Estimating the Effects of Information Surprises and Trading on Stock Returns Using a Mixed Jump-Diffusion Model

M. Nimalendran
University of Florida

I present a methodology that uses the mixed jump-diffusion model for stock returns to estimate the separate effects of information surprises and strategic trading around corporate events. Using simulation techniques, I show that for events with multiple announcements spread over a long time, the estimators derived from the mixed jump-diffusion model are more powerful compared to the traditional cumulative abnormal return estimators. The new methodology is used to study the separate effects of information surprises and strategic trading associated with blockholdings and subsequent targeted repurchases. I find that for more than 93 percent of the firms in our sample the mixed jump-diffusion model is statistically superior to the pure diffusion model in describing stock returns. More important, I find a statistically significant negative effect due to trading, while the average effect around announcements is statistically insignificant. In contrast, the stan-

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dard cumulative abnormal return is not statistically different from zero.

Virtually all event studies use a variant of the methodology developed by Fama et al. (1969) to determine the economic impact of informational events on stock prices. This approach requires a model for expected returns, conditional on the information available prior to the event, to determine the excess returns conditional on the event. Many studies have evaluated the robustness of the estimators with respect to the theoretical and statistical assumptions underlying the methodology.[1] The general finding is that the specification, power, and efficiency of the estimators are seriously compromised if (i) the event date is incorrectly specified, (ii) there is a significant change in volatility, or (iii) the underlying stochastic process is not correctly modeled. In addition, traditional event-study methodology does not model the process by which private information is incorporated into prices through strategic trading.

Several articles analyze the informational role of prices and the trading strategies of privately informed agents [for a detailed review, see Admati (1991)]. For example, Kyle (1985) shows that, when private information is short-lived, the optimum trading strategy of an informed agent, trading in a specialist market with noise traders, reveals only part of the information. If the information is long-lived, then the informed agent would trade continuously, which results in a smooth release of all the information to the market through order flow. If informed agents behave in this manner, then event studies that neglect the impact of their trading on prices could lead to incorrect inferences about the economic impact of the event. In the extreme case where all the information is incorporated into prices through trading, a researcher will erroneously infer that the event had no economic effect. In addition, with multiple announcements over a long time, the actual event dates are difficult to specify.

Three examples of corporate events which could involve strategic trading and multiple announcements over a long time are as follows: (i) targeted share repurchases,[2] (ii) open-market share repurchases,[3]

[1] See Brown and Warner (1980, 1985). Binder (1985), Malatesta and Thompson (1985), Thompson (1985). Malatesta (1986), Connolly and McMillan (1987), Ball and Torous (1988). and Boehmer, Musumeci, and Poulson (1991).

[2] In a targeted share repurchase, a firm buys a block of shares at a premium above the market price. There are three periods during the life of a block that is repurchased. First, an individual acquires the block of shares and announces his or her intention to obtain control of the firm; then there is an interim period in which more information about the corporate control process is released; finally, the block is repurchased. To assess the impact of the process on shareholder wealth, it is necessary to consider all three phases. However, during the interim period the market often reacts to events that alter the likelihood of a profitable takeover or effective defensive actions. The event dates in

and (iii) effects of legislative changes on stock prices.[4] Such events produce two effects on stock prices. First, the stock price reacts to information that is conveyed through order flow (trading effects). Second, the price reacts to the residual information that is released to the markets through public announcements. The traditional approach, which uses the cumulative abnormal returns over the entire period to measure the economic impact and test hypotheses, has two major drawbacks. First, the cumulative abnormal returns pool both the announcement and the trading effects, thus losing valuable information about the separate effects of strategic trading and announcements. Second, aggregating abnormal returns for announcement and non-announcement dates reduces the efficiency of the estimators.

In this model, I assume that the return-generating process for stocks consists of two independent processes: a Wiener (diffusion) process which captures continuous fluctuations in stock prices due to strategic trading by informed traders, trading by liquidity/noise traders, and market microstructure effects; and an independent compound Poisson (jump) process that models the discrete jumps in stock prices due to unanticipated (or residual) information released to the public. I posit that unanticipated information arrives according to a Poisson process, and that this information causes discrete jumps in stock prices. The resulting model is the mixed jump-diffusion model initially proposed by Press (1967). To study the impact of a specific event, I compare the parameter estimates of the mixed jump-diffusion model during the event period to the estimates from a non-event period. Shifts in the estimates of the diffusion process parameters provide measures of the marginal effects of trading, while shifts in the estimates of the jump process parameters measure the effects of information released to the public through announcements.

The jump-diffusion model has several advantages over a traditional event-study method, particularly for events with multiple announcements. First, Akgiray and Booth (1987), Ball and Torous (1985), and Jarrow and Rosenfeld (1984) find that the mixed jump-diffusion model is superior to a pure diffusion model in describing daily stock price dynamics. Second, public release of unexpected information is gen-

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this interim period are difficult to specify, and it is likely that informed agents would incorporate some of the information through trading.

[3] Open-market share repurchases are carried out by managers over a period of one to two years, with the quantity and the timing of the repurchases undisclosed to the public. Therefore, part of the information content of the repurchase will be incorporated in prices through the strategic trading by managers; only the residual information will be reflected at the time of public disclosure.

[4] Legislative changes, such as deregulation of the airline industry or changes in the relative tax rates of income versus capital gains, may cause changes in the equilibrium returns of securities that are affected. However, the lengthy period between the introduction of the legislation and its final passage could involve many events as the market reacts to new information about the final outcome.

erally associated with discrete jumps in prices; therefore, a jump-diffusion model is likely to be better than a pure diffusion model in describing stock returns.[5] Finally, separating the jump and diffusion components allows researchers to assess the significance of informed trading around events such as proxy contests and earnings announcements.

I compare the performance of the jump-diffusion model estimators to the traditional event-study methodology through a simulation technique, and I show that the estimators based on the jump-diffusion model are well specified and generally more powerful than the estimators based on the usual event-study methodology, particularly for events involving multiple announcements spread over a long time. Finally, I demonstrate the advantages of the jump-diffusion model over the traditional event-study method by using both methodologies to evaluate the economic effects associated with blockholdings and subsequent target share repurchases.

This article is organized as follows. The first section presents the model and the maximum likelihood technique to estimate the parameters, and it assesses the finite sample properties of the estimators. Section 2 describes the jump-diffusion model estimators and the traditional event-study estimators, and compares the performance of the two estimators through simulations. Section 3 illustrates the use of the jump-diffusion model to study the impact of blockholdings and targeted share repurchases on stock returns, and shows the advantages of the jump-diffusion model estimators over the traditional event-study estimators. The final section contains a brief summary and conclusions.

1. The Jump-Diffusion Model

The mixed jump-diffusion model consists of a geometric Brownian motion augmented by an independent compound Poisson process with lognormally distributed jump amplitudes. If S_t is the price of the stock at time t, and $w_t = \ln(S_t/S_{t-1})$ is the continuously compounded return, then the discrete time version of the model is

$$w_t = \left(\alpha - \frac{\sigma^2}{2}\right) + \sigma Z_t + \sum_{i=1}^{q_t} \ln Y_i, \qquad (1)$$

[5] The mixed jump-diffusion model is equivalent to a mixture of normals model with the mixing probabilities given by the Poisson density. The skewness is modeled by mixing the mean effects, and the kurtosis is modeled by mixing the variances. The observed kurtosis in stock returns can also be modeled using an autoregressive conditional heteroskedasticity process as in Connolly and McMillan (1987). However, this model does not allow one to separate the effects of trading and information.

where Z_t = a standard Wiener process with instantaneous mean and variance per unit time of a and σ^2; q_t = a Poisson process with parameter λ; and In Y_i = one member of family of independent and identically normally distributed random variables with mean μ and variance σ^2 per unit time, which are also independent of q. In the above model for stock returns, I assume that effects due to strategic trading, noise trading, and microstructure biases cause stock prices to fluctuate randomly; this is modeled by a Wiener (diffusion) process. In addition, I assume that over the interval $(t - 1)$ to t, information that has a significant effect on stock price arrives according to a Poisson process q_t, and each Poisson event causes a discrete jump in stock price of size Y_i, $i = 1, 2, \ldots, q_t$. The jumps are assumed to be independent and lognormally distributed random variables. This results in the compound Poisson process $\{X_t, t \geq 0\}$, where

$$X_t = \sum_{i=1}^{q_t} \ln(Y_i).$$

The unconditional mean and variance of the above process per unit time are $\lambda\mu$ and $\lambda[\mu^2 + \delta^2]$, [1] respectively. The mean and variance of the joint process w_t are $(\alpha - (\sigma^2/2) + \lambda\mu)$ and $\Sigma^2 = [\sigma^2 + \lambda(\mu^2 + \delta^2)]$, respectively, over a unit time. Further, the density of w_t is leptokurtic for $\lambda > 0$, and skewed when μ is not equal to zero. The skewness and kurtosis are given by $\lambda\mu(\mu^2 + 3\delta^2)/\Sigma^{3/2}$ and $\lambda(\mu^4 + 6\mu^2\delta^2 + 3\delta^4)/\Sigma^4$, respectively.

To estimate the separate effects due to trading and to public announcements, I assume that the stock price dynamics in the event and non-event periods are characterized by the following mixed jump-diffusion models:

$$\text{Event period:} \quad \ln\left(\frac{S_t}{S_{t-1}}\right) = \left(\alpha_e - \frac{\sigma_e^2}{2}\right) + \sigma_e Z_t + \sum_{j=1}^{m_t} \ln Y_{ej}$$

$$\text{Non-event period:} \quad \ln\left(\frac{S_t}{S_{t-1}}\right) = \left(\alpha_o - \frac{\sigma_o^2}{2}\right) + \sigma_o Z_t + \sum_{j=1}^{n_t} \ln Y_{oj} \qquad (2)$$

where the subscripts "e" and "o" refer to event and non-event periods, and

- α_o, α_e = instantaneous mean per unit time for the Wiener processes;
- σ_o, σ_e = instantaneous variances per unit time for the Wiener processes;
- m_t, n_t = Poisson processes with parameters λ_e and λ_o, which model the information arrival processes;

and

Y_{ei}, Y_{oj} = jumps in stock prices due to significant unexpected information, where $\{Y_{ej}, i = 1, 2, \ldots, m_t\}$ and $\{Y_{oj}, j = 1, 2, \ldots, n_t\}$ are family of independent, identically, and log normally distributed random variables with means μ_e and μ_o, and variances δ_e^2 and δ_o^2, respectively.

Based on the above models for stock returns in the event and nonevent periods, any shifts in the mean and variance of the diffusion process during the event period relative to the nonevent period would measure the trading effects due to the event; changes in the parameters of the jump process would measure the information effects. However, market microstructure biases and market-wide systematic effects could introduce errors in the above measures. The effect of these errors on the estimators are minimized by using a portfolio of firms with events dispersed over calendar time.

I estimate the parameters by numerically optimizing the log-likelihood function $L(\Theta; \mathbf{W})$ with respect to the parameter vector $\Theta = (\alpha, \sigma^2, \mu, \delta^2, \lambda\}$, for a given set of continuously compounded daily returns $\mathbf{W}$. The Appendix describes the calculation of the likelihood function and the necessary and sufficient (for a local maximum) conditions for an optimum. Maximum likelihood estimators have several desirable properties: The estimators are consistent, invariant to transformations, and asymptotically normal. Further, through the Hessian matrix, we can obtain standard errors for the estimates. The invariance property also allows us to estimate directly the unconditional mean of the jump process $\phi = \lambda\mu$) by substituting ϕ/λ for μ in the likelihood function. In addition, maximum likelihood technique permits statistical tests of alternative models for stock returns. Since the pure diffusion model is nested within the jump-diffusion model, we can use the likelihood ratio test to compare the two models statistically. Specifically, if $L(\Theta_D^*; \mathbf{W})$ is the maximized log-likelihood function under the pure diffusion model (null) and $L(\Theta_J^*; \mathbf{W})$ is the maximized log-likelihood function under the jump-diffusion model, then the statistic A described in Equation (3) is asymptotically distributed chi-squared with three degrees of freedom:

$$\Lambda = -2[L(\Theta_D^*; \mathbf{W}) - L(\Theta_J^*; \mathbf{W})] \sim \chi^2(3). \tag{3}$$

1.1 Finite sample properties using simulations

The desirable properties of the maximum likelihood estimators are valid only asymptotically and under certain regularity conditions. Therefore, to evaluate the finite sample properties of the estimators, I use a simulation technique and report the results in Table 1. The

Table 1
Finite sample properties of the MLE estimators of the jump-diffusion mode model based on simulations

Set	Parameter	Sim val	T = 100			T = 300		
			NC	Mean	SEM	*NC*	Mean	SEM
1	$\alpha \times 10^3$	1.00	196	0.56	0.36	198	0.76	0.14
	$\sigma^2 \times 10^4$	9.00	196	7.21	0.18	198	8.70	0.08
	$\phi \times 10^3$	1.00	196	2.04	0.35	198	1.19	0.11
	$\delta^2 \times 10^4$	100.00	196	69.78	6.65	198	91.58	4.43
	λ	0.05	196	0.26	0.02	198	0.08	0.01
2	$\alpha \times 10^3$	1.00	195	0.01	0.35	197	0.88	0.15
	$\sigma^2 \times 10^4$	9.00	195	7.90	0.17	197	8.71	0.09
	$\phi \times 10^3$	2.00	195	2.81	0.36	197	1.99	0.17
	$\delta^2 \times 10^4$	100.00	195	77.97	4.69	197	89.93	2.85
	λ	0.10	195	0.22	0.02	197	0.13	0.01
3	$\alpha \times 10^3$	1.00	194	0.56	0.41	198	1.00	0.21
	$\sigma^2 \times 10^4$	9.00	194	8.79	0.28	198	8.87	0.13
	$\phi \times 10^3$	10.00	194	10.07	0.57	198	9.86	0.34
	$\delta^2 \times 10^4$	100.00	194	105.29	3.71	198	99.77	1.65
	λ	0.50	194	0.53	0.02	198	0.51	0.01
4	$\alpha \times 10^3$	1.00	198	0.96	0.55	197	0.77	0.29
	$\sigma^2 \times 10^4$	9.00	198	12.19	0.75	197	9.70	0.27
	$\phi \times 10^3$	20.00	198	20.60	0.84	197	20.24	0.50
	$\delta^2 \times 10^4$	100.00	198	121.80	4.83	197	107.71	1.57
	λ	1.00	198	0.89	0.02	197	0.95	0.01
5	$\alpha \times 10^3$	−2.00	198	−2.77	0.18	199	−2.08	0.09
	$\sigma^2 \times 10^4$	3.00	198	2.46	0.05	199	2.91	0.02
	$\phi \times 10^3$	3.00	198	3.68	0.17	199	3.14	0.07
	$\delta^2 \times 10^4$	9.00	198	8.52	0.59	199	8.47	0.44
	λ	0.05	198	0.19	0.02	199	0.07	0.01
6	$\alpha \times 10^3$	−2.00	196	−3.32	0.25	200	−2.20	0.13
	$\sigma^2 \times 10^4$	3.00	196	2.11	0.06	200	2.77	0.04
	$\phi \times 10^3$	3.00	196	4.30	0.25	200	3.30	0.13
	$\delta^2 \times 10^4$	9.00	196	6.20	0.42	200	7.47	0.33
	λ	0.10	196	0.40	0.03	200	0.18	0.01
7	$\alpha \times 10^3$	−2.00	195	−1.88	0.28	198	−2.14	0.15
	$\sigma^2 \times 10^4$	3.00	195	2.55	0.09	198	2.96	0.07
	$\phi \times 10^3$	3.00	195	2.54	0.31	198	2.95	0.17
	$\delta^2 \times 10^4$	9.00	195	10.22	0.60	198	9.96	0.39
	λ	0.50	195	0.63	0.03	198	0.54	0.02
8	$\alpha \times 10^3$	−2.00	198	−1.38	0.32	200	−1.75	0.19
	$\sigma^2 \times 10^4$	3.00	198	3.69	0.16	200	3.51	0.10
	$\phi \times 10^3$	3.00	198	2.78	0.38	200	2.79	0.21
	$\delta^2 \times 10^4$	9.00	198	13.33	0.56	200	10.99	0.28
	λ	1.00	198	0.75	0.03	200	0.83	0.02

The finite sample properties are based on 200 replications of either 100 or 300 observations, according to the procedure described in Section 1.1. The set of parameter values used in each replication is shown in the column Sim val. The column NC gives the number of replications for which the optimization converged to feasible estimates. The mean estimates (Mean) reported are the means of the parameter estimates based on the replications that converged, and the standard errors of the means (SEM) are based on the sampling distribution of the estimates:

$$\text{mean} = \frac{1}{NC}\sum_{i=1}^{NC}\hat{\theta}_i \text{ and SEM} = \frac{1}{\sqrt{NC}}\left[\frac{1}{(NC-1)}\sum_{i=1}^{NC}(\hat{\theta}_i - \text{mean})^2\right]^{1/2},$$

where, $\hat{\theta}_i \in \{\hat{\alpha}_i, \hat{\sigma}_i^2, \hat{\mu}_i, \hat{\delta}_i^2, \hat{\lambda}_i\}\ \forall i = 1, 2, \ldots, NC.$

finite sample properties (bias and efficiency) depend on the number of observations and on the choice of parameter values.[6] Therefore, I use two sets of parameters for the means and variances of the diffusion and jump processes $(\alpha, \sigma^2, \mu, \delta^2)$ in our simulations. The parameter values used in the first set are similar to the parameter estimates for an average market value stock traded on the NYSE/AMEX. For the second set, I use the mean estimates obtained from the sample of firms involved in targeted share repurchases. In addition, each set of parameters is augmented by four different Poisson parameter values $(\lambda = 0.05, 0.1, 0.5, \text{and } 1.0)$, where the Poisson parameter λ is the average number of jumps per unit time.

Simulated samples are obtained using IMSL (Institute for Mathematical and Statistical Library) routines and the following procedure. First, generate a random number q from a Poisson distribution with a parameter λ. Second, obtain q independent normal variates, each with a mean of μ and variance δ^2. Third, the sample for the Wiener process is generated using the normal random number generator with a mean of $(\alpha - \sigma^2/2)$ and variance σ^2. Fourth, the normal random variables from the compound Poisson process and the Wiener processes are added to obtain a single observation. I repeat the above steps to obtain samples with 100 and 300 observations, respectively. Finally, each parameter-observation combination is replicated 200 times with different seeds for the random number generator.

In Table 1, I show the simulation results for the eight different combinations of parameters. The means and the standard errors shown are based on the replications that converged to an interior maximum.[7] The results indicate that when λ is either very small (0.05) or very large (1.0) the estimators are significantly biased irrespective of the number of observations. For intermediate values λ (0.5), however, the estimators have very little bias when the sample size equals 300 observations. For example, in set one, when $\lambda = 0.5$, the bias for the estimated diffusion mean is zero, while the bias for the mean of the

[6] The likelihood function given by Equation (A.2) and the first and second partial derivatives of the likelihood function require the evaluation of an infinite sum. Therefore. the successful implementation of the numerical technique depends on adequate approximations to this infinite sum by truncating it at a finite number J. The effect of truncation was studied through simulation, and it was found that, for $\lambda < 1$, truncating at $J = 5$ was sufficient to obtain convergence to the true parameters (the results are available on request). Ball and Torous (1983) suggest truncating at $J = 10$ based on an analytic approximation for the truncation error.

[7] The maximum likelihood estimators are based on numerically optimizing the likelihood function, and the estimates of standard errors obtained through the Hessian matrix are valid only for an interior optimum. Therefore. we require that feasible estimates of all the variances and the Poisson parameter be greater than zero. From Table 1 we observe that when the number of observations per replication is 300 (T), then at least 98.5 percent of the replications converged to an interior optimum. However. for 100 observations the number that converged drops to 97 percent or more. Since the MLE's are only consistent and asymptotically unbiased, one would expect the point estimates to be biased in finite samples. The bias could lead to infeasible estimates, particularly in small samples.

jump process is only 1.4 percent. The biases for the other parameters are less than 2 percent. As expected, the efficiency of the estimators increases with the number of observations. However, using a large number of observations spread over a long time could compromise the assumption that the parameters are stationary. The simulation results provide valuable information about the number of observations required to obtain reasonable estimates of the parameters of the jump-diffusion model. Further, it also shows the sensitivity of the estimators to different sets of parameter values.

2. Event Study Estimators and Comparison of Performance

2.1 Jump-diffusion model estimator and test statistic *(J_1, J_2)*

I derive the estimators and the test statistics for a portfolio of N stocks with events distributed randomly in calendar time. This ensures that errors due to market-wide effects or idiosyncratic firm-specific effects are minimized through diversification. Let

$$\begin{aligned}\hat{\theta}_{ei} &\in \{\hat{\alpha}_{ei}, \hat{\phi}_{ei}, \hat{\sigma}^2_{ei}, \hat{\delta}^2_{ei}, \hat{\lambda}_{ei}\} \\ \hat{\theta}_{oi} &\in \{\hat{\alpha}_{oi}, \hat{\phi}_{oi}, \hat{\sigma}^2_{oi}, \hat{\delta}^2_{oi}, \hat{\lambda}_{oi}\}\end{aligned} \qquad \forall i = 1, \ldots, N.$$

where $\hat{\theta}_{ei}$ and $\hat{\theta}_{oi}$ are the estimators of the jump-diffusion model parameters for firm i during the event and non-event periods, respectively. In the model specification, the paired differences in the sample estimates, $\hat{\theta}_i = \hat{\theta}_{ei} - \hat{\theta}_{oi}$, measure the marginal effects of the event for firm i in addition to errors due to non-event related effects. However, if we assume that the errors are independent across the firms, then we can minimize the effect due to errors and estimate the marginal effect of the event under consideration by the cross-sectional average of the differences,

$$\bar{\theta} = \frac{1}{N} \sum_{i=1}^{N} \hat{\theta}_i.$$

An estimate for the standard error of $\bar{\theta}$ is obtained from the cross-sectional sampling distribution of the estimates $\hat{\theta}_i$. Further, under the null hypothesis that there is no shift in the model parameters during the event period compared to the non-event period, the statistic J_1 (Equation 4) has a standard normal distribution for large values of N:

$$J_1 = \sqrt{N}\frac{\bar{\theta}}{\hat{\sigma}_\theta} \sim \mathbf{N}(0, 1) \qquad \text{where} \quad \hat{\sigma}^2_\theta = \frac{1}{N-1} \sum_{i=1}^{N} (\hat{\theta}_i - \bar{\theta})^2. \tag{4}$$

The above statistic assumes that the estimation errors for the cross section of firms are homoskedastic and independent. However, the maximum likelihood technique also provides an estimator for the variance of the sample estimates for each firm. Further, this estimator is asymptotically normal. Therefore, if η^2_{ei} is the error variance of the estimator $\hat{\theta}_{ei}$ and η^2_{oi} is the error variance of the estimator $\hat{\theta}_{oi}$, then

$$\hat{\theta}_{ei} \sim \mathbf{N}(\theta_e, \eta^2_{ei}) \quad \text{and} \quad \hat{\theta}_{oi} \sim \mathbf{N}(\theta_o, \eta^2_{oi}) \qquad \forall i = \{1, \ldots, N\}.$$

Assume that the estimation errors in the two periods are uncorrelated; then, under the null hypothesis, $\theta_e = \theta_o$,

$$(\hat{\theta}_{ei} - \hat{\theta}_{oi}) \sim \mathbf{N}(0, \eta^2_{ei} + \eta^2_{oi}) \qquad \forall i = \{1, \ldots, N\}.$$

Dividing by the standard deviation and aggregating across all N stocks, I obtain the statistic J_2 (Equation 5) which is distributed approximately standard normal for large N:

$$J_2 = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \frac{(\hat{\theta}_{ei} - \hat{\theta}_{oi})}{\sqrt{\hat{\eta}^2_{ei} + \hat{\eta}^2_{oi}}} \sim \mathbf{N}(0, 1). \tag{5}$$

The statistic J_2 allows for the estimation errors to be heteroskedastic. Further, the interval between the initial foothold and subsequent targeted repurchase is variable across firms. Therefore the statistic J_2 would be more efficient than J_1, as J_2 would give higher weights to estimates with low standard errors. In addition, the statistic is based on estimates for a cross-section of firms for which the assumption of homoskedastic errors is likely to be violated.

2.2 Multiday event study estimators and test statistics (Z_1, Z_2)

For the traditional event study estimators, I will consider the mean-adjusted return model specification as the benchmark. Brown and Warner (1980, 1985) found that the specification of a benchmark model for returns is not critical in event studies where there is no event date clustering. The mean-adjusted model assumes that the ex ante expected return for a given security i is equal to m_i; therefore, the predicted ex post expected return in the event period t is also equal to m_i. If the return to security i at event time t is r_{it}, then the abnormal return e_{it} is given by, $e_{it} = r_{it} - m_i \; \forall t \in \{1, \ldots, T_e\}$ and $i \in \{1, \ldots, N\}$. The expected return m_i is estimated from non-event period returns. Finally, we estimate the average cumulative abnormal return for a portfolio of N firms by

$$\bar{c} = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T_{ei}} (r_{it} - \hat{m}_i), \qquad \text{and} \qquad \hat{m}_i = \frac{1}{T_{oi}} \sum_{t=1}^{T_{oi}} r_{it}, \tag{6}$$

where T_{ei} and T_{oi} are the number of observations in the event and non-event periods, respectively, for firm i. The choice of a variance estimate for a test statistic will depend on the serial and cross-sectional dependencies of the sample returns. Brown and Warner (1985) document that adjusting for serial dependencies in returns results in only a small improvement in the specification of the test statistics. Also, if the returns are not clustered in calendar time, then estimators based on cross-sectional independence are also well specified. In Appendix A.2.1, I derive a test statistic Z_1 based on the assumption that returns are serially and cross-sectionally independent. The statistic also assumes that there is no change in variance conditional on the event.

Brown and Warner (1985) and Boehmer, Musumeci, and Poulson (1991) find that substantial changes in the event period variance can lead to misspecification of the test statistic Z_1. An increase in return variance would bias Z_1 upwards and increase type I errors. A decrease in the variance would increase type II errors. To account for conditional heteroskedasticity, I derive an alternative estimator Z_2 in which the standard error is estimated using the cross-sectional distribution of the cumulative abnormal returns of the N firms. Appendix A.2.2 describes the estimator and the test statistic.

2.3 Relative performance of jump-diffusion model and standard event study estimators

When the economic impact of the event on security prices is small, an estimator with higher power is always preferable. Therefore, I assess the performance of the competing methods through simulated data and empirical power functions. The jump-diffusion model parameters for each firm are generated from a uniform distribution whose minimum and maximum supports are chosen to approximate values estimated for the sample of targeted share repurchases. Using the above parameters and the steps outlined in Section 1.1, I generate 400 observations. The first 200 observations represent the event period returns, and the next 200 represent post-event period return. Next I simulate the impact of the events with a jump-diffusion model with six different sets of parameters $(\alpha_e, \sigma_d^2, \phi_d, \delta_d^2, \lambda_d)$ with average cumulative mean effects, $200(\alpha_d + \phi_d)$ ranging from zero to 0.20 over 200 days. The above procedure was replicated to obtain 100 portfolios consisting of 20 firms, For each of the 100 portfolios, I estimate the statistics for the competing models. The empirical power is the percentage of times the null hypothesis is rejected. I also estimate the theoretical power based on the statistic Z_1, which is described in Appendix A.3.

In Table 2 I show the empirical power functions. The results emphasize important differences between the jump-diffusion model estimators and the traditional multiday estimators. In case 1, I set $\alpha_d = 0$ and $\phi_d = 0$. That is, the mean effects due to trading and public announcements based on the events are zero. For these parameter values, the statistic Z_1 rejects the null hypothesis 27 percent of the

Table 2
Theoretical and empirical power functions for the traditional multiday event study estimators and the jump-diffusion model estimators

	Case 1			Case 2			Case 3			Case 4			Case 5			Case 6		
Estimator	Sim	$p = .10$	$p = .01$	Sim	$p = .10$	$p = .01$	Sim	$p = .10$	$p = .01$	Sim	$p = .10$	$p = .01$	Sim	$p = .10$	$p = .01$	Sim	$p = .10$	$p = .01$
$m_d \times 10^2(\pi_1)$	0.00	0.10	0.01	0.05	0.78	0.44	0.05	0.78	0.44	0.00	0.10	0.01	0.10	1.00	0.99	0.05	0.78	0.44
$m_d \times 10^2(\pi_2)$	0.00	0.10	0.01	0.05	0.50	0.18	0.05	0.50	0.18	0.00	0.10	0.01	0.10	0.95	0.76	0.05	0.61	0.26
$m_d \times 10^2 - Z_1$	0.00	0.47	0.27	0.05	0.68	0.41	0.05	0.63	0.46	0.00	0.49	0.25	0.10	0.97	0.91	0.05	0.81	0.58
$m_d \times 10^2 - Z_2$	0.00	0.17	0.02	0.05	0.30	0.09	0.05	0.38	0.08	0.00	0.19	0.04	0.10	0.83	0.55	0.05	0.47	0.16
$s_d^2 \times 10^4$	1.90	1.00	1.00	1.90	1.00	1.00	1.92	1.00	1.00	1.92	1.00	1.00	2.00	1.00	1.00	0.92	1.00	1.00
$\alpha_d^2 \times 10^2$	0.00	0.09	0.01	0.05	0.51	0.16	0.00	0.13	0.02	−0.05	0.37	0.16	0.00	0.13	0.00	0.00	0.08	0.01
$\sigma_d^2 \times 10^4$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00	0.17	0.03
$\phi_d \times 10^2$	0.00	0.13	0.01	0.00	0.11	0.01	0.05	0.24	0.04	0.05	0.25	0.05	0.10	0.83	0.42	0.05	0.46	0.11
$\Delta_d^2 \times 10^4$	0.90	1.00	1.00	0.90	1.00	1.00	0.92	1.00	1.00	0.92	1.00	1.00	1.00	1.00	1.00	0.92	1.00	0.09
λ_d	0.10	0.96	0.79	0.10	0.97	0.75	0.10	0.95	0.64	0.10	0.99	0.99	0.10	0.91	0.61	0.10	1.00	0.97

Theoretical and empirical power for the estimators are based on Monte Carlo simulation according to the procedure described in Section 2.3. The power is based on the statistic J_2 [Equation (5)] for all the estimators except for s_d^2 and Δ_d^2, which are based J_1 [Equation (4)] The reported values are the percentage of times the null hypothesis is rejected at the appropriate p value for a two-tailed test based on 100 replications. Each replication consists of a portfolio of 20 firms. The theoretical power for the estimator π_1 is based on Equation (A.5) with the average variance for the simulated returns in the non-event period. The theoretical power for the estimator π_2 is based on the average variance for the simulated returns in the event period. The events are simulated using the jump-diffusion model [Eq. (l)] with parameters α_d, σ_d^2, μ_d, δ_d^2, and λ_d, where, $\phi_d = \lambda_d \mu_d$ and $\Delta_d^2 = \lambda_d(\mu_d^2 + \delta_d^2)$ The unconditional mean and variance of the total event process (diffusion plus jumps) is given by m, and s_d^2, respectively. The column Sim gives the simulated effects due to the event process.

time when the theoretical value is only 1 percent. On the other hand, the statistic Z_2 is well specified. The misspecification of the statistic Z_1 is due to the assumption that there is no increase in return variance during the event period. The empirical power functions of the estimators of the mean effect due to trading $(\hat{\alpha}_d)$ and due to information surprises (ϕ_d) based on the jump-diffusion model are similar to the theoretical values for both levels of significance.

In case 2, $\alpha_d = 0.0005$ and $\phi_d = 0$. The estimator $\hat{\alpha}_d$ has a power of 0.51, which compares favorably with the theoretical power based on the event-period variance of 0.50. However, the test statistic Z_2 has a power of only 0.30. This highlights the advantage of separately estimating the trading and information effects. In case 3, I simulate with a jump process mean $\phi_d = 0.0005$, and the power of f_d is 0.24, compared to the theoretical power of 0.50. Further, the estimator $\hat{\alpha}_d$ has slightly higher rejection rates compared to the theoretical level (0.13 versus 0.10). This suggests that when the jump amplitudes are small, the model is unable to discriminate between the trading and information effects. To analyze this further, in case 5 I increase the jump mean to 0.01. This results in an empirical power of 0.83 for f_d which is closer to the theoretical level of 0.95.

In case 4, the event is simulated with a diffusion mean $\alpha_d = -0.0005$, and a jump process mean $\phi_d = 0.0005$. This results in an overall unconditional mean of zero. As expected, the traditional estimator has low power. However, the jump-diffusion model is able to detect the separate effects of trading and information with power levels of 0.37 and 0.25, respectively. This highlights a possible scenario under which my methodology will be able to detect significant separate effects, while the traditional estimator will show no effects. In case 6, the events are simulated using only a jump process ($a_d = 0$ and $\sigma_d^2 = 0$) I find that the model is well specified: The estimators for the diffusion mean and the diffusion variance have significance levels close to the theoretical values. In addition to the power studies, I also estimate the bias in the estimators, it is generally less than 2 percent.

The simulation results indicate that for estimating the cumulative event returns over long periods of time, the estimators based on the jump-diffusion model are well specified, and the empirical power under simulated conditions is equal to or better than that of the traditional event study estimators.

3. The Overall Economic Effect of Blockholdings and Subsequent Targeted Share Repurchases on Nonparticipating Stock Holders

A targeted repurchase (commonly called greenmail) occurs when a firm buys a block of its common stock at a premium from either a single shareholder or from a group of shareholders. The use of greenmail is controversial because it deliberately discriminates among various shareholders. This has led to legislative proposals to outlaw greenmail or to require shareholder approval for payment of greenmail. In assessing the desirability of regulating targeted repurchases, one must consider the economic effects of the block formation, the interim period, and the repurchase on stock returns. However, the long interim period makes it difficult to evaluate the overall wealth effect. During this interim period, the market often reacts to public information about a possible takeover by the blockholder or to the defensive actions taken by the management. Moreover, during the long interim period, part of the information will be incorporated in prices due to trading by informed agents. Therefore, on the day of the repurchase announcement, the price reaction would only reflect the residual information that is not already incorporated in the prices. This results in low power and possible bias in the traditional event study estimators.

Empirical studies that examine the effect of greenmail test the Management Entrenchment Hypothesis versus the Shareholder Welfare Hypothesis (see, for example, Mikkelson and Ruback 1989). The proponents of the Management Entrenchment Hypothesis argue that greenmail is paid by management to defeat a takeover attempt by the blockholder at the expense of the non-participating shareholders. On the other hand, Shleifer and Vishny (1988) argue that managers pay greenmail to signal that the firm is undervalued. The Management Entrenchment Hypothesis predicts a negative abnormal return around the date of targeted repurchase, while the shareholder welfare hypothesis predicts a positive impact on stock returns. However, these predictions implicitly assume that no information regarding the control contest is released to the market through trading after the block is formed and before the payment of greenmail.

Mikkelson and Ruback (1989) argue that the repurchase is an outcome of an ongoing corporate control process. Therefore, the relevant measure of the impact on non-participating stockholders is the cumulative abnormal return from the formation of the block through the date of repurchase. However, during the long interim period, the market participants revise their expectations as new information regarding the intentions of the blockholder and the manager is revealed, and this information is incorporated into prices through their trading. Therefore, when testing the two hypotheses, it is important to consider the abnormal returns due to trading, in addition to the abnormal reactions around announcement dates. Traditional event studies find that the average cumulative abnormal return during the overall period is not statistically different from zero for the repur-

300 observations spanning the interval from 50 to 349 trading days after the repurchase.

3.1 Tests of alternative specifications for the stock price process

Before evaluating the economic effects of targeted repurchases, I first test whether the stock price dynamics for the greenmail sample is better described by a pure diffusion model or a mixed jump-diffusion model. I evaluate the likelihood ratio statistic Λ given in Equation (3) for all three periods. If Λ is greater than the critical value at the 5 percent level of significance, I reject the pure diffusion model in favor of the jump-diffusion model. Table 3 shows the number of firms for which the pure diffusion model is rejected in favor of the jump-diffusion model for the greenmail sample and for a sample of ran domly selected firms. For the greenmail sample, the rejection rate is greater than or equal to 93 percent for all three periods. This supports using the mixed jump-diffusion model for the greenmail sample. For a random sample of firms, the rejection rate is greater than or equal to 86 percent, confirming the findings of previous researchers.

3.2 The effects of trading and information surprises associated with blockholdings and repurchases

The results of my empirical investigation are presented in Table 4. The difference in parameter estimates for the event period and the post-event period are shown in the first column. Using the traditional method, the average cumulative abnormal return, $T_e(m_e - m_{po})$ is negative but not significantly different from zero at the 5 percent level for a two-tailed test (-11.17 percent, *t*· stat = -1.77). For the jump-diffusion model I find that all the parameters except the jump process mean, *f*, are statistically different in the two periods. The cumulative mean diffusion effect, $T_e(\alpha_e - \alpha_{po})$, is -11.46 percent (*t*· stat = -2.38) which is statistically different from zero at the 5 percent level, while the cumulative mean effect due to the jumps, $T_e(\phi_e - \phi_{po})$ is an insignificant 0.95 percent (*t*· stat of 0.95). Further, I End that the volatility of the diffusion process is 48.5 percent higher in the event period compared to the post-event period ($\ln[\sigma_e^2/\sigma_{po}^2] = 0.396$). Similarly the increase in the jump process volatility is 37.3 percent. The above Endings suggest that most of the effects associated with the blockholding and subsequent repurchase are incorporated into prices through trading, and the average effect due to public announcements is insignificant.

In the second column of Table 4, the results for the difference in parameter estimates for the event period and the pre-event period are presented. The traditional method results in an average cumu-

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Table 4
Comparison of parameter estimates from the event, post-event, and pre-event periods for the greenmail sample and for a random sample of firms

	Event − Post-event $e = 1$, $po = 2$		Event − Pre-event $e = 1$, $pr = 2$		Post-event − Pre-event $po = 1$, $pr = 2$		Random sample $po = 1$, $pr = 2$	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
Model 1—Pure diffusion model								
$(m_1 - m_2) \times 10^2$	−0.015	−0.80	0.042	1.66	0.057	2.93	0.005	0.85
$(s_1^2 - s_2^2) \times 10^4$	1.770	4.06	1.109	3.03	−0.661	−1.75	−0.021	−0.07
$\ln(s_1^2/s_2^2)$	0.335	5.51	0.244	4.29	−0.091	−1.44	−0.001	−0.01
$T_1(m_1 - m_2) \times 10^2$	−11.170	−1.77	4.593	1.11	14.631	2.97	1.580	0.31
Model 2—Jump diffusion model								
$(\alpha_1 - \alpha_2) \times 10^2$	−0.029	−2.38	0.026	0.17	0.055	2.16	0.022	1.25
$(\sigma_1^2 - \sigma_2^2) \times 10^4$	0.683	7.74	−0.237	−1.16	−0.921	−8.49	0.270	2.60
$\ln(\sigma_1^2/\sigma_2^2)$	0.396	4.09	−0.006	−0.07	−0.402	−3.98	0.108	1.57
$(\phi_1 - \phi_2) \times 10^2$	0.017	0.95	0.015	1.13	−0.003	−0.30	−0.016	−0.79
$(\mu_1 - \mu_2) \times 10^2$	0.123	0.51	0.083	0.41	−0.040	−0.15	0.105	0.52
$(\delta_1^2 - \delta_2^2) \times 10^4$	6.292	4.85	7.362	4.50	1.070	0.29	−2.590	−1.06
$\ln(\delta_1^2/\delta_2^2)$	0.493	3.82	0.593	3.51	0.100	0.54	−0.350	−1.88
$(\Delta_1^2 - \Delta_2^2) \times 10^2$	1.045	3.25	1.213	4.04	0.168	0.62	−0.218	−0.78
$\ln(\Delta_1^2/\Delta_2^2)$	0.317	4.26	0.354	4.75	0.037	0.51	−0.059	−0.96
$\lambda_1 - \lambda_2$	−0.118	−3.21	−0.082	−1.23	0.036	1.76	0.005	0.04
$\ln(\lambda_1/\lambda_2)$	−0.239	−1.99	−0.132	−1.04	0.107	0.76	0.015	0.12
$T_1[\alpha_1 - \alpha_2] \times 10^2$	−11.464	−2.38	8.765	0.17	14.769	2.16	6.730	1.25
$T_1[\phi_1 - \phi_2] \times 10^2$	0.952	0.95	−4.875	−0.41	−1.444	−0.16	−4.730	−0.80

Model 1 assumes that the continuously compounded daily returns are independent, identically, and normally distributed with mean m and variance s^2. Model 2 assumes that daily returns in the event period *(e)*, post-event period *(po)*, and the pre-event period *(pr)* are described by the jump-diffusion model given by Equation (2). The r-statistic for the difference in parameters s^2, Δ^2, and μ^2 is based on the estimator J_1 (Equation 4); for all the other estimators it is based on J_2 (Equation 5). $N = 100$ and T is the number of trading days in the period. The random sample is based on 120 firms selected from the CRSP database at random. For each firm a random event date is assigned in the period 1976-1986, and the parameters are estimated using 300 trading days each for the post. and pre-event periods. The subscripts 1 and 2 denote the appropriate estimation period under consideration.

lative abnormal return, $T_e(m_e - m_{pr})$ of 4.59 percent (*t* -stat = 1.11), and an increase in total volatility, S_e^2/S_{pr}^2) of 27.6 percent. The jump-diffusion model estimators provide additional information about the effects of trading and announcements on stock returns in the two periods. The means and variances of the diffusion processes in the two periods are not statistically different, and virtually all the increase in volatility stems from the jump process. The similar volatilities of the diffusion processes in the two periods suggest that the level of trading in the two periods is comparable. Therefore, a researcher using the pre-event period as a benchmark may erroneously conclude that the event had no impact on stock returns. In the third column, I compare the post and pre-event periods. I find that the jump process parameters are not significantly different in the two periods. However, the diffusion process has a higher variance and a lower mean in the pre-event period relative to the post-event period. This suggests that the intensity of trading is significantly higher in the pre-event period when compared to the post-event period.

These findings highlight the relative merits of my model over the usual event study method. First, the jump-diffusion model is shown to be statistically superior to the pure diffusion model in describing the underlying price process. Second, one obtains more powerful tests of the economic effects of the event. Finally, one gets additional information about the relative effects of trading versus information in the different estimation periods.

3.3 Effects of market microstructure and market wide systematic information

In the specification of my test statistic, the effects due to market-wide information and firm-specific information that is unrelated to the event are a main concern. I assume that aggregating the estimates for a portfolio of firms whose event dates are dispersed in calendar time will mitigate the effect of these errors on the estimators. Another potential concern is the bias in the volatility measures due to the increase in volume of trading over time. For example, Clark (1973) and Tauchen and Pitts (1983) provide models in which the trading volume is positively related to volatility of price changes. This would mean that the volatility in the post-event periods is likely to be higher than in the event or pre-event periods. I study the impact of the above problems on the specifications of the test statistics by comparing in two adjoining periods the jump-diffusion model estimates for a random sample of firms selected from the CRSP data base. For each firm, I assign a random event date during the 1976-1986 period, and estimate the parameters using 300 trading days each for the post and the pre-event periods. The results are reported in the fourth column of

Table 4. The parameter estimates based on the pure diffusion model are not significantly different in the two periods. For the jump-diffusion model, all the parameters-except the variances of the diffusion processes in the two periods-are not statistically different at the 5 percent level of significance. The variance of the diffusion process in the post-event period is 0.27×10^{-4} (*t* -statistic of 2.60) higher than the variance in the pre-event period: The increase in the diffusion variance is consistent with an increase in volume of trading over time. This also supports the trading-time hypothesis, which argues that volatility is generated through trading. In my study of targeted share repurchases, I find that the trade-induced diffusion process variance is significantly higher in the event period compared to the post-event period. Therefore, any positive trend in the volume of trading will only result in biasing downwards the observed increase in variance in the event period relative to the post-event period. From the results described here, I conclude that the estimators based on the jump-diffusion model are well specified-except for the increase in the variance of the diffusion process.

4. Summary and Conclusions

Event studies are used to evaluate the economic impact of specific events. Traditional approaches analyze the abnormal returns around the announcement dates to determine the economic impact on securities. In addition, hypotheses tests are based on statistics derived under the assumption that returns are normally distributed. However, many researchers have documented that the probability distribution of daily stock returns deviate substantially from normality, and the price path consists of significant discrete jumps. Incorrectly modeling the underlying price process may lead to inconsistent test statistics and biased inferences. In addition to the incorrect specification of the underlying process for stock prices, the standard framework which looks at only the abnormal returns around announcements ignores the economic effects of trading by informed agents prior to the announcements. Previous studies that use cumulative abnormal returns pool both the announcement effects and trading effects and lead to loss of information and inefficient estimators. In this article, I proposed a framework based on a mixed jump-diffusion model for stock prices to separately estimate the economic effects of trading versus publicly released information. The relative merits of the jump-diffusion model and the traditional model are compared using simulations and through an application to a corporate event involving blockholdings and targeted repurchases.

I find that for the repurchase sample the jump-diffusion model is statistically superior to the pure diffusion model in describing stock price behavior. I next document that the overall economic effect on stock returns spanning the blockholdings and repurchases is negative, and the entire impact is due to trading. The average stock price reaction around announcements is not significantly different from zero. The traditional cumulative abnormal return estimator, however, does not allow one to separate the effects and leads to an average negative effect that is not statistically significant.

The framework developed in this article is particularly useful for studies with multiple events and a high probability of informed trading. For example, in open-market share repurchases, the managers can time their repurchase based on information. This would result in part of the information being incorporated into prices through trading and only the residual information being reflected in prices at the time of a public disclosure. Therefore, abnormal returns around public disclosures may not provide the true economic effect of the repurchases, and estimators of cumulative abnormal returns will have low power. Another application is analyzing the effects of legislative changes on stock returns. These changes must be passed through Congress before they are written into law. During this time, many revisions are likely. Therefore, the true valuation effect should take into account the price reactions around these revisions. Due to the long event window and multiple events, the jump-diffusion model as opposed to the traditional event study should be better suited to measure the economic impact of such legislative events.

Appendix

A.1 Maximum likelihood estimation

The parameters of the compound events model are estimated via maximum likelihood technique. Let w_t be the logarithm of price relative at time t and $W = (w_t;\ t = 1, \ldots, T)$ be the daily continuously compounded security returns in the estimation period. If $\theta = (\alpha, \sigma^2, \mu, \delta^2, \lambda)$ denotes the parameters of the jump-diffusion model described in Equation (1), then the unconditional density of daily returns is

$$f(X) = \sum_{j=0}^{\infty} \frac{1}{[2\pi(\sigma^2 + \delta^2 j)]^{1/2}} \exp\left(\frac{-(X - \alpha + \sigma^2/2 - \mu j)^2}{2(\sigma^2 + \delta^2 j)}\right) \frac{e^{-\lambda}\lambda^j}{j!}. \tag{A.1}$$

Assume that the daily returns are independent and identically distributed; then the logarithm of the likelihood function for T return realizations is

$$L = \ln l(\Theta; W) = -T\lambda - \frac{T}{2}\ln(2\pi) + \sum_{t=1}^{T} \ln(Z_t), \qquad \text{where}$$

$$Z_t = \sum_{j=0}^{\infty} \frac{1}{(\sigma^2 + \delta^2 j)^{1/2}} \exp\left[\frac{-\left(w_t - \alpha + \dfrac{\sigma^2}{2} - \mu j\right)^2}{2(\sigma^2 + \delta^2 j)}\right] \frac{\lambda^j}{j!}. \tag{A.2}$$

As usual, necessary conditions for the existence of MLE's for q are provided by setting the first partial derivatives of the likelihood function with respect to the parameters equal to zero. The corresponding sufficient conditions require that the matrix of second partial derivatives evaluated at the optimum is negative semi-definite. Subject to regularity conditions, the inverse of the information matrix evaluated at the optimum gives an estimate for the asymptotic variance-covariance matrix of the estimators, and the MLE's are asymptotically normal. Hence, the maximum likelihood method allows us to construct approximate confidence intervals for the parameter estimators of interest, which are asymptotically efficient. The equations obtained from the first-order conditions are nonlinear in the parameters, and an analytic solution does not exist. Hence, a numerical technique (the quadratic hill-climbing algorithm proposed to Goldfeld, Quandt, and Trotter, 1966) is employed to find the estimates that maximize the likelihood function.

A.2 Multiday event study test statistics

A.2.1 Test statistic based on no change in conditional variance. To derive a test statistic, I need to estimate the variance for the cumulative abnormal returns. For each stock i, I estimate the variance of the excess returns using data from the non-event period by

$$\hat{s}_i = \frac{1}{(T_{oi} - 1)} \sum_{t=1}^{T_{oi}} (r_{it} - \hat{m}_i)^2 \qquad \text{and} \qquad \hat{m}_i = \frac{1}{T_{oi}} \sum_{t=1}^{T_{oj}} r_{it},$$

where the returns to security i on day t in the non-event period are given by r_{it}, and T_{oi} is the number of observations in the non-event period for firm i. Assuming that the abnormal returns in the event period are serially uncorrelated, one can then estimate the standard error for the cumulative abnormal return by $\hat{S}_i\sqrt{T_{ei}}$. Each cumulative abnormal return for firm i is then divided by the estimated standard deviation to yield a standardized cumulative abnormal return c_i', where

$$c_i' = \frac{\sum_{t=1}^{T_{ei}} (r_{it} - \hat{m}_i)}{\hat{s}_i\sqrt{T_{oi}}}.$$

Finally the test statistic based on the average cumulative abnormal returns for N firms is

$$Z_1 = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} c'_i. \tag{A.3}$$

If the standardized cumulative excess returns are independent and identically distributed with finite variance, under the null hypothesis of zero cumulative abnormal returns, the test statistic Z_1 will be distributed standard normal for large N.

A.2.2 Multiday test statistic based on change in conditional variance. If I assume that the cumulative abnormal returns, c_i, are cross-sectionally independent and identically distributed, which is a reasonable assumption if there is no calendar time clustering, then I can estimate the standard deviation using the cross-sectional distribution of the cumulative abnormal returns. If c_i is the cumulative abnormal returns in the event period for firm i, then for large N the statistic Z_2 is distributed unit normal,

$$Z_2 = \sqrt{N} - \frac{\bar{c}}{\hat{s}_c} \sim \mathbf{N}(0, 1), \tag{A.4}$$

where

$$\bar{c} = \frac{1}{N} \sum_{i=1}^{N} c_i \quad \text{and} \quad \hat{s}_c^2 = \frac{1}{N-1} \sum_{i=1}^{N} (c_i - \bar{c})^2.$$

A.3 Theoretical power function

Ball and Torous (1988) derive the theoretical power for a two-tail test, $\Pi(c, p)$ based on the statistic Z_1 which is given by

$$\Pi(c,p) = \Phi\left(-Z_{p/2} - \frac{c}{s_0}\sqrt{\frac{N}{T_e}}\right) + \Phi\left(-Z_{p/2} + \frac{c}{s_0}\sqrt{\frac{N}{T_e}}\right), \tag{A.5}$$

where c is the cumulative abnormal returns, S_o is the standard deviation, p is the level of significance, Z_p is implicitly defined by 1 - $\Phi(Z_p) = p$, and $\Phi(\cdot)$ denotes the cumulative density function for the standard normal distribution. For the jump-diffusion model estimators J_1 and J_2, I cannot derive analytically the theoretical power.

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