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A Characterization of the Daily and Intraday Behavior of Returns on Options

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ABSTRACT

The daily and intraday behavior of returns on Chicago Board Options Exchange options is examined. Option returns contain systematic patterns even after adjusting for patterns in the means and variances of the underlying assets. This is consistent with the hypothesis that informed trading in options can make the order flow in the options market informative about the value of the underlying asset, making options nonredundant. The intraday patterns in adjusted option return variances are further consistent with a model of strategic trading by informed and discretionary liquidity traders.

THIS PAPER EXAMINES THE daily and intraday behavior of returns on options. We have two goals: our first objective is to identify systematic patterns in the means and variances of daily and intraday returns on options. Our second objective is to decompose option returns into patterns that are related to the means and variances of the underlying stocks, and by inference, those patterns that are independent of patterns in the means and variances of the underlying assets.[1]

Our work is important for a number of reasons. First, options have become as important as common stocks, yet there is no detailed investigation of the behavior of returns on options. Second, it is important to identify similarities and differences in return patterns across different securities and market structures. An understanding of these similarities and differences would allow us to develop better models of returns that capture these properties. Closely related to this, it is instructive to examine option returns in light of the partial equilibrium models we use to value them; specifically, are the return patterns in options driven exclusively by the underlying stocks, or do option returns contain patterns of their own? Identifying independent, yet similar, patterns in options returns may lead to an identification of factors that are common across two different market structures: the New York

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[1] Whenever we refer to returns, we mean changes in natural logarithms.

Stock Exchange's (NYSE) specialist system and the Chicago Board Options Exchange's (CBOE) hybrid of the specialist and market maker systems. In turn, identifying independent and different patterns in returns may lead to an identification of exchange and/or security specific characteristics that drive security returns.

In a perfect market, with symmetric information and no frictions, if the underlying asset follows a diffusion with a nonstochastic variance, then options are redundant assets and their return distribution is determined by the return distribution of the underlying asset.[2] Market imperfections, however, can cause this redundancy to break down. Back (1992) questions the redundant asset hypothesis by attributing differential information to the purchase of options' nonlinear payoffs. Thus, the presence of informed trading in options may induce components in option returns that are independent of the returns of the underlying assets. Moreover, strategic or systematic behavior by informed traders and discretionary liquidity traders may induce systematic patterns in the independent components of option returns (see, e.g., Admati and Pfleiderer (1988) and Foster and Viswanathan (1990)). Because the information arrival process for both options and their underlying assets is the same, there may be similarities in patterns in stock returns and in the independent returns of options on the stocks.

Previous analysis has considered whether, due to their greater leverage, informed traders choose to trade in options, thereby causing option prices to lead those of stocks (see Manaster and Rendleman (1982), Bhattacharya (1987), Anthony (1988), Stephan and Whaley (1990), and Chan, Chung, and Johnson (1993)). Our work, in contrast, examines patterns in contemporaneous stock and option returns and in option returns that are adjusted for contemporaneous changes in the price and volatility of the underlying asset. Thus, our analysis sheds light on whether informed and liquidity traders may simultaneously trade in both markets, inducing independent yet similar patterns in option returns.

We find remarkable similarities in the means of day-end stock returns and adjusted option returns, as well as in the variances of intraday stock and option returns. Mean stock returns, adjusted call returns, and adjusted put returns are, on average, positive and largest towards the end of the trading day. Moreover, variances of stock returns, adjusted call returns and adjusted put returns exhibit an intraday U-shaped pattern.

There are, however, patterns in option returns that are not replicated in stock returns. Adjusted call and put returns are on average negative between 9 and 10 A.M. Adjusted call and put returns are significantly positive on Tuesdays and Thursdays. Moreover, there are patterns in put returns that differ from patterns in call returns; adjusted put returns are, on average,

[2] The variance may be stochastic provided it is either a function of the price of the underlying asset or if the variance itself is a traded asset. Note, however, that options need not be redundant when introduced in an incomplete market and can have real effects on prices of all assets.

significantly positive on Fridays and negative over the weekend, whereas adjusted call returns do not exhibit such a pattern.

This article is organized as follows: the next section develops a model of time-varying stock returns and derives the dynamics for option returns under the assumption that they are redundant securities. This section discusses the patterns that would arise in option returns due solely to patterns in the returns of the underlying asset and identifies specific hypotheses that are to be tested. Section II discusses the test methodology and the data. Section III contains the empirical analysis and discusses the empirical results, and Section IV concludes.

I. Theory

A. A Simple Model of Time-Varying Asset Mean Returns and Variances

Denote by $S(t)$ the stock price at time t. We assume that $S(t)$ follows the lognormal diffusion

$$d \log S(t) = \alpha(t)\, dt + \delta(t)\, dz(t), \tag{1}$$

where $\alpha(t)$ and $\delta(t)$ are at most functions of time and $z(t)$ is a standard Wiener process. Over any discrete interval $[t - \Delta t, t]$ of length Δt, equation (1) may be represented exactly by

$$R_t \equiv \Delta \log S(t) = \mu(t) + \sigma(t) q(t), \tag{2}$$

where

$$\mu(t) \equiv \int_{t-\Delta t}^{t} \alpha(s)\, ds \tag{3}$$

$$\sigma^2(t) \equiv \int_{t-\Delta t}^{t} \delta^2(s)\, ds \tag{4}$$

and $q(t)$ is distributed $N(0, 1)$.

Daily and intraday variations in mean returns and variances of returns are readily captured in this model by making the functions $\alpha(t)$ and $\delta(t)$ periodic. Specifically, for daily returns, we assume that $\alpha(t)$ and $\delta(t)$ repeat themselves every week, and for intraday returns, we assume that $\alpha(t)$ and $\delta(t)$ repeat themselves every 24 hours. Then, for all $[t - \Delta t, t]$ and $[s - \Delta t, s]$, both of type k and length Δt,

$$\mu_t = \mu_s = \mu_k$$
$$\text{and} \quad \sigma_t^2 = \sigma_s^2 = \sigma_k^2$$

where μ_k and σ_k^2 are constants specific to the type of period. If we define

$$D_{tk} \equiv \begin{cases} 1 & \text{if } [t - \Delta t, t] \text{ is of type } k \\ 0 & \text{otherwise} \end{cases}$$

and assume there are K different types of periods,[3] then the return-generating process in equations (2) to (4) may be written as

$$R_t - \sum_{k=1}^{K} \mu_k D_{tk} = \epsilon_t, \tag{5}$$

$$\left(R_t - \sum_{k=1}^{K} \mu_k D_{tk} \right)^2 - \sum_{k=1}^{K} \sigma_k^2 D_{tk} = u_t, \tag{6}$$

where $\epsilon_t \sim N(0, \sigma_t^2)$, and $E(u_t) = 0$.

Note that equations (5) and (6) may be written for multiple stocks, and one may allow for cross-sectional dependence in the ϵ_t and u_t. Thus, we obtain a system of $2S$ equations, where S is the number of stocks in the sample. Denote by v_t the vector of prediction errors from these $2S$ equations and define $D_t \equiv [D_{t1}, D_{t2}, \ldots, D_{tK}]'$. Then

$$E(v_t \otimes D_t) = 0. \tag{7}$$

Equation (7) defines a system of $2S \times K$ moment conditions which just identify the parameters $\mu_{ik}, \sigma_{ik}^2, i = 1, \ldots, S, \; k = 1, \ldots, K$. These parameters may be estimated by the generalized method of moments (GMM, Hansen (1982)).

B. The Process for Option Returns

Under the assumed stock price process, options are redundant securities and may be priced by arbitrage. Denote by $W(S, t)$ the price of an option on the stock at time t and by E the exercise price of the option. Assuming that $W(S, t)$ is sufficiently regular to apply Ito's Lemma,

$$d \log W[S(t), t] = \left[\eta_S \alpha(t) + \tfrac{1}{2}\delta^2(t) \left(\eta_S - \eta_S^2 + S^2 \frac{W_{SS}}{W} \right) - \frac{\eta_\tau}{\tau} \right] dt + \eta_S \delta(t)\, dz(t), \tag{8}$$

where

$$\eta_S \equiv \frac{\partial W[S(t), t]}{\partial S(t)} \bigg/ \frac{W[S(t), t]}{S(t)}$$

$$W_{SS} \equiv \frac{\partial^2 W[S(t), t]}{\partial S^2(t)}$$

$$\eta_\tau \equiv \frac{\partial W[S(t), t]}{\partial \tau} \bigg/ \frac{W[S(t), t]}{\tau}$$

$\tau \equiv$ the time to expiration of the option.

Moreover, under the assumed stock price process of equation (1), it is easy to show that if we hold S/E and τ fixed, then η_S, $S^2 W_{SS}/W$ and η_τ/τ are

[3] For example, for the five weekdays, $k \in$ [Monday, Tuesday, ..., Friday], and $K = 5$.

functions—say $\overline{\eta}(t)$, $a(t)$, and $b(t)$—of time only, and

$$\begin{aligned} d \log W[S(t), t] &= \left(\overline{\eta}(t)\alpha(t) + \left\{[\overline{\eta}(t) - \overline{\eta}^2(t) + a(t)]\tfrac{1}{2}\delta^2(t) - b(t)\right\}\right) dt \\ &\quad + \overline{\eta}(t)\delta(t)\, dz(t). \end{aligned} \tag{9}$$

Equations (8) and (9) provide us with benchmarks for how option returns should behave if options are redundant securities priced completely by lack of arbitrage. The case where S/E and τ may be held constant provides an interesting point of departure for our analysis. As shown in equation (9), in this case option returns possess the same properties as the underlying stock: both have time-varying means and variances and may be represented by equations (2) to (4). Patterns in option returns may then be investigated by estimating equation (7). Moreover, the time-varying behavior of the variance of option returns tracks the time-varying behavior of the variance of the underlying asset. The mean of the option returns, however, is influenced by patterns in both the mean return and the variance of returns of the underlying asset.

These properties carry over to the general case with two important differences: now both the mean and the variance of option returns become stochastic because they depend on $S(t)$, which is stochastic. Moreover, the representation of option returns over discrete intervals is not obvious.

We take two steps to address these complications. First, in our sampling of options, we restrict our attention to the nearest-maturity, nearest-the-money options. This constrains S/E and τ to lie within fixed ranges, and hence we treat the stochastic coefficients in equation (8) as being approximated by functions of time only. Moreover, our analysis of option returns provides insights into the patterns of returns for these types of options, which are the most actively traded.

Our second step is motivated by our desire to examine patterns in option returns that are unrelated to patterns in the returns of the underlying stocks. In a continuous time setting, this would involve subtracting the conditional return of the option given the contemporaneous stock price and volatility change (the right hand side of eq. (8)) from the actual return of the option. Because our empirical analysis is necessarily in discrete time, we subtract the discrete time conditional return of the option from its actual return. Conditional call returns are computed from theoretical option prices via Merton's (1973) generalization of the Black-Scholes model and Sheikh's (1992) generalization of the Roll (1977) American call-pricing model,[4] whereas conditional put returns are computed via the binomial option pricing model.

[4] By Roll's (1977) formula, we mean the formula as corrected by Whaley (1981). This formula has been found to perform well in pricing American call options (see, e.g., Whaley (1982)). Sheikh (1992) extends the formula to incorporate a deterministically changing variance, which is in the spirit of our study.

Specifically, let $\hat{W}[S(t), t]$ denote the model price, and $W[S(t), t]$ the market price, of an option on the stock. We compute adjusted option returns as

$$R_{\mathrm{adj},t} = \{\log W[S(t), t] - \log W[S(t - \Delta t), t - \Delta t]\} \\ - \{\log \hat{W}[S(t), t] - \log \hat{W}[S(t - \Delta t), t - \Delta t]\}.$$

If options are redundant securities priced by lack of arbitrage, then we would expect adjusted option returns to be nonzero due only to noise and measurement error. In particular, we would not expect systematic behavior in the adjusted returns. If, on the other hand, options are not redundant, then adjusted option returns may exhibit systematic behavior. Such behavior may be related to informed and liquidity trading in options, or simply to the structure of options markets.[5]

II. Methodology

A. Estimation

We estimate the parameters in equation (7) and their covariance matrix via GMM. The equation is estimated for stock returns, call returns, put returns, adjusted call returns, and adjusted put returns. Our theoretical model assumes, as is common, that stock and option returns are serially uncorrelated. Our empirical analysis, however, reveals that some stocks and options have returns that exhibit a small positive first order serial correlation. Adjusted option returns, on the other hand, exhibit negative serial correlation, which is consistent with measurement error in model option prices. Moreover, we would expect stock returns, as well as option returns, to be cross-sectionally correlated. Furthermore, our theoretical model allows for deterministic variations in the variances of returns. Using GMM to estimate the covariance matrix of the estimators explicitly accounts for this serial and cross-sectional correlation, and heteroskedasticity in the prediction errors. The exact form of the covariance matrix of the estimators is based on the heteroskedasticity and autocorrelation corrected estimator provided by Newey and West (1987).

B. Tests

Denote by Θ the parameter vector, by $\hat{\Theta}$ the GMM estimator of Θ and by T the sample size. Then, as shown in Hansen (1982), $\sqrt{T}(\hat{\Theta} - \Theta) \overset{a}{\sim} N(0, \Sigma)$,

[5] The existence of systematic patterns in adjusted option returns may alternatively be interpreted as a rejection of the deterministic variance models used to compute model option prices. We explore this possibility by examining, via analytics and simulations, the patterns in adjusted option returns that may arise because of stochastic variances. As we note in the concluding section of the paper, stochastic variances provide only a partial explanation for our empirical results. Details of the analysis of stochastic variances are available on request.

where Σ is the asymptotic covariance matrix of $\sqrt{T}\hat{\Theta}$.[6] Thus, we can test the restriction $R\Theta = r$, where R is a $q \times 2S$ matrix and r is a $q \times 1$ vector, by noting that under the null hypothesis, $T(R\hat{\Theta} - r)'(R\Sigma R')^{-1}(R\hat{\Theta} - r) \overset{a}{\sim} \chi^2(q)$. When $q = 1$,

$$z = \frac{\sqrt{T}(R\hat{\Theta} - r)}{\sqrt{R\Sigma R'}} \overset{a}{\sim} N(0, 1).$$

For example, when testing that mean daily returns are, on average, zero for all days of the week, the test statistic $T(R\hat{\Theta} - r)'(R\Sigma R')^{-1}(R\hat{\Theta} - r)$ is asymptotically $\chi^2(5)$. On the other hand, when testing that Monday mean returns are, on average, zero, we can use the statistic $z = \sqrt{T}(R\hat{\theta} - r)/\sqrt{R\Sigma R'}$, which is asymptotically $N(0, 1)$.

The first set of hypotheses we test relates to day-of-the-week patterns in the means of stock and option returns. Define $\overline{\mu}_k \equiv \Sigma_{i=1}^{S} \mu_{ki}/S$, where k indexes days of the week, i indexes stocks, and there are S stocks in the sample. First, we test whether mean returns on stocks and options are, on average, zero for all days of the week. Here, we compute the χ^2-statistic for the hypothesis that $\overline{\mu}_k = 0$, jointly for all k. Second, we test whether mean returns are, on average, zero for a given day of the week. This is tested by computing the z-statistic for the hypothesis that $\overline{\mu}_k = 0$, for each k. Third, we test if mean returns are, on average, equal across different days of the week. We do two tests here. First, we test whether mean returns are, on average, equal across all days of the week. This is done by computing the χ^2-statistic for the hypothesis that $\overline{\mu}_k = \overline{\mu}_l$, jointly for all k and l, where k and l denote different days of the week. Second, we test whether mean returns are, on average, equal for different pairs of weekdays, i.e., we test whether Monday mean returns are, on average, equal to Tuesday mean returns, Monday mean returns are, on average, equal to Wednesday mean returns, etc. For each pair k and l, where k and l denote two different days of the week, the equality, on average, of the mean returns for the two days in the pair is tested by computing the z-statistic for the hypothesis that $\overline{\mu}_k = \overline{\mu}_l$.

The second set of hypotheses we test relates to intraday patterns in the means of stock and option returns. Here we test whether (1), the mean returns are, on average, zero for all intraday periods, (2), the mean return for a particular period is, on average, zero, and (3), mean returns are, on average, equal across different periods. These hypotheses are tested in the same way as the day-of-the-week hypotheses.

Third, we test whether the variance of daily and intraday returns is stationary. This is done (1), by testing the equality of the average variance across all days of the week or intraday periods, and (2), by making pairwise

[6] See Hansen (1982) and Newey and West (1987) for the exact form of Σ. We allow for four lags in the computation of Σ for our daily tests, and six lags for our intraday tests. We chose these cutoffs because the residuals from estimation of equation (7) did not show any correlation beyond these lags.

comparisons of the average variance for a particular period with every other period. Defining $\overline{\sigma}_k^2 \equiv \sum_{i=1}^{S} \sigma_{ki}^2/S$, we compute the χ^2-statistic for the hypothesis that $\overline{\sigma}_k^2 = \overline{\sigma}_l^2$, jointly for all k and l, where k and l denote different days of the week or intraday periods. Moreover, we compute the z-statistic for the hypothesis that $\overline{\sigma}_k^2 = \overline{\sigma}_l^2$, for each pair k and l, where k and l denote two different days of the week or two different intraday periods.[7]

C. Data

Options data from January 1, 1986 to September 30, 1987 are obtained from the Berkeley Options data tapes. These tapes contain a time-stamped record of every trade or bid-ask quote that occurred on the CBOE. The data set contains, on average, well over 100,000 observations per day, and it is difficult to use all of the data for our tests. Moreover, our cross-sectional tests require the computation of the covariance matrix of option returns, and we can only use observations for periods where every sampled option has an available return. Thus, we have to balance our desire for generality with the necessity of having a reasonable number of observed returns on each day of the week or each intraday period. Sampling a large cross-section of options adds generality but at the same time reduces the number of available observed returns, because there may be no bid-ask quotes or trades for less frequently traded options.

Accordingly, for our daily return tests, we limit our attention to the thirty most actively traded equity option classes during 1987, which (1), were among the sixty most actively traded equity option classes in 1986, (2), were neither newly listed nor delisted during 1986 and 1987, and (3), had shares traded on the NYSE. Within these option classes, we further restrict our attention, on any given day, to the nearest-the-money, shortest maturity options, with the restrictions that the bid price of the option is at least \$1.00, and the maturity is at least eight days. We choose these option series because they are the most actively traded. We exclude options that mature in less than a week because of possible expiration week effects.

On a given day, for every option class in our sample, we find the option that satisfies the above criteria. We sample the last bid-ask quote for the option, as well as the last bid-ask quote for the same option on the following day, and use the average of the bid and ask prices to compute the return for the option.

For our intraday tests, we further restrict our attention (1), for call options, to the fifteen most active of the above thirty option classes, and (2), for put options, to the ten most active of the above thirty option classes. We have to do this to obtain a reasonable number of observations in each intraday

[7] Note that we are testing for variations in the mean of mean returns, and the mean of the variances of returns, instead of variations in the vector of mean returns and the vector of variances of returns. We do this because we are interested in whether, *on average*, there are systematic variations in the means and variances of stock and option returns. For example, are stock return variances, *on average*, higher at the open and close?

period.[8] Within each intraday period, we pick the first bid-ask record for the option satisfying our sampling criteria. We then pick the first bid-ask record in the next intraday period and compute the resulting return. The only exception is our choice of the closing price, which is obtained from the last bid-ask quote of the day. For example, to obtain an intraday series of option returns for IBM on a given day, we sample the first bid-ask quote after 9 A.M. for an option that satisfies our other sampling criteria. We then search for the first bid-ask quote for the option after 10 A.M., and use these two quotes to compute the return from 9 to 10 A.M. If no bid-ask quote is found for the option between 10 and 11 A.M., we treat the 9 to 10 A.M. return as missing. We then sample another (possibly the same) option at 10 A.M. and repeat the process. For the 2 P.M.-to-close returns, however, we sample the last bid-ask quote for the day as our closing price. Similarly, for overnight returns, we use the last bid-ask quote as the beginning price and the first bid-ask quote after 9 A.M. as the ending price.[9] Returns are computed from the average of the bid and ask prices, because we wish to abstract from patterns in returns that may be driven by systematic patterns in the position of trade prices within the quoted spread (Harris (1989)).[10]

Adjusted call returns are computed as follows. We first estimate the variances of daily returns and intraday returns for the underlying stocks (using equation (7)). Treating the patterns in these variances as deterministic, we then compute $\hat{W}[S(t), t]$ and $\hat{W}[S(t - \Delta t), t - \Delta t]$, via Merton's (1973) generalization of the Black-Scholes model or Sheikh's (1992) generalization of the Roll (1977) model, depending on whether or not dividend-related early exercise is optimal.[11] To simplify our computations, we restrict our attention

[8] In an earlier version of the article, we conducted our tests with the sixty-one most actively traded option classes and restricted our attention to options that had at least thirty days to expiration. The problem with these tests was that the set of days or intraday periods with observations on each of the sixty-one stocks was empty. This kept us from accounting for cross-sectional correlation in the returns across the sixty-one stocks and options. The results of that analysis, however, are broadly consistent with the results reported here.

[9] We discovered that the time on records from 8:30 to 9 A.M. had been miscoded in the following way: a record that occurred x minutes before 9 A.M. had been coded as having occurred x minutes after 9 A.M. Thus, the 8:30 to 9 A.M. records are mixed with the 9 to 9:30 A.M. records, and there is no way of telling them apart. We minimize the impact of this miscoding by picking the record that has the coded time as being the first after 9 A.M. This record will be the closest to 9 A.M., in light of the miscoding, and records that occur much before 9 A.M. are thus not sampled.

[10] In a previous version, we used trade prices and found broadly similar results.

[11] Note that model option prices are based on the actual variance patterns over the period of the study. An alternative is to use implied variances. The implied variance approach, however, detracts from our objective of separating patterns in option returns from patterns in the mean returns and variances of returns of the underlying stocks. For example, suppose we use the implied variance on Monday to compute the model option price for Tuesday. Assuming that the Black-Scholes model is valid, the implied variance on Monday measures the average per-period variance between Monday and expiration. If there are significant variations in daily variances, the average per-period variance on Tuesday may be very different from that on Monday, and using Monday's implied variance is incorrect. On the other hand, using Tuesday's implied variance will make model prices equal market prices, resulting in zero adjusted returns. Using the ex post variance patterns does not suffer from such problems.

to those call records for which early exercise is not optimal except at the last ex-dividend date before maturity. As a practical matter, after we have imposed all data screens and converged on the set of observations where there is a return for all the stocks in our sample, this results in deletion of only one record for the daily returns tests and five observations for the intraday tests. Inclusion of these records does not alter our findings.

Adjusted put returns are computed using model prices obtained from the binomial option pricing model with 120 periods. We account for systematic changes in the variances of the underlying stocks in the following way. At every point in time, t, we compute the total variance to expiration, $\Sigma_{s=t}^{T} \sigma^2(s)$, where T denotes the expiration date of the put. We then divide this total variance to expiration evenly over each period in our binomial tree. This approach is equivalent to defining a new time scale given by $\nu(t) = \int_0^t \delta^2(s)\,ds$, where $\delta^2(s)$ is the instantaneous variance of stock returns at time s. This change in the time scale results in a stock price process that is homoskedastic, and which may be approximated by a simple binomial tree.[12]

In computing model option prices, we use the actual dividends for the underlying stocks. The dividend data are obtained from the CRSP monthly master files. The interest rate used is the yield-to-maturity of the Treasury bill with maturity closest to the maturity of the option. Treasury bill yields are obtained from the CRSP Fama term-structure files. These data are reported monthly and are interpolated between monthly dates to form a daily interest rate series.

The sample of option returns is further screened to remove records that may contain errors. For the daily call and put tests, we eliminate all records where (1), the ask price was less than the immediate exercise value of the option, (2), the bid or the ask was zero or negative, or the ask was less than the bid, or (3), the bid-ask spread was larger than 50 cents. For the daily adjusted option returns, we further exclude any records where the model price is less than half or more than twice the actual option price. Such a large price divergence is most likely the result of a miscoded stock or option price. Indeed, examination of such records shows that they are dominated by coding errors. For all of the intraday tests, in addition to screens (1) to (3) above, we exclude any records where the model option price is less than 2/3 of or more than 1.5 times the actual option price. Note that we apply a tighter screen to the ratio of intraday model prices to actual prices

[12] The change does, however, induce a time-varying drift. Under the risk-neutral probability density, at time s this drift is given by $r/\delta^2(s)$. This approach is asymptotically equivalent to the one outlined in Amin (1991). In calibrating the binomial model using American call values with dividends (for which we have an exact solution), however, we found that for large variations in the variance process, adjusting the drift results in pricing errors that are of the order of a few cents, whereas leaving the drift unadjusted results in prices that are within a penny of the exact prices. For small to medium variations in the variance, the unadjusted and adjusted drifts both produce American call values that are within a penny of the exact prices. Because the approximation without the drift adjustment appears to be more robust to extreme variations in the variance, we use the binomial model without adjusting the drift.

than that for daily prices. We do so because our examination of the records remaining after we apply the wider screen to intraday records shows that some records with obvious errors remain, whereas none remain for the daily records. Applying the tighter screen eliminates the miscoded records from the intraday data.[13]

III. Results

A. Day-of-the-Week Mean Returns

Table I contains the results of the tests on mean daily returns. The table provides, for each asset and each day of the week, the cross-sectional mean of the mean returns of the asset for individual stocks, the significance level of the cross-sectional mean, and the number of stocks for which the asset's mean return is positive. The table further gives the χ^2 statistics that test, for each asset, whether the cross-sectional means are (1) zero for all days of the week and (2) equal across all days of the week. For example, the first entry in the column under "Monday" shows that the cross-sectional mean of the mean Monday returns of individual stocks is 0.0001, and that this mean is insignificantly different from zero. The second entry in the column shows that eleven of the thirty stocks had positive mean returns on Monday. The first entry in the column under "$\chi^2(5)$ All Cross-sectional Means are Zero" gives the χ^2 statistic, 12.60, that tests the null hypothesis that mean stock returns are, on average, zero for all days of the week and shows that we can reject the null hypothesis at the 5 percent level. Similarly, the first entry in the column under "$\chi^2(4)$ All Cross-sectional Means are Equal" gives the χ^2 statistic, 4.66, that tests the null hypothesis that mean stock returns are, on average, equal across all days of the week, and shows that we may not reject the null hypothesis at conventional significance levels. To keep the table simple, it does not provide the results of the pairwise comparisons across days; we will, however, discuss these results when relevant.

Table I shows that mean stock returns are, on average, significantly different from zero only on Wednesdays for the period of the study, and the mean of the mean Wednesday returns is significantly positive. Although the means of the mean Friday and Monday returns are the smallest, they are not significantly different from zero. Moreover, we cannot reject the hypothesis that the cross-sectional means of mean stock returns are equal across all days of the week. Further analysis reveals, however, that the mean of the mean returns for Mondays and Fridays is significantly smaller than the mean of the mean returns for the other three days ($z = -1.94$, with a p value of 0.0524). Thus, for the period and stocks being studied, there is

[13] The daily stock return tests are based on observations obtained from the CRSP files. The intraday stock return tests are based on the stock prices obtained from the same records as the intraday call and adjusted call return tests. We use the call records, because they allow a larger cross-section of stocks as well as more observations for each intraday period than the put records.

Table I

Cross-sectional Properties of Mean Daily Returns

The table is based on daily stock and option logarithmic returns between January 1, 1986 and September 30, 1987, for thirty NYSE stocks with options listed on the CBOE. The stocks (1) had the most actively traded options during 1987, (2) were among the sixty with most actively traded options during 1986, and (3) were neither newly listed nor delisted on the CBOE in 1986 or 1987. The options are the nearest-the-money, shortest maturity options, with the restrictions that the bid prices of the options are at least $1.00 and their maturities are at least eight days. Adjusted option returns are computed by subtracting returns computed via model prices from returns computed via market prices. Call model prices are computed using Merton's (1973) generalization of the Black-Scholes (1973) model or Sheikh's (1992) generalization of the Roll (1977) model, depending on whether or not dividend-related early exercise is optimal. Put model prices are computed using the binomial model with 120 periods to expiration. The table provides, for each asset, (1) for each day of the weeks (a) the cross-sectional mean of the mean returns of the asset for individual stocks, and (b) the number of stocks with positive mean returns for the asset, (2) the χ^2 statistic that tests whether the cross-sectional means are zero for all days of the week, and (3) the χ^2 statistic that tests whether the cross-sectional means are equal across all days of the week. All estimators and test statistics are computed via GMM.

		Day of the Week					$\chi^2(5)$ All Cross-sectional Means are Zero	$\chi^2(4)$ All Cross-sectional Means are Equal
Asset	Statistic	Monday	Tuesday	Wednesday	Thursday	Friday		
Stocks	Mean	0.00010	0.00152	0.00263***	0.00173	0.00001	12.60**	4.66
	Number positive	11	24	27	26	14		
Calls	Mean	−0.03874**	−0.02938*	0.01627	−0.00817	−0.03543***	15.26***	12.37**
	Number positive	4	3	23	13	4		
Puts	Mean	−0.05580***	−0.05146***	−0.06531***	−0.04191***	−0.03516**	63.61***	3.12
	Number positive	3	0	0	0	5		
Adjusted call	Mean	0.00328	0.00740**	0.00046	0.00708**	−0.00060	13.09**	4.94
	Number positive	20	25	13	21	15		
Adjusted put	Mean	−0.01317***	0.00544*	0.00083	0.00390**	0.00510*	44.98***	43.38***
	Number positive	3	18	16	18	23		

* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

evidence of smaller mean returns on Fridays and Mondays than other days of the week.

Call returns exhibit stronger day-of-the-week patterns. The mean, across the sample of stocks, of the mean call option returns over weekends is -0.03874, and is significantly negative. Moreover, only four out of thirty stocks have positive mean call returns over the weekend. We can reject both hypotheses that the cross-sectional means of the mean call returns are (1), zero for all days of the week and (2), equal for all days of the week. Pairwise comparisons further reveal that Monday mean call returns are, on average, significantly smaller than Wednesday mean call returns. Similarly, Friday call returns are on average significantly negative and significantly smaller than Wednesday call returns. Corresponding to the large stock return on Wednesdays, mean call returns on Wednesdays are, on average, significantly larger than call returns on Mondays, Tuesdays, and Fridays.

Put returns, on the other hand, do not exhibit any significant patterns. Although mean put returns are on average significantly negative regardless of the day of the week, we cannot reject the hypothesis that cross-sectional means of the mean put returns are equal across all days. The negative put returns are not surprising, because puts may be thought of as short positions in the underlying stocks (coupled with lending), and the stocks in the sample had positive returns for the period of the study. The negative put returns are consistent also with a loss in value due to the declining lives of options.

Turning to adjusted option returns, we find that the cross-sectional mean of the means of adjusted call returns is not significantly different from zero over weekends or on Fridays. This indicates that the significantly negative weekend and Friday call returns are driven by (1), smaller stock returns on weekends and Fridays and (2), the decline in the life of call options, and hence in the total variance to maturity, as time progresses. Adjusted call returns, however, do show that call returns have significant independent patterns, because adjusted call returns are, on average, significantly positive on Tuesdays and Thursdays. Moreover, we can reject the hypothesis that the means of adjusted call returns are, on average, zero for all days of the week.

A similar Tuesday and Thursday pattern emerges in adjusted put returns. The cross-sectional mean of the means of adjusted put returns is significantly positive on Tuesdays and Thursdays. In addition, adjusted put returns are, on average, significantly negative over the weekend and positive on Fridays. We can reject both hypotheses that adjusted put returns are, on average, (1), zero for all days of the week and (2), equal across all days of the week. In pairwise comparisons, we find that Monday mean returns are, on average, significantly smaller than mean returns on all other days of the week.

In sum, call option returns are, on average, significantly negative over weekends. Our analysis of adjusted call returns, however, reveals that this pattern in call returns is attributable to the behavior of underlying stock returns. Mean put returns are significantly negative for all days of the week and do not exhibit systematic patterns. Moreover, call returns are, on average, significantly positive on Tuesdays and Thursdays after we have adjusted for contemporaneous stock price and variance changes. Similarly, adjusted put returns are, on average, significantly positive on Tuesdays and Thursdays. Additionally, adjusted put returns are significantly positive on Fridays and negative over the weekend.

B. Intraday Mean Returns

Table II provides the results of tests on mean intraday stock and option returns. The table is similar to those for the day-of-the-week tests and should be read in the same way.

Our analysis of stock returns replicates Harris' (1986, 1989) finding of a significant positive stock return at the end of the trading day. The cross-sectional mean of the 2 P.M. (Central time) to close mean stock returns is 0.00092 and is significantly positive at the 1 percent level, with fourteen of fifteen stocks earning positive mean returns between 2 P.M. and close. Moreover, 9 to 10 A.M. and 1 to 2 P.M. stock returns are, on average, significantly positive, and we can reject the hypothesis that the means of the mean stock returns are zero for all intraday periods.

A day-end pattern also emerges for call options. The cross-sectional mean of the 2 P.M. to close mean call returns is significantly positive, and the 2 P.M. to close mean call return is positive for fourteen of fifteen stocks. We can reject both hypotheses that the means of the mean call returns are (1), zero for all intraday periods and (2), equal across all intraday periods. Moreover, pairwise comparisons show that the 2 P.M. to close mean returns are, on average, significantly larger than the mean returns during all other periods of the day except the 1 to 2 P.M. period.

In light of the positive day-end stock return, and the loss of an hour of volatility, we expect day-end put returns to be negative. This expectation is not supported by the data. The mean of the mean put returns at the end of the day is not significantly different from zero. Indeed, the mean day-end return is positive for nine out of ten stocks in the sample. Note that the mean of the overnight mean put returns is the only one that is significantly negative. This indicates that the negative daily put returns occur mostly overnight. Moreover, the cross-sectional mean of the 12 to 1 P.M. mean put returns is significantly positive. As we shall see, this may be due to the negative, albeit insignificant, mean stock returns between 12 and 1 P.M.

Adjusted call returns are also, on average, significantly positive between 2 P.M. and close. The mean of the 2 P.M. to close mean returns is significantly positive and, in pairwise comparisons, significantly larger than the mean of the mean returns for the overnight, 9 to 10 A.M., 10 to 11 A.M., and 1 to 2 P.M. periods. Interestingly, the means of the adjusted call returns are, on average, negative between 9 and 10 A.M. (the z-statistic, -1.62, is barely insignificant at the 10 percent level). Moreover, pairwise comparisons show that the mean of the 9 to 10 A.M. means of adjusted call returns is significantly smaller than the means of 11 A.M. to 12 P.M., 12 to 1 P.M., and 2 P.M. to close mean returns.

Table II

Cross-sectional Properties of Mean Intraday Returns

The table is based on intraday stock and option logarithmic returns between January 1, 1986 and September 30, 1987. For the stock, call and adjusted call returns, the sample consists of the fifteen NYSE stocks with options listed on the CBOE that (1) had the most actively traded options during 1987, (2) were among the sixty with most actively traded options during 1986, and (3) were neither newly listed nor delisted on the CBOE in 1986 or 1987. For the put and adjusted put returns, the sample consists of the ten NYSE stocks with options listed on the CBOE that (1) had the most actively traded options during 1987, (2) were among the sixty with most actively traded options during 1986, and (3) were neither newly listed nor delisted in 1986 to 87. The options are the nearest-the-money, shortest maturity options, with the restrictions that the bid prices of the options are at least \$1.00 and their maturities are at least eight days. Adjusted option returns are computed by subtracting returns computed via model prices from returns computed via market prices. Call model prices are computed using Merton's (1973) generalization of the Black-Scholes (1973) model or Sheikh's (1992) generalization of the Roll (1977) model, depending on whether or not dividend-related early exercise is optimal. Put model prices are computed using the binomial model with 120 periods to expiration. The table provides, for each asset, (1) for each intraday period, (a) the cross-sectional mean of the mean returns of the asset for individual stocks, and (b) the number of stocks with positive mean returns, (2) the χ^2 statistic that tests whether the cross-sectional means are zero for all intraday periods, and (3) the χ^2 statistic that tests whether the cross-sectional means are equal across all intraday periods. All estimators and test statistics are computed via GMM.

		Intraday Period							$\chi^2(7)$ All Cross-sectional Means are	$\chi^2(6)$ All Cross-sectional Means are
Asset	Statistic	Overnight	9–10	10–11	11–12	12–1	1–2	2–Close	Zero	Equal
Stocks	Mean	0.00041	0.00051*	0.00019	0.00027	−0.00012	0.00054**	0.00092***	20.70***	10.56
	Number positive	11	14	10	12	4	15	14		
Calls	Mean	−0.00337	0.00096	−0.00153	0.00297	−0.00265	0.00473	0.01236***	14.37**	12.70**
	Number positive	5	10	6	10	5	14	14		
Puts	Mean	−0.01651***	−0.00991	0.00243	0.00343	0.01223**	0.00229	0.00754	29.60***	27.04***
	Number positive	1	1	8	5	9	7	9		
Adjusted call	Mean	−0.00054	−0.00183	−0.00084	0.00131	0.00160	−0.00012	0.00376***	13.96*	12.10*
	Number positive	8	6	6	9	8	5	10		
Adjusted put	Mean	−0.00512***	−0.00528**	−0.00180	−0.00422*	0.00105	0.00141	0.00744***	44.27***	40.37***
	Number positive	2	3	5	4	5	6	7		

* Significant at the 10 percent level.

This positive day-end and negative 9 to 10 A.M. behavior is replicated in adjusted put returns. The cross-sectional mean of the means of the 2 P.M. to close adjusted put returns is significantly positive, and pairwise comparisons show that the mean of the 2 P.M. to close mean returns is significantly larger than the means of the mean returns in all other intraday periods. The mean of the 9 to 10 A.M. mean returns, on the other hand, is significantly negative and significantly smaller than the means for 12 to 1 P.M., 1 to 2 P.M., and 2 P.M. to close. In addition, adjusted put returns are, on average, significantly negative overnight and between 11 A.M. and 12 P.M. Note, however, that adjusted put returns do not differ significantly from zero between 12 and 1 P.M., whereas unadjusted put returns are positive. This indicates that the positive put returns between 12 and 1 P.M. are driven by the negative mean returns of stocks in the same period.

The pervasiveness of the positive, and largest, stock, call, and adjusted option returns at the end of the day is consistent with similar price behavior in experimental markets (Forsythe, Palfrey, and Plott (1984)).[14] This similarity in the behavior of day-end returns across different markets shows that there are similar forces in financial markets, regardless of their structure, that result in similar patterns in returns. At the same time, adjusted option returns are, on average, negative between 9 and 10 A.M. This pattern is not replicated in stock returns, and may be related to the structural differences between the CBOE and the NYSE.

C. Variances of Daily Returns

The mean variances of daily returns are given in Table III. The table is structured in the same way as the tables for the mean returns and should be read in the same way. For example, referring to the numbers in the row entitled "Stocks," the number under the column entitled "Monday" shows that the mean, across the sample of stocks, of the variances of stock returns for Mondays is 0.00034. Moreover, the number under the column entitled "$\chi^2(4)$ All Cross-sectional Means are Equal" gives the χ^2 statistic, 14.75, associated with the null hypothesis of equal mean variances across all days of the week.

The table shows that there are significant variations in stock return variances across days of the week. The variance of returns is, on average, largest on Tuesday, and pairwise comparisons show that the mean Tuesday variance is significantly larger than the mean variance on Wednesdays and Fridays. This pattern is repeated in call returns. Puts exhibit similar behavior, although we cannot reject the hypothesis that the means of put return variances are equal across days of the week.

Examination of adjusted call return variances shows that the behavior of call return variances is driven by the behavior of the variances of the

[14] The similarity of mean intraday returns across the NYSE and experimental markets was first noted by Harris (1989).

Table III

Cross-sectional Properties of Variances of Daily Returns

The table is based on daily stock and option logarithmic returns between January 1, 1986 and September 30, 1987, for thirty NYSE stocks with options listed on the CBOE. The stocks (1) had the most actively traded options during 1987, (2) were among the sixty with most actively traded options during 1986, and (3) were neither newly listed nor delisted on the CBOE in 1986 or 1987. The options are the nearest-the-money, shortest maturity options, with the restrictions that the bid prices of the options are at least \$1.00 and their maturities are at least eight days. Adjusted option returns are computed by subtracting returns computed via model prices from returns computed via market prices. Call model prices are computed using Merton's (1973) generalization of the Black-Scholes (1973) model or Sheikh's (1992) generalization of the Roll (1977) model, depending on whether or not dividend-related early exercise is optimal. Put model prices are computed using the binomial model with 120 periods to expiration. The table provides, for each asset, (1) for each day of the week, the cross-sectional mean of the variances of returns of the asset for individual stocks and (2) the χ^2 statistic that tests whether the cross-sectional means are equal across all days of the week. All estimators and test statistics are computed via GMM.

		Day of the Week					$\chi^2(4)$ All Cross-sectional Means are
Asset	Statistic	Monday	Tuesday	Wednesday	Thursday	Friday	Equal
Stocks	Mean	0.00034	0.00041	0.00031	0.00035	0.00029	14.75***
Calls	Mean	0.05721	0.06420	0.04669	0.06310	0.04516	20.92***
Puts	Mean	0.05303	0.06602	0.05634	0.06084	0.05054	6.80
Adjusted call	Mean	0.00705	0.00662	0.00607	0.00642	0.00662	3.29
Adjusted put	Mean	0.00808	0.00749	0.00657	0.00660	0.00787	10.50**

** Significant at the 5 percent level.
*** Significant at the 1 percent level.

underlying stocks. We cannot reject the equality of the means of adjusted call return variances across days of the week. On the other hand, adjusted put return variances exhibit distinct patterns, and we can reject the hypothesis that the variances are, on average, equal across all days of the week. Adjusted put returns are most variable on Mondays and Fridays. In pairwise comparisons, the means of the Monday and Friday variances are significantly larger than the means of variances on Wednesdays and Thursdays.

D. Variances of Intraday Returns

The mean variances of intraday returns are given in Table IV.

As in previous studies, stock return volatility declines after the opening of trade and then increases during the last hour of trading. Moreover, we can reject the equality of mean variances across different intraday periods. Pairwise comparisons reveal that the mean of the variances of 9 to 10 A.M. returns is significantly larger than the means of the variances of all other

Table IV

Cross-sectional Properties of Variances of Intraday Returns

The table is based on intraday stock and option logarithmic returns between January 1, 1986 and September 30, 1987. For the stock, call and adjusted call returns, the sample consists of the fifteen NYSE stocks with options listed on the CBOE that (1) had the most actively traded options during 1987, (2) were among the sixty with most actively traded options during 1986, and (3) were neither newly listed nor delisted on the CBOE in 1986 or 1987. For the put and adjusted put returns, the sample consists of the ten NYSE stocks with options listed on the CBOE that (1) had the most actively traded options during 1987, (2) were among the sixty with most actively traded options during 1986, and (3) were neither newly listed nor delisted in 1986 or 1987. The options are the nearest-the-money, shortest maturity options, with the restrictions that the bid prices of the options are at least $1.00 and their maturities are at least eight days. Adjusted option returns are computed by subtracting returns computed via model prices from returns computed via market prices. Call model prices are computed using Merton's (1973) generalization of the Black-Scholes (1973) model or Sheikh's (1992) generalization of the Roll (1977) model, depending on whether or not dividend-related early exercise is optimal. Put model prices are computed using the binomial model with 120 periods to expiration. The table provides, for each asset, (1) for each intraday period, the cross-sectional mean of the variances of returns of the asset for individual stocks and (2) the χ^2 statistic that tests whether the cross-sectional means are equal across all intraday periods. All estimators and test statistics are based on GMM.

		Intraday Period							$\chi^2(6)$ All Cross-sectional Means are
Asset	Statistic	Overnight	9–10	10–11	11–12	12–1	1–2	2–Close	Equal
Stocks	Mean	0.00007	0.00004	0.00004	0.00002	0.00002	0.00003	0.00004	223.25***
Calls	Mean	0.01284	0.01015	0.00728	0.00514	0.00442	0.00598	0.00964	221.08***
Puts	Mean	0.01282	0.01180	0.00894	0.00808	0.00618	0.00684	0.01485	69.67***
Adjusted call	Mean	0.00366	0.00304	0.00246	0.00243	0.00232	0.00229	0.00332	104.30***
Adjusted put	Mean	0.00393	0.00351	0.00292	0.00277	0.00273	0.00274	0.00327	35.25***

*** Significant at the 1 percent level.

trading hours except 2 P.M to close. Similarly, 2 P.M. to close returns have variances that are, on average, larger than return variances during all other trading periods except 9 to 10 A.M. and 10 to 11 A.M. Overnight stock returns have the largest average variance. But note that the overnight hourly variance is much smaller than trading period variances, because the overnight close is 17.5 hours long, whereas the total overnight variance is, on average, only about twice the variance for each trading hour.

A similar U-shaped pattern of intraday variances exists for calls, with the largest trading hour variances occurring between 9 and 10 A.M. and between 2 P.M and close. We can reject the hypothesis that the mean of the variances of returns is stationary during the day. Pairwise comparisons further reveal that 9 to 10 A.M. call return variances are, on average, significantly larger than return variances in all other trading periods except 2 P.M. to close. Similarly, 2 P.M. to close return variances are, on average, larger than return variances in all other trading periods except 9 to 10 A.M. As with stocks, overnight returns have the largest variance, but the hourly variance of overnight returns is considerably smaller than the return variance during trading hours.

Put return variances also exhibit an intraday U-shaped pattern, and we can reject the hypothesis of stationarity of intraday put return variances. Pairwise comparisons show that 9 to 10 A.M. put return variances are, on average, significantly larger than variances in all trading hours except 2 P.M. to close. Similarly, variances of 2 P.M. to close put returns are, on average, significantly larger than return variances in all trading periods except 9 to 10 A.M. In contrast to stock and call returns, the mean of the overnight put return variances is not significantly larger than the mean of the variances of 9 to 10 A.M. and 2 P.M. to close returns.

Moreover, our analysis of adjusted call returns reveals that call return variances exhibit an intraday U-shaped pattern, even after we control for patterns in the means and variances of the underlying stocks. We can reject the hypothesis that adjusted call return variances are, on average, constant across intraday periods. Pairwise comparisons further show that 9 to 10 A.M. adjusted call return variances are, on average, larger than variances in all trading periods except 2 P.M. to close. Similarly, 2 P.M. to close return variances are, on average, significantly larger than return variances in all trading hours except 9 to 10 A.M. Overnight return variances are, on average, larger than variances in all periods except 2 P.M. to close.

A significant U-shaped intraday pattern emerges also in the variances of adjusted put returns. Pairwise comparisons show that 9 to 10 A.M. adjusted put returns have, on average, variances that are significantly larger than return variances in all trading periods except 2 P.M. to close. Similarly, 2 P.M. to close returns have variances that are, on average, significantly larger than 12 to 1 P.M. and 1 to 2 P.M. return variances. Overnight return variances are, on average, larger than return variances during all other periods except 9 to 10 A.M.

The intraday U-shaped pattern in the variances of adjusted option returns shows that the CBOE is more volatile in the morning and at the close of trade, even after we have corrected for the greater volatility of the underlying stocks in these periods. This indicates that the greater volatility near the open and at the end of the trading day is pervasive and, like the positive day-end return, cuts across different market structures.

IV. Conclusion

The existence of systematic patterns in adjusted option returns is consistent with Back's (1992) model of informed trading in options markets and with the notion that options are not simply redundant securities priced completely by lack of arbitrage. Back's model predicts that the presence of informed trading in options may induce components in option returns that are independent of the underlying asset's returns. We conjecture that strategic behavior by informed and discretionary liquidity traders may induce systematic patterns in these independent components of option returns. Further, if the arrival of private information about the underlying asset is identical across the stock and options markets, then there should be similarities in the behavior of stock returns and adjusted option returns. The pervasiveness of the positive mean of day-end returns and the U-shape in variances of intraday returns supports these conjectures.

The intraday U-shaped pattern in variances is similar to a U-shaped pattern in volume in the stock and options markets (see, e.g., Stephan and Whaley (1989) and Foster and Viswanathan (1993)).[15] This concentration of trade and accompanying larger variances is consistent with the predictions of the Admati and Pfleiderer (1988) and the Foster and Viswanathan (1990) models, in which discretionary liquidity traders pool their trades at times when trading costs are lowest. As periods of concentrated trading and low trading costs are also times when informed traders choose to trade, prices are most informative and variable in such periods.[16]

Coupled with the finding of Chan, Chung, and Johnson (1992) that neither stocks nor options lead the other, our findings are consistent with simultaneous or randomized informed trading in both stock and options markets. This is also consistent with theoretical predictions. For example, John, Koticha, and Subrahmanyam (1991) argue that if informed traders choose to trade only in options (due to their greater leverage), then adverse selection costs in the options market would become very large. This would eliminate any leverage advantages that the options market may have, forcing informed traders back to the market for the underlying asset. In equilibrium, informed traders choose to trade in both options and the underlying assets.

The pervasiveness of the positive, and largest, average day-end returns, and the existence of similar positive returns in experimental financial markets, strongly indicates that there are common forces across financial markets that induce positive expected returns at the end of the trading day. The positive day-end expected returns may be compensation for the increased risk of these securities at the end of the day and at the open of trade on the next day. Alternatively, the positive day-end mean returns may be due to increased liquidity-based buying activity at the end of the trading day (Brock and Kleidon (1992)), which causes both the bid and the ask to be revised upward

[15] We find a U-shaped pattern in intraday option volumes for our sample as well. Option volumes are, on average, significantly largest between 8:30 and 10 A.M., decline to a low between 11 A.M. and 12 noon, and then increase to their second largest intraday value between 2 P.M. and close. 2 P.M. to close volumes are smaller than only 8:30 to 10 A.M. volumes. We cannot separate the 9 to 10 A.M. volumes from the 8:30 to 10 A.M. volumes because the 8:30 to 9 A.M. trade records are mixed with the 9 to 9:30 A.M. records and the time stamp on these records is incorrect; see footnote 9 for details on this miscoding.

[16] Note that we do not test the predictions of these models with regard to costs of trading. Although we are interested in these issues, such an analysis is beyond the scope of the current work and is deferred to the future.

at the end of the day. This conjecture is partially supported by Harris' (1989) finding the last stock trade occurs more frequently at the ask than the bid.

The U-shaped pattern in option return variances and the positive day-end returns are replicated in the underlying stocks. Equally interesting, however, are the patterns in option returns that are not replicated in the underlying stocks. These systematic differences in the patterns of adjusted option returns and the returns of the underlying stocks may be due to structural differences between the stock and options markets. Moreover, the differences in the behavior of adjusted call and adjusted put returns indicate that even within a single market the design of securities influences their return behavior in systematic and different ways. For example, the positive adjusted put returns on Fridays and negative adjusted put returns over the weekend may be due to an anticipated, but unrealized, negative weekend stock return. Put prices may have been bid up on Fridays as investors placed themselves to gain from expected negative stock returns. These returns, however, were not realized in this period, and put prices declined to reflect this on Mondays. Such an effect may be restricted to put options, because exploiting expected stock price declines via call options requires writing calls, which exposes the writer to an unlimited downside in the event of large upward jumps in the prices of the underlying stocks. Buying puts avoids this unlimited downside.[17]

Although our findings are consistent with the presence of strategic informed and liquidity trading in options, it is important to note that our findings are also consistent with a rejection of a model that assumes deterministic changes in variances of stock returns. We address this interpretation by examining, via analytics and simulations, the patterns that would arise in unadjusted and adjusted option returns due to a stochastic variance of the underlying asset. We find that the patterns in adjusted and unadjusted option returns may not be attributed completely to stochastic variances. Although the direction of some of the patterns in adjusted option returns may be captured by a stochastic variance model in which the long-run mean of the variance and the variance of the variance change, the magnitudes of the observed patterns are too large to be captured by such a model. Moreover, stochastic variances are unable to capture (1), the insignificant unadjusted put returns between 2 P.M. and close, (2), the significantly negative adjusted option returns between 9 and 10 A.M., and (3), systematic differences between calls and puts in the daily behavior of the variances of adjusted returns. Thus, stochastic variances are, at best, only a partial explanation for our findings.

Our work indicates several interesting directions for further research on the interaction of equity and option markets. First, in the same vein as our study and that of Foster and Viswanathan (1993), it is of interest to examine the behavior of the adverse selection component of option bid-ask spreads. Comparisons of patterns in these costs across stock and options markets

[17] We are not arguing here that buying puts is, in general, a superior alternative to writing calls.

may allow an identification of the times that informed traders choose to trade in either or both markets, as well as times when informed traders have the greatest informational advantage. Furthermore, comparison of the patterns (if any) in the adverse-selection component of the spread with patterns in volumes and variances would allow direct tests of some of the predictions of models of options and stock market microstructure.

Similarly, it would be fruitful to examine whether systematic patterns in adjusted option returns that are not replicated in the stock market are related to institutional features that distinguish the two markets.[18] Such patterns may also be related to trading based on information that is of value only in the options market, e.g., information about the volatility of the underlying assets.

At a more pragmatic level, one could examine the behavior of quoted and effective bid-ask spreads in the options market. Coupled with our findings, this may lead to an identification of times when it is most cost effective to buy or sell options. For example, our analysis shows that call prices increase at the end of the day. If bid-ask spreads are also higher at these times, then buyers of calls may wish to execute their trades well before the close of business. Sellers of calls, however, would need to offset the increased trading costs against higher day-end prices for the options they are selling.

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