices. The asymmetry of information and the preference of trading venues would thus cause option transactions to convey information to market participants of impending changes in stock and option prices.

That options markets might play an important role in impounding information into security prices is not an idea original to this research. Black (1975) first suggested that the higher leverage available in options markets might induce informed traders to transact options rather than stocks. And an impressive range of researchers (Manaster and Rendleman (1982), Bhattacharya (1987), Vijh (1988; 1990), Anthony (1988), Conrad (1989), Stoll and Whaley (1990), Stephan and Whaley (1990), DeTemple and Jorion (1990), Damodoran and Lim (1991), Chan, Chung, and Johnson (1993), Srinivas (1993), Sheikh and Ronn (1994), Mayhew, Sarin, and Shastri (1995), Fleming, Ostdiek, and Whaley (1996)) have empirically investigated the links between options and equity markets. The evidence on market interrelationships, however, is inconclusive as to which of the two markets reflects new information earlier.[2] And a growing body of theoretical literature (see, for example, Blume, Easley, and O'Hara (1994)) emphasizes the crucial role of transaction volume as a statistic for technical analysis. It is this multimarket linkage of price, volume, and information that is the focus of our research.

Our principal finding is that options markets are a venue for information-based trading. This conclusion, the opposite of that reached by Vijh (1990),

[1] This incompleteness argument has several important dimensions. First, if information is asymmetric and information flows are not unidirectional, the standard option pricing models (for example, Black and Scholes (1973)) are not correctly specified. Back (1993) presents an impressive analysis of the effect of this on the option pricing framework. Grossman (1988) also raises the importance of the option trading mechanism by pointing out that options and synthetic options are not identical instruments due to their different information content. Second, if information is symmetric, then, as shown by DeTemple and Selden (1991), introducing options may change the hedging opportunities available to traders. This can also introduce price effects on the equity market. In this analysis, we do not consider such hedging-related effects.

[2] The early work on option–equity market linkages (for example Manaster and Rendleman (1982), Anthony (1988)) uses daily closing data and concludes that options lead stocks. Vijh (1988) argues that this result is spurious due to biases introduced by using daily closing prices. Research with intraday data by Stephan and Whaley (1990) concludes the opposite relationship holds, finding that equity prices lead option prices. Chan et al. (1993) argue that this lead is due to different price discreteness rules in the two markets. They conclude that neither market leads. Vijh (1990) and Srinivas (1993) examine this linkage issue indirectly by looking at how option prices move with option trades. Vijh concludes that option trades are not information related based on evidence from the price effects of very large trades. Srinivas argues this is due to a bias in Vijh's sample selection, and presents evidence that option trades are information related. Finally, Sheikh and Ronn (1994) examine option return patterns, and argue that differences between these and equity market returns are evidence of information-based trade in options.

arises from our demonstration that specific option volumes have information content for future stock price movements. What differentiates our analysis, and our results, from previous work is our explicit use of a microstructure model to predict why the volume of particular types of option trades might be indicative of information-based trading. These option volumes are *not* the standard call option or total option volumes investigated in virtually all previous work, but rather are based on the option trades that would be entered by traders acting on the basis of good and bad information.[3] We show empirically that it is these "positive news" option volumes and "negative news" option volumes that have predictive power for stock price movements.

Our approach in this research is to develop a multimarket sequential trade model that incorporates both options and stocks.[4] Our model, which builds from Easley and O'Hara (1987), provides an explicit characterization of the price-setting problem in the two markets, and this allows us to formulate and investigate specific hypotheses regarding market linkages. The key element of our model is that we allow informed traders to choose whether to buy or sell the stock, buy or sell a put, or buy or sell a call. We determine the conditions under which, in equilibrium, informed traders use options, stocks, or a mixture of the two assets.[5] As would be expected, these conditions in-

[3] Most previous empirical analysis (for example, Stephan and Whaley (1990), Anthony (1988)) have analyzed only call option data in examining the links between markets. An exception is Vijh (1990) who examines volume under a number of definitions. Whereas Vijh is interested in the link of option volume and option prices, our focus is on the predictive power of option volume for equity prices. Anthony examines the link between option volume and stock volume, but his results using daily volume data are subject to question.

[4] Our work here thus contributes to the growing body of work investigating option market microstructure. For example, Biais and Hillion (1994) analyze the effects of introducing options when information may be asymmetric. They show that options can affect price volatilities. John, Koticha, and Subrahmanyam (1993) employ a sequential trade approach like that developed here to address a similar question. Their analysis considers a one-trade model in which traders can trade either a stock or a put option (they do not allow trading in call options), and they allow a single wealth-constrained informed trader. Their model allows explicit characterizations of the effects of margin requirements, an issue we do not consider. Brennan and Cao (1996) analyze a noisy rational expectations model with trade in a risky asset and a quadratic option. They show that there is an equilibrium with a Pareto efficient allocation and that in this equilibrium trade in the option is not information based. Sheikh and Ronn (1994) examine the empirical behavior of options market returns. They demonstrate that option returns, although they share similarities with equity market returns, also have patterns peculiar to the options market. They interpret this as evidence of information-based trade in option markets, a conclusion in common with ours.

[5] In our model, asymmetric information dictates that option contracts are not redundant because put–call parity need not hold in the absence of complete markets. If put–call parity held at every instant, then analyzing the behavior of the put, for example, would be pointless because it could provide no information that is not already in the call and in the stock. Indeed, this may explain why previous researchers focused only on calls. With asymmetric information, however, this is not correct because, if prices are not full-information efficient, each of the stock, put, and call may affect the behavior of subsequent prices. Although arbitrage would be expected to bring prices ultimately together, this need not (and indeed, will not) be instantaneous given that there is private information.

volve the depths of the markets and the leverage available to the market. The most important results of our model, however, are its implications for the information content of specific option trades. Buying a call or selling a put are trades that benefit from a rise in the stock price, and our model predicts that in a pooling equilibrium these trades carry positive information about future stock prices. Similarly, selling a call or buying a put carries negative information about future stock prices.

We then empirically investigate these predictions of our model for the price–volume linkage between options and equity markets. Consistent with the findings of Stephan and Whaley (1990), we provide evidence that stock price changes seem to lead option volumes. Also consistent with previous empirical studies, we find little or no evidence that put or call option volumes lead stock price changes. Using the information-based aggregation suggested by our theory, however, reveals a different story. When we aggregate option trades into positive-news trades (buying a call or selling a put) and negative-news trades (selling a call or buying a put), *we can reject the hypothesis that option volumes carry no information about future stock price changes.* Thus, we conclude that the markets are not in a separating equilibrium with no informed trade in the options market. Using Granger causality tests, we find that option volumes respond to stock price changes with lags of between twenty and thirty minutes, but that option volumes affect stock price changes much more rapidly. We also find, however, that the direction of the effect is not straightforward, suggesting that information is not the only factor influencing stock and option market short-term movements.

The paper is organized as follows. In Section I we develop our model of multimarket trading and derive conditions needed for equilibria in the two markets. Our model predicts several properties of the linkage between the options and the equity markets, and in Section II we structure these as formal hypotheses and describe the statistical properties of our test procedures. Section III describes the data and our trade classification algorithm. In Section IV we test our hypotheses and discuss our findings and their relation to previous work. Section V is a summary and conclusion.

I. The Model

In this section we develop a simple model of multimarket trading. Our model is a sequential trade model in the spirit of Easley and O'Hara (1987), wherein traders choose to transact in option and/or security markets with risk neutral, competitive marketmakers. As we will demonstrate, constructing the equilibrium in this model requires determining conditions under which informed traders choose to "pool" and trade in both markets, or to "separate" and trade in only one market.

In the model, there is an asset (a security) that trades in an equity market and options on that security which trade in an options market. The asset has a value at some time T in the future given by the random variable V, where $V \in \{\underline{V}, \bar{V}\}$. We define an information event as a signal, Ψ, about V, where the signal can take on one of two values, L and H. The probability that the signal is low is δ, with $(1 - \delta)$ the corresponding probability that the signal is high. The value of the asset conditional on the signal is $\underline{V}$ if $\Psi = L$ or $\overline{V}$ if $\Psi = H$. If no information event has occurred, we denote this as $\Psi = 0$, and the expected value of the asset remains at its unconditional level $V^* = \delta\underline{V} + (1 - \delta)\overline{V}$.

Trade in the stock and options markets occurs during a sequence of days indexed by $j = 1,\ldots,J$.[6] Information events need not occur every day, reflecting that in markets it is not generally known whether other traders are actually trading on the basis of new information. We capture this feature of markets by assuming that information events occur probabilistically between trading days. We assume that exactly one information event will occur, and that the probability of occurrence before the start of trade on day j, conditional on an information event not having already occurred, is η_j. This sequence of conditional probabilities is common knowledge, but when an information event occurs only some of the traders know of its existence. If an information event occurs, fraction μ of the universe of traders is informed and fraction $1 - \mu$ is uninformed; if no information event occurs, by definition all traders are uninformed.

In our analysis, there is a competitive marketmaker who sets prices to buy or sell the security, and a competitive marketmaker who sets prices to buy or sell option contracts. A trade consists of a single round lot of stock equaling γ shares or a single option contract controlling θ shares of stock.[7] To abstract from difficulties connected with varying times to maturity and exercise prices, we restrict our attention to two option contracts: a put option with expiration date J and exercise price $X \in [\underline{V},\overline{V}]$, and a call option with expiration date J and exercise price $Y \in [\underline{V},\overline{V}]$. We also assume that option contracts can only be exercised at maturity (i.e., are European options), and hence we do not deal with the complexities introduced by early exercise.

At each time t in a trading day, each marketmaker sets prices to yield zero expected profit conditional on the security or contract being traded. In our model, the option and equity marketmakers watch both markets. This dictates that prices at any time are conditional expected values given the history of trade in both markets *and* a trade at that price in their specific market. We denote by b_s and a_s the bid and ask prices in the security market; b_p and a_p the bid and ask prices for the put option; and b_c and a_c the bid and ask prices for the call option. Because the marketmakers share the same

[6] We call the trading periods days and assume information events occur overnight to link the model with our empirical work. Obviously, the theory applies to any period length.

[7] Our analysis can be extended, as in Easley and O'Hara (1987), to multiple trade sizes. This enrichment of the analysis does not affect our conclusions about the information content of positive and negative options trades. The additional insight that the extension provides is that, in equilibrium, large trades have at least as much information content as small trades. This result, which follows directly from our earlier work, comes at a large cost as informed traders now have twelve possible transactions to consider (combinations of buy or sell; stock, put, or call; and large or small) and ensuring analysis is cumbersome.

information set, there is no role for arbitrageurs, as both marketmakers have the same expected value for the asset. In actual markets, such complete information is unlikely to be available, and lags in information transmission would be likely to occur. We investigate such lags in our empirical work, but we do not assume any exogenous lead–lag structure here.

Trades arise from uninformed and/or informed traders. The uninformed are assumed to trade for liquidity-based reasons that are exogenous to the model. This "noise trader" assumption is standard in microstructure models and it reflects the difficulty noted by Milgrom and Stokey (1982) that, in the presence of traders with better information, uninformed traders acting solely on speculative motives would be better off not trading. Interestingly, such a liquidity trader assumption is a natural property of option markets, where many trades are motivated by hedging or other non-speculative desires.

Let the history of trade and transaction prices in the options and stock markets to time t be h_t. Thus, h_t consists of t observations of trades and their transaction prices. We assume that the propensity of the uninformed to buy or sell the stock or options is determined by the stochastic process:

$$\Pr\{\text{buy stock at } t | h_{t-1}\} = a_t(h_{t-1});$$

$$\Pr\{\text{sell stock at } t | h_{t-1}\} = b_t(h_{t-1});$$

$$\Pr\{\text{buy put at } t | h_{t-1}\} = c_t(h_{t-1});$$

$$\Pr\{\text{sell (write) put at } t | h_{t-1}\} = d_t(h_{t-1});$$

$$\Pr\{\text{buy call at } t | h_{t-1}\} = e_t(h_{t-1});$$

$$\Pr\{\text{sell (write) call at } t | h_{t-1}\} = f_t(h_{t-1}),$$

where for each time t, $a_t(h_{t-1})$, $b_t(h_{t-1})$, $c_t(h_{t-1})$, $d_t(h_{t-1})$, $e_t(h_{t-1})$, and $f_t(h_{t-1})$ are measurable functions of the history h_{t-1}, are all positive, and sum to one. There is no trading history for the day prior to the first trade of the day, so we let $a_1(h_{-1}) = a$, $b_1(h_{-1}) = b$, $c_1(h_{-1}) = c$, $d_1(h_{-1}) = d$, $e_1(h_{-1}) = e$, and $f_1(h_{-1}) = f$. This history dependence in uninformed trade is intended to incorporate uninformed hedging behavior. For example, if a unit of the stock is purchased at time t then the probability of an uninformed purchase of a put, or sale of a call, at some future date may be increased. The only restriction that we place on uninformed trade is that an option trade at time t does not change the probabilities of uninformed trade at time $t + 1$; that is, $a_t(h_{t-1}) = a_{t+1}(h_t)$, and so on, if $h_t = (h_{t-1}, \text{option trade})$.

Informed traders are not allocated to specific markets, but instead choose where and what to trade based on the profits available. A trader informed of good news could profit from buying the stock, buying a call, or writing (selling) a put. Similarly, a trader knowing bad news could sell the stock, sell a call, or buy a put. Informed traders are assumed to be risk neutral and competitive. This latter assumption rules out any strategic behavior, and it dictates that when an informed trader has the opportunity to trade, she will choose the trade that results in the highest expected profit. Notice that we do not allow traders to *simultaneously* execute multiple trades (i.e., buy the stock and sell the call). A trader wishing to execute multiple transactions would enter one trade, and then trade again at her next trading opportunity.[8]

The informed trader's decision problem can thus be specified as follows. If the trader knows that $V = \underline{V}$, then her profit is given by

$$\underline{\pi} = \begin{bmatrix} (b_s - \underline{V})\gamma & \text{if sell the stock,} \\ -a_p + \theta(X - \underline{V}) & \text{if buy a put,} \\ b_c & \text{if sell a call.} \end{bmatrix} \tag{1}$$

If the trader knows that $V = \overline{V}$, then her profit is given by

$$\overline{\pi} = \begin{bmatrix} (-a_s + \overline{V})\gamma & \text{if buy the stock,} \\ b_p & \text{if sell a put,} \\ -a_c + (\overline{V} - Y)\theta & \text{if buy a call.} \end{bmatrix} \tag{2}$$

Given an opportunity to trade, the informed trader selects the trade that maximizes her profit given her information. We denote by α_v the fraction of traders informed of V who choose to trade in the security market, and by β_v the fraction of traders informed of V who choose to use calls given that they trade in the options markets. The exact values of $(\alpha_{\underline{V}}, \alpha_{\overline{V}}, \beta_{\underline{V}}, \beta_{\overline{V}})$ are determined in the equilibrium.

Before proceeding to that calculation, it may be useful to summarize the main parameters and structure of the game being considered. As Figure 1 indicates, the first move of the game is nature's decision regarding the existence and type of any new information. Following that determination, a trader is randomly selected to trade from the population of traders. A trade outcome (e.g., buying or selling stock, buying or writing a call, or buying or writing a put) occurs, and the game reverts back to the trader selection process. The game continues from that point (given by the dotted line in Figure 1) repeatedly throughout the trading day.

[8] Allowing multiple simultaneous trades introduces numerous problems into the analysis. First, the informed would want to trade an infinite amount. This can be mitigated by introducing a wealth constraint or by imposing some type of risk aversion (combined with imperfect information signals) on the informed, but these are clearly arbitrary in our framework. Second, marketmakers would not be willing to trade any amount at their given quote, and their resultant quote changes make calculating the actual transaction price problematic. Our approach allows for multiple trades, just not simultaneous ones. This seems more consistent with actual market behavior.

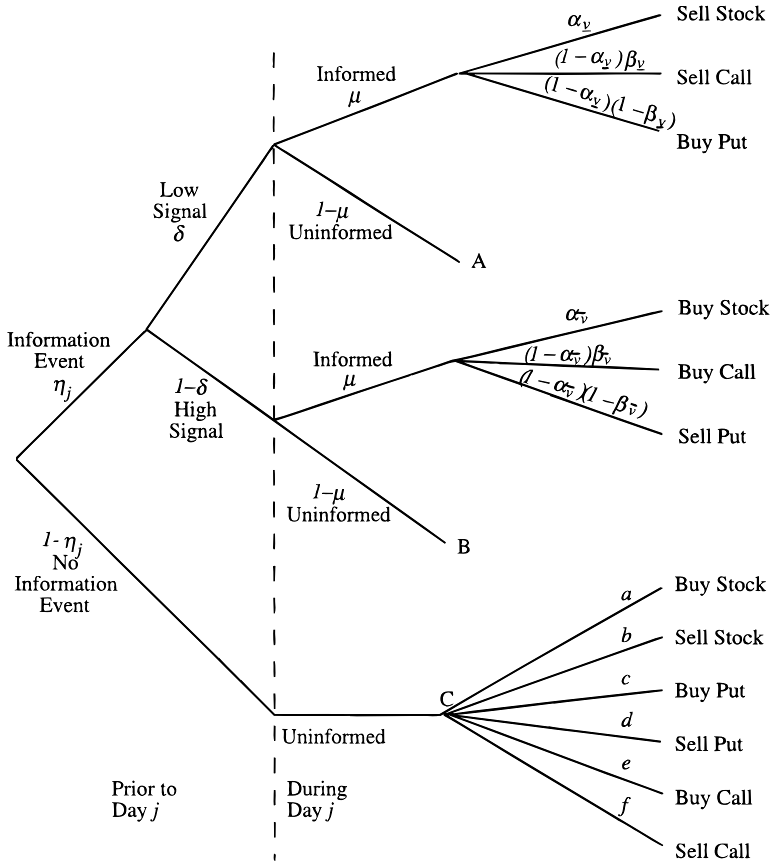

Figure 1. The structure of trading. The tree diagram gives the probabilistic structure of trading. The game begins at the first node with nature's draw for an information event. Subsequent nodes reflect the trader selection probabilities. The probabilities of trades are the same at each uninformed node A, B, and C. The game repeats from the dotted line throughout the trading day. The variable η_j is the probability of an information event occurring; δ is the probability that the signal is low, $(1 - \delta)$ the corresponding probability that the signal is high; μ is the fraction of the universe of traders who are informed, and $1 - \mu$ are uninformed; α_v is the fraction of informed who choose to trade in the security market, β_v the fraction of informed traders who choose to use calls given that they trade in the options markets; a, b, c, d, e, f are the propensity of the uninformed to buy or sell the stock or options.

A. Equilibrium Prices in the Option and Security Markets

Equilibrium in the option and stock markets requires that the prices the marketmakers set result in zero expected profit given their beliefs regarding the behavior of the informed, and that, given the marketmakers' prices, the optimal behavior for the informed is as conjectured. Because each marketmaker's price depends on how likely he believes the informed are trading in his market, the question of interest is, where will the informed trade? To determine this, we first solve for the marketmakers' optimal prices given probabilities of informed trade. We then derive conditions under which the informed will choose to trade in only one market (α_v and β_v are at their boundaries), and conditions when the informed will mix between the two markets (α_v and β_v are interior).

It is easy to show that the marketmakers' price to buy or sell any contract will be its conditional expected value given the specific trade that occurs. For the equity market, the marketmaker's bid price is then the expected value of the asset given that a trader wants to sell the asset to the marketmaker, and the ask price is the corresponding expected value if someone wants to buy the asset. Calculation of these conditional expected values follows from a standard application of Bayes' Rule, and it results in the following bid and ask prices for the first trade of day 1:

$$\begin{aligned} b_s &= E[V|\mathit{Sell\ Stock}] \\ &= \frac{\underline{V}\eta_1\delta(\mu\alpha_{\underline{v}} + (1-\mu)b) + \bar{V}\eta_1(1-\delta)b(1-\mu) + V^*(1-\eta_1)b}{\eta_1[\delta(\mu\alpha_{\underline{v}} + (1-\mu)b) + (1-\delta)b(1-\mu)] + (1-\eta_1)b} \end{aligned} \tag{3}$$

$$\begin{aligned} a_s &= E[V|\mathit{Buy\ Stock}] \\ &= \frac{\underline{V}\eta_1\delta(1-\mu)a + \bar{V}\eta_1(1-\delta)(\mu\alpha_{\bar{V}} + (1-\mu)a) + V^*(1-\eta_1)a}{\eta_1[\delta(1-\mu)a + (1-\delta)(\mu\alpha_{\bar{V}} + (1-\mu)a)] + (1-\eta_1)a}. \end{aligned} \tag{4}$$

The bid and ask prices in the options market will also be conditional expected values, but their determination is more complex. Because we restrict our attention to European options, the options' payoffs are a function of the asset's value at time J. With the marketmakers being risk neutral, only information affects prices; consequently, we can ignore factors such as inventory which might otherwise be expected to affect prices. Suppose we first consider the value of the call option. The call option gives the holder the right to buy the stock at time J for price Y. Suppose that a low information event has occurred. Then the right to buy the asset at Y is worthless, and the call value is zero. Alternatively, suppose that a high information event has occurred. Then the call option is worth $\theta(\bar{V} - Y)$. Finally, if there has been no new information, then the call is worth its expected value.

The bid price for the call option will be the conditional expected value of the call given that a trader wishes to sell the call to the market maker. This is given by

$$\begin{aligned} b_c &= E[\mathit{Value\ of\ Call}|\mathit{Sell\ Call}] \\ &= 0\,\Pr\{\underline{V}|\mathit{Sell\ Call}\} + (\bar{V} - Y)\theta\,\Pr\{\bar{V}|\mathit{Sell\ Call}\} \\ &\quad + (\delta\cdot 0 + (1-\delta)(\bar{V} - Y)\theta)\Pr\{\Psi = 0|\mathit{Sell\ Call}\}. \end{aligned} \tag{5}$$

Calculating the conditional probabilities yields the bid for the first call trade on day 1:

$$b_c = \frac{(\bar{V} - Y)\theta(1-\delta)f(1-\eta_1\mu)}{\eta_1[(1-\delta)(1-\mu)f + \delta(\mu(1-\alpha_{\underline{v}})\beta_{\underline{v}} + (1-\mu)f)] + (1-\eta_1)f}. \tag{6}$$

Notice that if $\delta = 1$ (the probability that $V = \underline{V}$), or if $f = 0$ (the fraction of uninformed traders), then the bid will be zero. This makes sense because if $V = \underline{V}$ an option to buy at Y is worthless. Similarly, if there are only informed traders in the market, the marketmaker's zero profit constraint can only be met at a price of zero. The ask price for the call option can be found in a similar fashion.

Now consider the determination of put prices. The put gives the holder the right to sell the asset at time J for price X. If the asset is worth $\bar{V}$, then the put value is zero. If the asset is worth $\underline{V}$, then the put value is $\theta(X - \underline{V})$. Finally, if the asset is worth V^*, the put is worth its expected value. Given these terminal values, the ask price for the put is its expected value given that a trader wishes to buy the put. This is given by

$$\begin{aligned} a_p &= E[\textit{Value of Put}|\textit{Buy Put}] \\ &= \theta(X-\underline{V})\Pr\{\underline{V}|\textit{Buy Put}\} + 0\cdot\Pr\{\bar{V}|\textit{Buy Put}\} \\ &\quad + (\delta\theta(X-\underline{V}) + (1-\delta)0)\Pr\{\Psi = 0|\textit{Buy Put}\}. \end{aligned} \tag{7}$$

Again, an application of Bayes' Rule yields an ask price for the first put on day 1 of

$$a_p = \delta\theta(X-\underline{V}) \cdot \frac{\eta_1\mu(1-\alpha_{\underline{v}})(1-\beta_{\underline{v}}) + \eta_1(1-\mu)c + (1-\eta_1)c}{\eta_1[(1-\delta)(1-\mu)c + \delta(\mu(1-\alpha_{\underline{v}})(1-\beta_{\underline{v}}) + (1-\mu)c)] + (1-\eta_1)c}. \tag{8}$$

These bid and ask prices in equations (3) through (8) give the marketmakers' initial prices for buying and/or selling the security, the call option, and the put option. Notice that each depends on the expected presence of informed traders in the respective market, and this is a function of the probability of informed trading overall (the $\mu\eta_1$), and of the fraction of informed traders believed to be in each market (the $\alpha_{\underline{v}}$ and $\beta_{\underline{v}}$, and $\alpha_{\bar{V}}$ and $\beta_{\bar{V}}$).

From an option pricing perspective, it is natural to ask how any option price changes as the underlying stock price changes. Calculating this derivative, the option's delta, implicitly treats the stock price process as an exogenous process that determines the option price process. In our equilibrium model, however, both processes are endogenous. At any time t, the notional price of the stock (its expected value conditional on the history of trades) is

$$p_{st} = \gamma[\delta_t \underline{V} + (1 - \delta_t)\overline{V}], \tag{9}$$

where δ_t is the conditional probability of $\underline{V}$ given the history of trades.[9] Similarly, the notional price of a put option is

$$p_{pt} = \theta(X - \underline{V})\delta_t \tag{10}$$

and for the call it is

$$p_{ct} = \theta(\overline{V} - Y)(1 - \delta_t). \tag{11}$$

These prices change only as beliefs change, and we can ask how a change in beliefs affects relative prices. The delta of the put (the implicit derivative of p_{pt} with respect to p_{st}) is thus

$$-\frac{\theta(X - \underline{V})}{\gamma(\overline{V} - \underline{V})} \tag{12}$$

and the delta for the call is

$$\frac{\theta(\overline{V} - Y)}{\gamma(\overline{V} - \underline{V})}. \tag{13}$$

These expressions for the option deltas hold regardless of where the informed trade. Notice that the relative leverage (the θ/γ terms) plays an important role. This is understandable as how much the price of the option contract changes with the stock price is affected by this leverage. Our analysis here focuses on a specific put and call, but these expressions also would hold more generally with θ indexed to reflect the specific option characteristics. We now turn to the derivation of equilibrium informed trading. Not surprisingly, the deltas affect the behavior of informed traders.

B. Where Do Informed Traders Trade?

We now wish to determine when informed traders will, in fact, trade in the options market. This involves determining the conditions under which the equilibrium will involve $\alpha_{\underline{v}}, \alpha_{\overline{V}} < 1$. We provide the calculations for the case where traders are informed that $V = \underline{V}$. Suppose that $\alpha_{\underline{v}} = 1$, or that there are no informed traders choosing to transact options. Then we seek conditions so that at $\alpha_{\underline{v}} = 1$, the profit to an informed trader of trading in the

[9] This is the expected value of the stock at t, prior to the arrival of any order to buy or sell. If we examine quotes, or actual trade prices, we must consider bids and asks, but it is not clear which is relevant for an option delta.

option exceeds the profit from trading in the security. These conditions dictate when in equilibrium we will find informed traders in the options market.[10]

Recall that from equation (1), a trader informed of $\underline{V}$ will choose to either sell the stock, sell the call, or buy a put. From our pricing equations above, it is easy to calculate that the expected profit from selling the stock (if $\alpha_{\underline{v}} = 1$) is

$$\frac{\gamma(1-\delta)(1-\eta_1\mu)b(\bar{V}-\underline{V})}{\eta_1\delta\mu + b(1-\eta_1\mu)}. \tag{14}$$

The expected profit from selling the call (if $\alpha_{\underline{v}} = 1$) is

$$(\bar{V} - Y)\theta(1-\delta), \tag{15}$$

and the expected profit from buying the put (if $\alpha_{\underline{v}} = 1$) is

$$(X - \underline{V})\theta(1-\delta). \tag{16}$$

These profit conditions dictate that some informed traders will use options if

$$(\bar{V} - Y)\theta \text{ or } (X - \underline{V})\theta > \frac{\gamma(1-\eta_1\mu)b(\bar{V}-\underline{V})}{\eta_1\delta\mu + b(1-\eta_1\mu)}. \tag{17}$$

This inequality determines where the informed traders will choose to trade. If the inequality in equation (17) is satisfied, then at least some informed traders will choose to transact in the options market. This corresponds to a "pooling equilibrium" in that both liquidity traders and some informed traders will be pooled together in the options market. If (17) does not hold, then no informed traders use options, leaving only liquidity traders in the option market. We call this a "separating equilibrium" in that the informed are separated from uninformed traders in the options market. In either equilibrium, there will be informed traders in the stock market, and there will be liquidity traders in both the options and the stock markets.

Inequality (17) clearly holds for large θ, small γ, small b, or large $\eta_1\mu$. Hence, if the leverage effect of options is large enough (i.e., the number of shares θ controlled by the option is large relative to the γ shares in the stock trade), or if the liquidity (or fraction of uninformed, b) in the stock is small, or there are many informed traders ($\eta_1\mu$ near 1) then at least some informed traders use options. As might be expected, inequality (17) can also be expressed in terms of the option deltas given in equations (12) and (13). If the absolute value of the put or call option delta is small enough, then informed

[10] This approach is essentially identical to Easley and O'Hara's (1987) analysis of equilibria with multiple trade sizes. There, informed traders have to select the trade that maximizes their profit, a problem isomorphic to that of selecting between the option and the stock. For a related approach see John et al. (1993).

traders do not use options. A similar analysis for those informed of $V = \bar{V}$ reveals that at least some traders informed of good news use options for large θ, small γ, and small a.

What is important to notice is that for some parameter values, the equilibrium is one where the informed traders *only* use stocks. This will occur, for example, if the liquidity of the options market is low. In this case, the profit to informed traders is higher trading in the stock market, and so the options market functions only to handle liquidity-based trading. Thus, it is not always true that options markets are venues for information-based trades. If inequality (17) is satisfied, however, such a separating equilibrium cannot prevail, and the informed are instead "pooled" with traders in both markets.

We can now compute the equilibrium fraction of informed traders who use each market and the resulting equilibrium prices. We consider pooling equilibria, and we provide necessary and sufficient conditions for the equilibrium to be of this type. To keep the results manageable (and useful for providing intuition), we display the equilibrium only for a special case. First, we make the realistic assumption that the uninformed are equally likely to buy or sell any asset. Second, we assume that an information event is known to have occurred. The primary effect on this assumption is to increase spreads in all markets. Finally, we assume that the strike prices of the options we study are at the limits of the price range; that is, $X = \bar{V}$ and $Y = \underline{V}$. Moving the strike prices into the price interval reduces the leverage on an option contract, and it thus has the same qualitative effect on equilibria as reducing θ.

Under our assumptions, calculation shows that necessary and sufficient conditions for an interior equilibrium are[11]:

$$b(1-\mu)(\gamma-\theta) < \left[\begin{array}{l} \delta\mu\theta \\ \text{and} \\ (1-\delta)\mu\theta \end{array}\right. \tag{18}$$

and

$$(d+f)(1-\mu)(\theta-\gamma) < \left[\begin{array}{l} \delta\mu\gamma \\ \text{and} \\ (1-\delta)\mu\gamma \end{array}\right. . \tag{19}$$

The keys to an existence of a pooling equilibrium are the relative number of shares controlled in a stock or option transaction (i.e., γ versus θ), and the

[11] During any trading day, the marketmaker's beliefs are updated and the probabilities of informed trade change in response to the trading history. Thus some of the parameters in equations (18) and (19) change over time. Nonetheless, the conditions for an interior equilibrium at any time t are just equations (18) and (19) with δ, b, d, and f replaced by their time t values.

depths of the markets b, d, and f.[12] When these conditions are satisfied, the equilibrium fraction of traders informed of $\underline{V}$ who use the stock market is

$$\alpha^*_{\underline{V}} = \frac{b[(d+f)(1-\mu)(\gamma-\theta)+\gamma\delta\mu]}{\delta\mu[(d+f)\theta+\gamma b]}. \tag{20}$$

For those informed of $\overline{V}$, the result is the same, but with δ replaced by $1-\delta$. For either type of informed trader, the equilibrium fraction of those in the options market who use calls is

$$\beta_{\underline{V}} = \beta_{\overline{V}} = f/(d+f). \tag{21}$$

Informed traders move across markets to equalize profits in each market. Hence, where informed traders trade can be determined by looking at how market characteristics affect the profit from trading in each market. Increasing the depth of the stock market (b), or reducing the depth of the options markets ($d + f$), results in more informed traders using stocks, and the converse induces more informed trading in options. Market depth also affects the composition of trading, in that the informed traders who use options split across puts and calls according to the depth of each market. Finally, increasing the relative leverage in the options market ($\theta - \gamma$) results in more informed traders using options.[13]

Recall that our analysis has considered only the case where traders are allowed to trade in a given put and a given call if they choose to trade options. To the extent that more option contracts are available, the ability to "hide" in the options markets for informed traders will be enhanced, and this suggests a greater likelihood of a pooling equilibrium. It also suggests, however, that *within* option series the question of pooling versus separating equilibria will arise because informed traders may prefer to trade specific types of contracts. We do not consider these equilibria here, although the same general analysis above would apply. Provided that at least some informed traders choose to trade in options markets, then the volume of these trades will provide a signal of the underlying private information.

The most interesting implication of our results is what they reveal about this information content of trades in the various markets. We can ask, for example, which of a stock sale, the purchase of a put, or the sale of a call increases the posterior probability of a low event more. We define one trade to have greater information content than another if it moves posterior beliefs by more. Calculation shows that if the leverage on an option trade (θ) is greater than that on a stock trade (γ), then option trades carry more information than do stock trades. This is consistent with Black's (1975) conjecture regarding the advantages of leverage in options markets for informed

[12] If multiple trade sizes are allowed in each market, then the number of shares controlled by various sized trades and the depth of the markets at various sizes will all matter.

[13] These leverage effects are investigated empirically by Mayhew et al. (1995).

traders. What may be more intriguing is that information content is *not* affected by market depth. This result arises because in equilibrium informed traders offset the effect of depth by moving across markets.[14]

We can now display equilibrium quotes for the first trade in each market. For the stock market, we have

$$b_s^* = V^* - \frac{(1-\delta)(\bar{V} - \underline{V})[(d+f)(1-\mu)(\gamma-\theta) + \gamma\delta\mu]}{\gamma[(1-\mu)(b+d+f) + \delta\mu]} \tag{22}$$

$$a_s^* = V^* + \frac{\delta(\bar{V} - \underline{V})[(d+f)(1-\mu)(\gamma-\theta) + \gamma\delta\mu]}{\gamma[(1-\mu)(b+d+f) + \delta\mu]}. \tag{23}$$

These prices show that, as is usually the case in an asymmetric information world, a spread develops around the prior expected value of the asset. This spread generates profits from uninformed traders which offset the losses to informed traders.

Market conditions in each market affect the equilibrium probability of informed trade, and so also affect the spread. For example, making the options markets deeper, or increasing the relative leverage of options, attracts informed traders to options and reduces the spread in the stock market. Alternatively, an increase in the depth of the stock market has two effects. First, holding the probability of informed trade constant, it reduces the spread, as greater depth lowers the risk of losses to the informed. Second, greater depth makes the stock market more attractive to the informed, and so increases the fraction of informed who use stocks. This effect increases the spread. Calculation shows that the total effect of increasing stock market depth is to reduce the spread. Finally, we note that an increase in the variance of stock prices (we use $\bar{V} - \underline{V}$ as a proxy for this) lowers the bid price and raises the ask price.

The equilibrium quotes for the first trade in the put market are:

$$a_p^* = (\bar{V} - \underline{V})\left[\frac{(1-\mu)\delta[(d+f)\theta + \gamma b] + \delta\mu\theta - (1-\mu)b(\gamma-\theta)}{(1-\mu)(d+f+b) + \delta\mu\theta}\right] \tag{24}$$

$$b_p^* = \frac{(\bar{V} - \underline{V})\delta(1-\mu)[(d+f)\theta + \gamma b]}{(1-\mu)(d+f+b) + (1-\delta)\mu\theta}. \tag{25}$$

Quotes for calls are the same but with δ replaced by $1-\delta$. In the options market, just as in the stock market, the potential for informed trading generates a spread. It is easiest to see this spread when $\delta = \frac{1}{2}$. In this case, the option spread is

[14] If multiple trade sizes are considered and the market is in an equilibrium in which informed traders use large transactions in each market, then the same conclusion holds where θ and γ are interpreted as the leverage on large options and large stock trades, respectively.

$$\frac{(\bar{V} - \underline{V})\left[\frac{\mu\theta}{2} - (1-\mu)b(\gamma - \theta)\right]}{(1-\mu)(d+f+b) + \frac{\mu\theta}{2}}. \tag{26}$$

Under our conditions for the existence of a pooling equilibrium, this spread is positive. The spread is decreasing in the depth of each of the markets. An increase in the variance of stock prices $(\bar{V} - \underline{V})$ raises both bid and ask prices for options as the options become more valuable, and causes the spread in the options market to increase as well.

Given any first-period trade, we could update the marketmakers' beliefs, evaluate the probabilities of uninformed trade, and quote new prices for subsequent trades in each market.[15] However, our primary interest is not in a detailed characterization of the time series of quotes and prices in stock and options markets. Instead, our focus is on the linkages between the two markets and on the particular role played by information. Our model provides a number of specific predictions regarding this information linkage, and in the next section we investigate these in more detail.

II. Option Volume and Stock Prices: Empirical Specification

Our theory predicts that if options markets are venues for information-based trading then, in equilibrium, option trades of various types convey information on future stock price movements. Buying a call or selling a put are option trades that will be used by traders informed of good news, and we call these trades *positive option trades.* Selling a call or buying a put we term *negative option trades*, as they will be entered by traders acting on bad news. In a pooling equilibrium, a positive option trade provides a positive signal to all marketmakers, who then increase their bid and ask prices. Similarly, a negative option trade depresses quotes. Because market participants can learn from trades in both markets, option trades will affect the subsequent behavior of the stock market.

We are interested in whether these predictions of our pooling equilibrium are consistent with the outcome of real markets. This suggests testing the basic hypothesis that knowledge of past option trades is valuable in predicting stock price changes. Our theory says that it is because of the option trading behavior of informed traders that the volumes of particular types of option trades have predictive power. If, instead, options are used *only* as hedging vehicles, then all option trades would be liquidity-based (i.e., un-

[15] Our model could be used, as in Easley, Kiefer, and O'Hara (1996, 1997), to produce likelihood functions for the trade process. If we assume that the fraction of informed traders who use options is fixed over time, then the parameters of the trade process could be estimated. This would produce an estimate of the information content of option trades. We have not pursued this approach here because we are skeptical of the hypothesis that the equilibrium fraction of the informed traders who use options is fixed over time.

informative) and we would not expect to find any link between option volumes and stock prices. Our theory tells us how to test this prediction by stipulating which option volumes to consider. A finding that neither positive nor negative option volumes are predictive is consistent with a separating equilibrium in which informed traders only use stocks.

Testing the alternative hypotheses of a pooling or a separating equilibrium requires recognizing some basic regularities of the trading process. In our theoretical model, information flows immediately from one market to another. This "instantaneous efficiency" is almost surely an abstraction from the frictions of actual markets. Order placement time, order reporting time, queuing time for orders submitted via electronic routing, even delays in the ticker, could all contribute to a "natural" rate of delay in the adjustment of prices between markets. To allow for the possibility that these frictions matter, we need to employ a testing approach that allows the linkages between the markets to exhibit some fixed regularities in addition to the patterns predicted by our model.

We use the technique of causality testing proposed by Granger (1969) and Granger and Newbold (1977) to investigate the relationship between option volume and stock price changes. Causality testing allows us to determine if one market leads the other, and if so, for how long. The first step in the causality test procedure involves identification of the individual univariate time series using autoregressive integrated moving average (ARIMA) models to generate prewhitened series. We discuss this prewhitening procedure after describing the data. The second step in the procedure involves formulation of causal regression models to be estimated using prewhitened data. Causality between the identified univariate series can be tested using multiple time series regressions of the form

$$\Delta S_t = \beta_{-1} + \sum_{i=0}^{K} \beta_i V_{t-i} + \varepsilon_t \tag{27}$$

and

$$V_t = \phi_{-1} + \sum_{i=0}^{K} \phi_i \Delta S_{t-i} + \xi_t, \tag{28}$$

where ΔS_t denotes the prewhitened time series of stock price changes, and V_t is the option volume series of interest—for example, positive option volumes. Lags of option volume and the stock price change series are denoted by subscripts $t-1, t-2, \ldots$, the coefficients with subscript -1 are constant terms, and ε_t and ξ_t are disturbance terms assumed to satisfy $E(\varepsilon_t | v_{t-i,i=0,1,\ldots,\kappa}) = 0$ and $E(\xi_t | \Delta S_{t-i,i=0,1,\ldots,\kappa}) = 0$.

Interpretation of the various parameters provides a way of differentiating between theories of market behavior. Given the prewhitening of our series, the constant terms would be expected to pick up any remaining market frictions. The other terms pick up the interactions between the markets. If these interactions occur simultaneously, we would expect β_0 and ϕ_0 to be significant, with none of the lag coefficients being significant. If, instead, market linkages take some time, then these lag effects would be identified by significance of the coefficients on the lagged stock price change or option volume series.

Our theoretical model provides specific predictions regarding these coefficients. Our model predicts that in a pooling equilibrium the coefficients on option volume (the β's) will be statistically significant when volume is measured as either positive option volume or negative option volume. This is consistent with the prediction that information is reflected in options markets, and some traders, expecting a change in the price of the underlying stock, trade in specific options first. If this information transfer occurs quickly, we would only expect β_0 and ϕ_0 to be significant. It is equally consistent with our approach, however, that this adjustment could take time, in which case we would expect to see the lagged coefficients significant as well. A finding that none of the β coefficients is significant is a rejection of our hypothesis of a pooling equilibrium.

It is important to stress that we are looking at the link predicted by our model between option volume and stock prices, and not price-to-price or volume-to-volume links. These other variables could well be contemporaneously linked because of trading in the stock which, by put–call parity, induces contemporaneous trading in the option. Starting with volume in the option, however, does not provide a reason for a contemporaneous move in the stock price unless the option volume is informative. In our model, liquidity-induced trading in the option should not change the stock price because it does not change the stock's fundamental value.[16]

Note that, in general, we would not expect to find *overall* option volume to have predictive power. This is because options are used for a wide variety of liquidity-based purposes, and these would generally involve using options to follow (rather than lead) movements in the underlying stock.[17] Similarly, we would expect to find significant coefficients on the ϕ variables. Significance of stock price changes on option volumes is consistent with hedging activity. A failure to find evidence of such behavior would raise concerns about the validity of our testing approach.

Formally, the null hypothesis that the markets are in a separating equilibrium and thus the option volume series does not have predictive power for stock prices can be stated as follows:

HYPOTHESIS 1: $\beta_1 = \beta_2 = \cdots = \beta_K = 0$.

[16] In Section IV, we discuss factors not in our model which could generate links between the option and stock markets.

[17] Moreover, because every option trade has both a writer and a buyer, simply looking at overall volume essentially "averages" the buyer and seller together. This makes it impossible to determine the active side of the trade, and so vitiates the information content.

Hypothesis 1 can be tested using the likelihood ratio test for the restricted ($\beta_1 = \beta_2 = \cdots = \beta_K = 0$) and unrestricted equation system. Under the additional assumption that ε_t is normally distributed, the likelihood ratio test statistic is

$$2 \ln L = N(\ln \sigma_R^2 - \ln \sigma_U^2), \tag{29}$$

where N is the sample size, and σ_R^2 and σ_U^2 are the determinants of the variance–covariance matrices of the residuals of the restricted and unrestricted equations, respectively. The test statistic is distributed χ^2 with K degrees of freedom, where K is the number of restrictions imposed.

If Hypothesis 1 of a separating equilibrium is rejected, a natural question to investigate is the timing and direction of the predictive power of the joint series. This can be addressed by examining the behavior of the individual lag coefficients. In particular, the null hypothesis that the series are only contemporaneously related can be formally stated as follows:

HYPOTHESIS 2: *β_i and $\phi_i = 0$, individually for $i = 1,2,\ldots K$.*

Hypothesis 2 can be tested by simple t-tests of the significance of the individual coefficients.

Before proceeding to our empirical testing, there are several implementation issues that must be considered. First is the question of the time period. Actual data do not come in discrete, fixed intervals with at most one trade per interval. Any choice of a time interval will necessitate aggregating transactions over that interval and choosing a price for the interval. To be consistent with previous empirical work on the linkage between stock and options markets (see Stephan and Whaley (1990)), we use a 5-minute interval. Within each interval we aggregate, separately, buys of puts, sells of puts, buys of calls, and sells of calls.

Second, our model assumes that option traders transact in either a given call option or a given put option. Actual markets have series of options, allowing traders a wide range of trading choices. In our empirical work, we include all option series for which sufficient trading volume exists to make our statistical inferences meaningful (more discussion of how much trading is needed is given shortly). This multidimensional trading ability increases the ability of informed traders to "hide" in the market, and it also reduces our ability here to find them. Of particular concern is that informed traders may select option contracts that are not otherwise heavily traded, and thereby fall below the volume level needed for our analysis. To the extent that this happens, our analysis will understate the information content of option trades.

The third choice we face is how to aggregate transactions of various sizes. We have chosen to aggregate by volume rather than just by counting the number of transactions. Again, this makes our empirical work consistent with the previous work on this topic. The implicit assumption underlying this choice is that an option trade's information content is linear in trade size (i.e., a trade of size $2X$ is equivalent to two trades of size X).[18] To the extent that this admittedly arbitrary aggregator is inappropriate, our ability to predict stock prices from options data will be reduced. Thus, if we find that past option volumes have information content, better aggregators could only strengthen this finding.

Finally, we need to decide how to measure the stock price change for each interval. Our theory says that in a pooling equilibrium option trades cause changes in stock quotes and, thus, in stock transaction prices. The simplest notion, and the one used in previous empirical work, uses the last available trade price for the stock in each 5-minute interval. The stock price change series is then the first differences of these prices. We adopt this approach in our empirical testing.

III. The Data

The data are taken from the Berkeley Options Data Base which is derived from the Market Data Report of the Chicago Board Options Exchange (CBOE). The Berkeley data provide complete information for every option transaction, including the time of the transaction (in seconds), expiration month, strike price (negative for puts, positive for calls), bid and ask prices for the quote record, and trade price and size for a trade record, and the price of the underlying stock as of the trade closest to the option trade or quote. This study covers two months, October and November 1990, comprising a total of 44 trading days.

Our sample consists of the first 50 firms ranked according to daily trading volume in the Market Statistics report of the CBOE. The list of firms, ranked according to trading volume, along with average daily trading volume, is given in Table I. As the table indicates, our sample includes a wide range of option trading activity, from IBM with an average daily volume of over 29,000 contracts to Delta with an average daily trading volume of 825 contracts. There were 266 firms whose options traded on the CBOE during the time period under study. The total volume in the selected sample forms about 81 percent of the total trading activity in stock options on the CBOE.

Because of the multiplicity of option contracts that trade for each stock, there can be difficulties in interpreting the behavior of specific option series. In particular, options not at-the-money, or with long times to maturity, may have very little liquidity. Because we require volume measurements over short time intervals, the lack of trading dictates that the price–volume relation for these series may not be reliable. Similarly, expiration effects can

[18] The extension of our theoretical model to multiple trades provides little guidance about aggregation. One problem is that actual trades come in a variety of sizes, not just the few sizes that we can analyze theoretically. More important is that the equilibrium fraction of informed traders who use each trade size varies over the day, across days, and across options. Implementing a theoretically correct aggregation procedure would require determination of these changing conditions.

Table I

Sample Firms and Option Volume

The sample consists of the 50 most actively traded firms on the CBOE during October and November 1990. The table gives average daily contract volumes during this period.

Firm Name	Average (Daily) Option Volume	Average (Daily) Call Volume	Average (Daily) Put Volume
IBM Corp.	29,186	19,385	9,801
UAL Corp.	8,824	5,939	2,885
Upjohn	8,250	7,329	921
LA Gear	6,756	4,283	2,474
American General Corp.	5,761	4,572	1,189
GE Corp.	5,605	3,921	1,684
Eastman Kodak	4,399	3,469	930
Boeing	3,949	3,016	933
GM Corp.	3,593	2,345	1,248
Walmart	3,588	2,444	1,144
Citicorp	3,338	1,770	1,569
Coca-Cola	3,287	2,019	1,268
Merck	3,274	2,067	1,206
AT&T	3,122	2,268	853
Bristol Myers Squibb	2,941	2,190	751
Syntex Corp.	2,894	2,312	582
NCR Inc.	2,762	1,806	956
MCI Corp.	2,693	1,955	738
Johnson & Johnson	2,592	2,005	587
Norton Co.	3,492	2,022	1,469
PepsiCo	2,440	1,749	691
Oracle Systems	2,417	1,806	611
Paramount Communications	2,296	1,942	354
Hewlett Packard	2,295	1,427	868
Exxon Corp.	2,220	1,650	570
Chrysler Corp.	2,145	1,446	699
Dow Chemical	2,006	1,383	624
Ford Motor Co.	1,997	1,258	740
Great Northern Nekoosa	1,822	1,177	645
Blockbuster Entertainment	1,746	1,097	649
Avon Products Inc.	1,712	1,446	266
Homestake Mining Co.	1,648	1,316	332
Motel 6 L.P.	1,631	1,556	75
Sears Roebuck	1,613	1,047	566
BankAmerica Corp.	1,488	1,014	474
Occidental Petroleum	1,422	1,125	297
McDonald's	1,402	973	429
Bolar Pharmaceutical	1,385	706	679
ToysRUs	1,290	848	442
Federal Express	1,240	873	367
Texas Instruments	1,221	915	306
Amoco	1,221	990	231
Baxter Labs	1,151	934	218
Limited Inc.	1,148	755	393
Minnesota Mining	1,102	767	335
Atlantic Richfield	1,094	731	362
Polaroid Corp.	1,082	827	255
Schlumberger	1,046	858	188
Xerox	973	720	253
Delta Airlines	825	448	377

introduce interpretation difficulties, as can trading surrounding dividend payments. This latter effect is due to the increased possibility of early exercise.

The liquidity issue is addressed by using two activity filters. These filters are designed to include only those option series that trade frequently. The first filter retains only option series with more than 50 trades per day, and the second retains option series with more than 100 trades per day. These filters were chosen after analyzing alternative filters, and they allow us to draw inferences from the largest possible number of option series without too many intervals of no-trade. We note, however, that this filtering limits our ability to address some interesting implications of our theoretical analysis, in particular those relating to the differential use of out-of-the-money and at-the-money options by informed traders.[19]

We adjust for expiration effects by excluding from our sample all transactions occurring on the expiration date of any option series. To control for ex-dividend date differences in option trading, we excluded all option trades on the ex-date for the relevant stocks in our sample. Finally, the data were also processed to remove obvious reporting errors.

A. Summary Statistics

The 44 trading days of data in our sample have 441,501 transactions, with 262,809 trades in October and 178,692 trades in November. Transactions in calls form 64 percent of these trades, with the rest being in puts. The total volume traded in this period is 4,884,474 contracts, with 64.7 percent in calls and the rest in puts. The mean trade size is 10.9 contracts per trade, with the mean trade size in calls being 11.02 contracts, and that in puts being 10.68 contracts.

The imposition of our "active" filters (i.e., the 50 and 100 trades a day filters) substantially reduces the sample size. With the 50 trades per day filter, the total number of transactions is 149,116, with calls accounting for 74.85 percent of the transactions. The total volume in these options is 1,683,407, and trading in calls forms 74.1 percent of total volume. The mean trade size in this subsample is 11.14 contracts, with mean call size of 11.03 contracts and mean put size of 11.45 contracts. The 100 trades per day filter reduces the subset to 81,903 transactions, and a total of 966,020 contracts traded. Trading in calls comprises 78.1 percent of transactions and 78.44 percent of volume, and the mean trade size is 11.86 contracts.

As can be seen from the preceding analysis, the active option series (with 50 trades per day) forms roughly one-third of the data in terms of transactions and traded volume. As would be expected, imposing activity filters increases the mean trade size. The proportion of trading in calls also goes up, providing evidence that calls are more actively traded than are puts. Interestingly, the mean trade size in puts approaches that of calls after the imposi-

[19] As might be expected, the frequency of trading in the out-of-the-money options is too small to make statistical inferences possible.

tion of the activity filters. Trading in both puts and calls is largely concentrated in the near-to-maturity, closest-to-the-money contracts. More than 90 percent of active trading (more than 100 trades per day) occurs in call option series expiring in the current month or in the succeeding month. For puts, this fraction is over 98 percent, both in terms of transactions and volume.

B. Trade Classification

Our theory predicts that in a pooling equilibrium traders acting on information transact in specific options, and this necessitates calculating finer partitions of our option volume series. In particular, we need to calculate the time series of long calls (i.e., a trader buys a call), short calls (a trader writes a call), long puts (a trader buys a put), and short puts (a trader writes a put). Because every trade has both a buyer and a seller, it is necessary to classify the "active" side of each option transaction. Given the trade classification, we then determine separate option volume time series for long call volumes, short call volumes, long put volumes, and short put volumes.

The Berkeley Options Data Base does not classify trades as buyer-initiated or seller-initiated. This classification must be done using quote and trade information. For researchers using transactions data, this classification problem is ubiquitous, and a cursory review of empirical papers using equity transaction data reveals many trade classification techniques. Lee and Ready (1991) present an excellent survey of techniques currently in use and evaluate their efficiency using NYSE transactions data.

The approach we pursue is as follows. For each trade, the active quote is identified. Then, we identify the trade as a buy or a sell by the following algorithm:

1. Trades occurring in the lower half of the spread, at the bid or below, are classified as sells. A similar scheme is used for trades in the upper half of the spread and these are classified as buys. Trades occurring below the bid or above the ask are classified similarly.
2. Trades occurring at the midpoint of the spread are first classified using the "tick test" applied to the previous trade. If the current trade price occurs at a price higher than the previous one, it is classified as a buy (trade on an uptick). A trade on a downtick is classified as a sell. Trades unclassifiable using the previous trade are classified using the "zero-uptick" or the "zero-downtick" test, which identifies the last price change and then uses the tick test strategy.[20]

[20] Lee and Ready suggest a classification scheme wherein the quote prevailing 5 seconds before the transaction is used to classify the current trade, rather than the most recent quote. They argue that because of reporting protocols on the NYSE, the quote revision resulting from a current trade is likely to be recorded before the current trade, thereby biasing the trade classification. On the CBOE, however, the frequency of quote revisions is less than five seconds, and so using the most recent quote does not cause a bias in classification. The classification scheme we use captures the natural concept that buys tend to go at higher prices, and sales at lower prices. We caution, however, that trading and reporting protocols on the CBOE may introduce timing difficulties in the data, and to the extent that these are large, our classification scheme will be affected.

Table II

Results of the Trade Classification Scheme

This table gives the results of the trade classification scheme used in this paper, in Vijh (1988), and in Stephan and Whaley (1990). The data from Oct. to Nov. 1990 are from our sample. Data from Jan. to Dec. 1988 are from Stephan and Whaley (1990). The remaining data are from Vijh (1988).

	Percentage of Trades Classified			
	CBOE			NYSE
Classification Rule	Sept.–Oct. '76	Mar.–Apr. '85	Oct.–Nov. '90	Jan.–Dec. '88
Above the quote midpoint	43.8	48.13	53.40	37.6
At the quote midpoint	21.02	17.38	7.77	22.8
Below the quote midpoint	35.18	28.98	38.83	39.6

Table II gives trade classification statistics using results published in Stephan and Whaley (1990) and Vijh (1988), along with findings of the current research. Several interesting observations can be made. First, the percentage of trades going off at the midpoint of the spread is far lower in CBOE trades than in NYSE trades. Vijh offers the explanation that the market design of the CBOE—a competitive dealer system—might be the cause of this phenomenon as marketmakers offer their lowest quotes, and hence are not willing to bargain on transactions prices. An alternative explanation is that if informed trading occurs on the CBOE, and, if it is harder to detect given the multiplicity of dealers, then marketmakers protect themselves by trading at quoted prices more often.

A second observation from Table II is that, over time, the percentage of trades executed at the spread midpoint shows a strong downward trend. This should make trade data more easily classifiable using quote data alone. Also, although studies of NYSE transactions report a roughly even split between buys and sells, it is clear that trades on the CBOE are increasingly buys. Hence, options are actively bought, rather than sold. This strengthens the argument against using transactions prices in studies of option market–stock market interactions, as these prices are more likely to be at the ask than at the bid and, hence, would bias upward the implied stock price.[21]

For each option series of interest that we construct from this trade classification scheme, we sum volumes over 5-minute intervals. The option volume series are then normalized by subracting the mean and dividing by the standard deviation for each day. This normalization is done to allow us to

[21] Chan et al. (1993) argue that a second problem biasing stock and option prices are differences in price discreteness rules between markets. In particular, since in our sample period equities are constrained to eighths but options can employ sixteenths, there can be spurious lead–lag relationships found that reflect merely these discreteness differences. They argue that this can explain some of the lead–lag results of Stephan and Whaley (1990). In our research, this difference is not a problem because our analysis involves stock prices and option volumes, not option prices.

aggregate option series across the 50 securities in our sample. The disparate levels of trading in our sample securities would otherwise result in overweighting the effects of the most heavily traded options.

Trading hours on the CBOE begin at 8:30 a.m. and end at 3:00 p.m., resulting in 78 5-minute intervals during each trading day.[22] The option volume series reveal a distinct U-shaped intraday pattern. Both put and call option trading reach a peak about 45 minutes after the opening. The peak volume is almost 2 percent of daily traded volume for calls and about 2.75 percent of daily volume for puts. The volume falls to less than 0.5 percent of the daily volume by noon. It rises again in the afternoon and, although the level of the afternoon peak is not as high as the morning one for puts, it is marginally higher than the morning peak for calls. Trading volume then quickly falls off toward the close.

These volume patterns have two interesting implications. First, because early morning and late afternoon are the periods of high volume, such periods may include more informed trades as it is easier for informed traders to "hide" in the volume at that time (see Admati and Pfleiderer (1988) and Foster and Viswanathan (1990) for discussion of such behavior). Second, because peak option volume lags peak stock volume (which occurs at the opening) by about 45 minutes, the multiple regression results of our study must take this into account.

C. Serial Correlation in the Stock Price Change Series

The stock price closest to 8:30 a.m. is treated as the opening price and the closing stock price for each 5-minute interval is the last recorded price in the interval. As with option volumes, the stock price change series was normalized by subtracting the mean and dividing by the standard deviation of the series for each day. This normalization allows us to control for price level effects, which might be expected to influence the size of price movements.

The stock price change series also presents the issue of bid–ask bounce. Roll (1984) shows that random movement between bid and ask prices can cause negative first-order serial correlation, under realistic assumptions on transaction frequency. Roll uses daily data, where this issue may not present a serious problem. In a sampling design as fine as is necessary for our analysis, however, serial correlation in stock prices could present a serious problem.[23] Table III presents the serial correlation in the standardized stock price change series. It can be seen that the correlation is strongest at lag one, with almost no significant correlation thereafter. Given the fineness of our time filter, the bid–ask bounce could account for a significant part of the price changes.

[22] The opening transaction is deleted. Trading on the CBOE actually closes at 3:10 p.m., but the NYSE closes at 3:00 CST. To avoid nonsynchronicity in the data, all option contracts after 3:00 p.m. are deleted.

[23] Existence of negative first-order serial correlation has also been shown by Glosten (1987) and Stoll (1989).

Table III

Serial Correlation in the Stock Price Change Series

This table shows the impact of prewhitening the stock price change series using a moving average MA(1) process. Each lag interval is 5 minutes long. The MA(1) model parameter estimate is 0.1026, with the standard error of estimate = 0.0054 (t-ratio = 16.93).

Lag	Serial Correlation in Stock Price Series	Serial Correlation in Residual Series
1	−0.0911	0.005
2	−0.0409	−0.044
3	−0.0196	−0.026
4	−0.0111	−0.015
5	−0.0116	−0.015
6	−0.0149	−0.017
7	−0.0032	−0.005
8	−0.0032	−0.004
9	−0.0004	−0.002
10	−0.0137	−0.015

In our hypotheses testing, we are interested in determining the linkages between these stock price changes and option volumes. If the raw stock price change series is used without removal of the serial correlation, the noise in the series due to the bid–ask bounce is likely to dampen any relationship that may exist between the option volume and stock price change series. Thus, the approach taken in previous studies has been to correct for the bid–ask bounce by prewhitening the data. This prewhitening changes our price movements to price innovations, but it should not introduce any difficulties into the interpretation of our results.

Negative first-order serial correlation in the stock price change series can be modeled as an MA(1) process.[24] The residuals from this model are expected to be serially uncorrelated, and we use these residuals in our lead–lag hypothesis testing. The autocorrelation structure resulting from an MA(1) process is that there is correlation at lag one and no autocorrelation thereafter. Table III also shows the autocorrelations in the residual series. We find that no significant serial correlation exists in the residual series, and hence the MA(1) representation is an adequate model for the data.

IV. The Results

We now investigate the linkage between the options market and the equity market. Our testing procedures, detailed in Section II, involve multiple time-series regression analyses using normalized option volume and the prewhitened stock price series. For these regressions, we analyze different lag-length structures and find that almost all significant effects occur within six

[24] Stephan and Whaley (1990) use a similar formulation.

Table IV

Likelihood Ratio Tests of Option Volume on Price

This table gives likelihood ratio test results for stock price changes as a function of lagged option volumes. The designation "All" includes volume for all option trades aggregated over 5-minute intervals. "Positive option" volume includes volume for all long call and short put option trades aggregated over 5-minute intervals. "Negative option" volume includes volume for all long put and short call option trades aggregated over 5-minute intervals. Call includes volume for all call option trades aggregated over 5-minute intervals. Put includes volume for all put option trades aggregated over 5-minute intervals. Positive and negative option volume includes both variables, separately, as regressors.

	Likelihood Ratio Statistic	
Option Volume Definition Used	Contemporaneous Option Volume Included	Contemporaneous Option Volume Not Included
All	13.05	12.75
Positive options	29.08	11.17
Negative options	37.97	7.63
Call	13.02	12.96
Put	6.20	1.91
Positive and negative option volume	68.10	18.23
Critical χ^2 at 0.010	18.48	16.81

lags of option volume and stock price changes. Consequently, we present our results based on a six-lag specification.

We also run our analyses using three sets of data. In the first, all option series with at least 50 trades per day are studied. In the second, the 100 trades per day active option filter is used. Third, keeping intraday patterns in option volume results in view, the first 45 minutes of trading data are discarded and the estimations repeated. These data sets are designed to test whether option liquidity effects or intraday volume patterns affect our results. Our results with the three data sets are identical, suggesting a robustness to our testing approach. In the following tables, we report the results from the 50 trades per day filter.

A. The Multiple Regression Results

As discussed in Section III, we test our hypotheses by looking at the relation of lagged values of option volume and stock price changes. We first consider Hypothesis 1, where we test whether option volumes have predictive ability with respect to stock price changes. Table IV presents the results of likelihood ratio tests for joint significance of the coefficients of the multiple time series regressions. The first column gives the definition of option volume used in the regression. We segregate option volume into the standard definitions of put, call, and total volumes, and into the information-based definitions of positive and negative option volumes. The second column reports the likelihood statistic when contemporaneous option volumes and stock price changes are included as explanatory variables. Column three uses only past option volume and stock price changes in the regressors.

The first result to note in Table IV is that the hypotheses stating that total, put, or call option volumes do not have information content cannot be rejected at the 0.01 level with contemporaneous option volume included. The critical χ^2 value at this level is 18.48 and the likelihood ratio statistics for these hypotheses are 13.05, 6.20, and 13.02, respectively. Without contemporaneous option volume, the critical χ^2 value falls to 16.81 and the likelihood ratio statistics are all below 13. Thus, if option volumes are not sorted using our information-based theory, there is little or no evidence of information content in option trades.

Decomposing option volume into information-based components tells a different story. If the markets are in a separating equilibrium, then there will be no information content in option trades. Alternatively, if the markets are in a pooling equilibrium, there will be information in positive option trades (those that benefit from a rise in stock prices) and in negative option trades (those that benefit from a fall in the stock price). The last row of Table IV uses these volumes separately as regressors, and the resulting likelihood statistic is 68.10. Thus, we strongly reject the hypothesis that the markets are in a separating equilibrium: there is clearly information content in option trades.

Much of what appears to drive these results is the effect of contemporaneous volume. It should be noted that "contemporaneous" in these regressions is the most recent 5 minutes of volume. The third column of Table IV demonstrates that this relationship is weaker once contemporaneous option volumes are removed from the regressors. However, the last row of the column shows that this is not the only effect. At the 0.01 significance level, past option volumes, aggregated according to our model, jointly contain information about future stock price changes. Thus the hypothesis of a separating equilibrium is rejected even if contemporaneous volume is ignored. This is evidence that past option volume could be useful in predicting stock price changes. Equally important is the fact that when option volumes are aggregated without using the insight of our information-based theory, that is, as all contracts, all puts, or all calls, the effect of past option volumes on stock prices is not significantly different from zero.[25]

An interesting feature of our results is the asymmetry between the negative- and positive-position effects. The negative-option effects are stronger (in terms of statistical significance), suggesting that options markets may be relatively more attractive venues for traders acting on "bad" news. An often-conjectured role for options markets is to provide a means of avoiding short-sales con-

[25] We also consider the effect of stock price changes on option volume. The null hypothesis that past and contemporaneous stock price changes have no information content for future option volumes can be rejected at the 0.01 level for all definitions of option volume except put volumes. This relationship holds even if only past stock price changes are considered. We discuss this price–volume link in more detail shortly.

straints in equity markets, the most important of which are the rules limiting short sales following price downticks and zero ticks. Our results support this conjecture, suggesting a greater complexity to the mechanism through which negative information is impounded into stock prices.

That option volumes do have predictive power is an important result of our analysis. More insight into why this relation holds can be found by testing for individual lead–lag relationships, as specified in Hypothesis 2. We first present in Table V results of our regressions using the residuals from our MA(1) stock price change series and volume, defined, respectively, by total option volume, call option, and put option volume. Examining these traditional option volume measures permits comparison with previous empirical studies, and it then allows us to differentiate the effects that arise with our information-based definitions. In each panel, the first three columns show the relationship of lagged option volumes to current stock prices, and the last three columns show the effect of lagged stock price changes on current trading volumes.

It is clear from Table V that although stock price changes lead option volumes by almost 20 minutes, traditional option volumes do not lead stock price changes. In Panel A, the coefficients on the past total option volume, individually, are not significantly different from zero. A similar relationship is observed in Panel B, which relates call volumes to price changes. The panel shows that positive changes in stock price are likely to be followed by increases in call option volume. The leading effect of call option volume, however, is not significant. Panel C shows the lead–lag relationship for put option volumes. Although the evidence is weaker, the signs on the coefficients indicate that a rise in the stock price reduces trading activity in puts.

These results clearly illustrate the role of option markets as venues for hedging. Such a hedging role for options is both expected and reasonable; a finding that stock price changes did not lead option volume would be difficult to reconcile, both with the general use of option pricing theory in markets and with the extensive use of derivative markets for portfolio protection purposes. These results provide no support though for the contention that options markets are also venues for information-based trading. Neither put, call, nor total option lagged volumes, individually, appear to have predictive power in forecasting movements in stock prices. From our results in Table IV, however, this is to be expected; if, using traditional definitions, overall lagged volumes are not significant, it is not surprising that individual volumes also tell us little.

Tables VI and VII present regression results using information-based option volumes. Option volumes behave very differently, and with a complexity not suggested by traditional analyses. The negative-option volumes in Table VI appear to affect stock prices up to 15 to 20 minutes ahead. The contemporaneous effect is strongest, but it is not the only statistically significant influence of volume on stock prices. The effect of positive-option volume in Table VII is much more contemporaneous, but it is still strongly significant.

Table V

Option Volume and Stock Price Change Regression

In Panels A, B, and C, each lag interval is 5 minutes long and the stock price change is the movement in the stock price over the 5-minute interval. Panel A gives the estimated parameter values of our regressions using the residuals from our MA(1) stock price change series and total option volume. The option volume is the total volume for the 5-minute interval. Panel B gives the estimated parameter values of our regressions using the residuals from our MA(1) stock price change series and call option volume. The option volume is the total volume of call options for the 5-minute interval. Panel C gives the estimated parameter values of our regressions using the residuals from our MA(1) stock price change series and put option volume. The option volume is the total put option volume for the 5-minute interval.

Panel A: Total Option Volume

Dependent Variable: Stock Price Change			Dependent Variable: Option Volume		
Coefficient of Option Volume at Lag	Estimate	t-ratio	Coefficient of Stock Price Change at Lag	Estimate	t-ratio
0	−0.0011	−0.180	0	−0.001	−0.165
1	0.0066	1.048	1	0.0215	3.539
2	−0.0069	−1.110	2	0.031	5.087
3	−0.0103	−1.647	3	0.0161	2.644
4	−0.0026	−0.423	4	0.0168	2.768
5	−0.0128	−2.048	5	0.0066	1.083
6	−0.0072	−1.153	6	−0.00001	−0.003
F stat. = 1.697			F stat. = 7.399		

Panel B: Call Option Volume

Dependent Variable: Stock Price Change			Dependent Variable: Call Option Volume		
Coefficient of Option Volume at Lag	Estimate	t-ratio	Coefficient of Stock Price Change at Lag	Estimate	t-ratio
0	0.0026	0.401	0	0.0031	0.491
1	0.0093	1.416	1	0.0264	4.135
2	−0.0073	−1.117	2	0.0405	6.355
3	−0.0107	−1.632	3	0.0209	3.271
4	−0.0029	−0.447	4	0.0231	3.630
5	−0.0106	−1.630	5	0.0074	1.154
6	−0.0092	−1.409	6	0.0007	0.106
F stat. = 1.63			F stat. = 11.236		

Panel C: Put Option Volume

Dependent Variable: Stock Price Change			Dependent Variable: Put Option Volume		
Coefficient of Option Volume at Lag	Estimate	t-ratio	Coefficient of Stock Price Change at Lag	Estimate	t-ratio
0	−0.0245	−1.891	0	−0.0268	−2.113
1	−0.0054	−0.417	1	−0.0024	−0.191
2	0.0062	0.477	2	−0.0324	−2.554
3	0.0085	0.655	3	−0.0083	−0.650
4	−0.0055	−0.428	4	−0.0192	−1.513
5	−0.0157	−1.209	5	−0.0108	−0.848
6	0.0127	0.980	6	−0.0169	−1.331
F stat. = 0.985			F stat. = 2.051		

Table VI

"Negative" Option Volume and Stock Price Change Regression

This table gives the estimated parameter values of our regressions using the residuals from our MA(1) stock price change series and negative option volume. "Negative option" volume includes volume for all long put and short call option trades aggregated over 5-minute intervals. The stock price change is the movement in the stock price over the 5-minute interval.

Dependent Variable: Stock Price Change			Dependent Variable: Short Call and Long Put Option Volume		
Coefficient of Option Volume at Lag	Estimate	t-ratio	Coefficient of Stock Price Change at Lag	Estimate	t-ratio
0	0.0187	3.035	0	0.0182	2.968
1	0.0071	1.146	1	0.0691	11.288
2	−0.0114	−1.851	2	0.0354	5.769
3	−0.0120	−1.933	3	0.0018	0.286
4	−0.0058	−0.935	4	0.0001	0.022
5	−0.0075	−1.218	5	−0.0080	−1.308
6	−0.0085	−1.381	6	−0.0109	−1.780
F stat. = 3.043			F stat. = 25.199		

Examining the signs of the estimated coefficients reveals several puzzling dimensions to this relation.[26] In Table VI, an increase in negative option volume causes the stock price to decrease for lags 2 to 6, but has the opposite effect for lags 0 and 1. Because negative volume is bad news, we might have expected all of the coefficients to be negative, but this is not the case. That more contemporaneous price movements are positive while previous ones are negative could be consistent with an overreaction effect, but this is not something predicted by our model. A more compelling explanation is the effect of uptick rules for short sales; if lagged option volumes put downward pressure on equity prices, then short-sale restrictions may preclude further downward effects on prices. Interestingly, the leading relation of stock prices on option volumes also now differs from our earlier results. An increase in stock prices generally, but not always, increases negative option volumes. Earlier we found that a higher stock price raised call volume but decreased put volume. Because our information-based definitions include both types of options, our mixed results could reflect different intensities of trading in these options in response to stock price movements.

The response of stock prices to positive-option volumes is similarly complex. Here, the mixed pattern of coefficient signs also arises, but the predominant effects are negative. The effect of stock prices on positive option volumes is also surprising. The overall impact of a stock price increase is to dampen positive volume at lags 0 and 1 and to increase it for longer time lags. One explanation for a fall in positive option volume following an in-

[26] We caution that interpreting the levels of the coefficients is extremely difficult due to the normalization and prewhitening of our price and volume variables.

Table VII

"Positive" Option Volume and Stock Price Change Regression

This table gives the estimated parameter values of our regressions using the residuals from our MA(1) stock price change series and negative option volume. "Positive option" volume includes volume for all long call and short put option trades aggregated over 5-minute intervals. The stock price change is the movement in the stock price over the 5-minute interval.

Dependent Variable: Stock Price Change			Dependent Variable: Long Call and Short Put Option Volume		
Coefficient of Option Volume at Lag	Estimate	*t*-ratio	Coefficient of Stock Price Change at Lag	Estimate	*t*-ratio
0	−0.0241	−6.059	0	−0.0218	−3.581
1	0.0034	0.290	1	−0.0395	−6.490
2	−0.00005	−0.051	2	0.0108	1.775
3	−0.0028	−0.603	3	0.0237	3.888
4	0.0024	−0.168	4	0.028	4.594
5	−0.0103	−1.687	5	0.0171	2.800
6	−0.0003	1.447	6	0.0128	2.107
F stat. = 2.743			F stat. = 15.911		

crease in stock price is that informed traders in the equity market have already incorporated new positive information into the stock price, obviating the need to do so via options trading. This does not explain, however, the reversal in effects. Overall, we view these results as providing only limited support for the directional hypotheses of our model.

Our failure to find the predicted directional effects in the data is puzzling, but perhaps not too unexpected. A pooling equilibrium in which informed traders transact in both markets could lead to mixed effects like those found here.[27] What we find more important is that option volume *informationally-defined* affects stock prices, but standard measures of option volume do not. This supports our premise that option markets are venues for informed traders.

There are, of course, other explanations that may be consistent with this effect. For example, hedging by risk-averse option marketmakers could potentially result in option transactions affecting equity prices. A marketmaker who writes a call, for example, could hedge this position by buying the stock, and this would result in the stock price moving to the ask. Although this behavior is not predicted by our model (because our marketmakers are risk neutral), and it is inconsistent with option pricing theory (which does

[27] We attempted to investigate our informed trading hypothesis further by considering whether particular option series have different directional effects. In particular, an informed trader would profit more by using a levered contract, which suggests using an out-of-the money contract. Conversely, a hedger would prefer the most liquid contract, which generally corresponds to the next-to-deliver, at-the-money contract. Unfortunately, the volume of trading in most option series does not provide enough observations to make our 5-minute intervals feasible. Moreover, over 85 percent of what little volume there was in the highly levered contracts was concentrated in one stock. Any analysis will thus not be representative of our sample at large.

not allow feedback effects from options to stock prices), it could result in option transactions affecting stock prices.

There are several dimensions to this hedging hypothesis to consider. First, if the initial trade (a trader buying a call) is from an informed trader, then this hedging behavior merely serves to transmit the information from the options market to the stock market, an action consistent with our information-based hypothesis. Second, if option marketmakers hedge every transaction in the stock market, then we might have expected to see evidence of this in the effects of total option volume and call option volume (Table V, Panels A and B) on stock price changes (put volume effects, being smaller, might not be expected to show up). Our results provide no evidence of this. This may suggest that option marketmakers hedge (at least partially) using option contracts, and so do not directly affect stock prices.

V. Conclusions

We investigate the informational links between options markets and equity markets. Our thesis is that under certain conditions a pooling equilibrium occurs in which some informed traders may choose to trade in the options market, resulting in particular option trades being informative for the future movement of stock prices. Our empirical testing reveals that stock prices lead option volumes—an expected result given that changes in stock prices should induce hedge-related trading in options. What is more significant is our finding that particular option volumes lead stock price changes. This result is strongly consistent with option markets being a venue for information-based trading.

Our results in this paper verify the general predictions of the pooling equilibrium in our model, but we caution that these results should be interpreted with care. Our model focuses only on information. This is undoubtedly important (and, as we have shown, very useful for providing new insights) but it is an abstraction from the multitude of factors that influence actual market behavior. It is possible that the phenomena we document here are due to factors other than those we ascribe. This can only be determined by further research, involving greater modeling and testing of market features. Whatever the cause, however, our research does show that particular option volumes carry information about future stock price changes.

There are two implications of these results that we feel are particularly important. The first involves the specification of option pricing models. As is well known, standard option pricing models do not allow multidirectional links from option markets to stock markets. If markets are perfect and complete, then assuming that causality runs strictly from the stock to the derivative is clearly appropriate. But if markets are not perfect (as will be the case if information is asymmetric), then the option price may no longer be exogenous to the stock price, and the parsimony of option pricing models may be chimerical. Our empirical results suggest that this is the case, and dictate the need for more complete option pricing models. Research by Back

(1993) and Brennan and Cao (1996) on the impact of asymmetric information on option pricing, and by Cherian (1993) on the existence of asymmetrically informed volatility traders in option markets, are examples of work in this direction.

A second area of importance is the role played by volume. In our research, we find that volume plays a role in the process by which markets become efficient. This focus on volume represents a striking departure from the traditional view, where volume (perhaps much like an option price) was viewed simply as the outcome of a trading process. If volume per se is informative, then how volume is correlated with information and what this implies for price movements is surely important. Our work here provides a first step toward recognizing this role in option markets, and complements research by Blume et al. (1994) on the information content of volume in equity markets. There clearly remains much to be learned, and much benefit to be gained, from a greater understanding of volume in asset markets.

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