Information stages in efficient markets

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ABSTRACT

Market efficiency, in its strong form, asserts that asset prices fully reflect all available information. The classical event study methodology attempts to make explicit this link by assuming rigid and universal pre-event, event, and post-event periods. As an alternative, our framework captures the progressive diffusion of information around events as well as the overlapping impacts of separate events. We also illustrate that our approach captures mean-reversion of expected returns and increased volatility around announcement dates. These features reflect latent regime switches and are associated with semi-strong market efficiency.

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1. Introduction

According to the (strong-form) efficient market hypothesis, equity prices fully reflect all available information (cf. Fama (1965a,b, 1970, 1991) and Lo (2007) for a recent perspective). To make explicit the link between price and information, one approach is to rely on an event study as developed by Ball and Brown (1968) and Fama et al. (1969). Following this standard methodology, the impact of an event is to be assessed on its announcement date or within a fixed time window including it (cf. MacKinlay (1997) and Kothari and Warner (2007) for extensive surveys). For the overwhelming majority of event studies involving stock prices, statistical tests are performed to ascertain the existence of a mean return effect. Their implementation assumes almost always constant volatility across three predetermined periods (pre-event, event, and post-event) that are applied to all events and stocks. However, one can easily make the case that (a) stock prices prior to the announcement date already incorporate information about the forthcoming event announcement, and (b) the starting point of this information integration is generally diffuse. For example, firms in the same sector tend to make their quarterly earnings announcements around the same time, thus creating

anticipative environments. In addition, Kaniel et al. (2012) provide evidence of trading activity with price impact that is linked to forthcoming earnings announcements. In fact, one can even challenge the actual dating of an event. Most publicly traded corporations communicate through newswire sources such as Dow Jones & Company and Reuters. The Broadtape produced by Dow Jones News is available to virtually all financial professionals and its content is typically reported next with variable time lags in the Wall Street Journal (online and print versions). Furthermore, many events are subject to leakage, as in mergers and acquisitions, where it is difficult to time stamp the start of rumors circulating before official announcements.

The application of the event study methodology in its classical form cannot detect the gradual incorporation of event-related information in stock prices (cf. Bhattacharya et al., 2000). Furthermore, for any classical event study, a variance increase during the event window is indistinguishable from an abnormal return effect, and there are a variety of issues concerning information arrival, partial anticipation of events, and cross-sectional variation (cf. Kothari and Warner, 2007). Finally, classical event studies assume that a given event is neatly isolated from any other and thus its effect can be clearly extracted. This is generally not the case. For example, on November 21, 2006, Alcoa announced a joint venture, a restructuring affecting 6700 positions and signed a letter of intent to acquire a significant share of Sapa AB; and on November

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22, it announced the closing of a facility, the layoff of close to 1600 employees, and the naming of a new president.

In this paper we propose a change point model that addresses the aforementioned issues. In this framework, it is possible for stock prices to reflect information in anticipation of an event announcement through regime changes. These occur according to a hidden Markov chain, thus capturing the notion of diffuse information integration. An immediate benefit of this approach is the relief from having to fix in advance the time interval within which one expects an event impact. Considering that our regimes are fully identified through mean and variance of abnormal returns, our model accounts for the possibility of either mean or variance changes – or both – in association with key developments as well.

Latent regime switches in equity price dynamics associated with key developments occur in various ways. They represent the convergence of explicit or implicit consensus regarding the associated event, expressing, for example, the likelihood of a rumor. In a semi-strong efficient market, they also capture a possible reaction to informed trades. In our specification, a regime switch corresponds to a change in either direction or volatility of return, or both. In this paper, we show the existence of a transition regime (high volatility around the announcement date) that can be attributed to increased activity by both informed and uninformed traders.

Our methodology is based on Chib (1998)'s change-point model, which has been successfully applied to the analysis of equity price dynamics. For example, Pastor and Stambaugh (2001) use it to estimate structural breaks in equity premium over a long return history (from 1834 to 1999), and Liu and Maheu (2008) use it to detect structural breaks in realized volatility of the S&P 500 index over a significantly shorter time-frame (from January 1993 to March 2004). Both papers employ large data sets, one with a long history and the other with intra-day trades, and yet seek to determine only a few structural breaks with long-lasting effects. Together, Pastor and Stambaugh (2001) and Liu and Maheu (2008) suggest the presence of structural breaks in both direction and volatility of equity returns at an aggregate level. Our work is focused on firm-specific key developments contained in announcement dates from financial media and their related abnormal return data. Instead of analyzing one long time-series as they do, we consider several, with each contained in a time window associated with a key event. This context is indeed ideally suited for the Bayesian framework of Chib (1998). Furthermore, in contrast to Liu and Maheu (2008), whose focus is on realized volatility based on high frequency data, we instead focus on daily returns to extract mean and volatility estimates on the one hand, and on the other, to reflect the uncertain nature of the actual dating of an event. Our main contribution from this setup is to help identify latent regime switches around key developments, thus providing an alternative to conventional event studies. Specifically, our approach enables us to estimate various regimes of random lengths and detect new directions and volatilities. In other words, it enables us to detect the progressive and diffuse integration of separate bits of information related to an event.

The remainder of the article is organized as follows. In Section 2, we present the application of Chib (1996)'s change-point model to our present event study. Section 3 contains our empirical results, which are then discussed and summarized in the concluding Section 4.

2. Methodology

This section describes the application of Chib (1998)'s change-point model to our event study. A critical component of an event study is the definition of the relative benchmark to help identify response returns (or abnormal returns, as they are typically labeled). Long-horizon (or long-term) studies, with event windows of one year or more, have been shown to be sensitive to their benchmark definitions (e.g., weighting schemes), thus leading to question their implications regarding market efficiency (Fama, 1998). In fact, Loughran and Ritter (2000) show that the standard benchmark model of Fama and French (1993) can predictably lead to different conclusions. On the other hand, the results of shorter horizon studies such as ours have been shown to be more robust (Brown and Warner, 1985). Event studies, in general, are inherently joint-test problems, involving the correct identification of the benchmark and whether the actual returns deviate from it in a significant fashion. As pointed out by Loughran and Ritter (2000), an evaluation of market efficiency must be based on a normative (equilibrium) model such as CAPM in order to avoid testing power bias due to benchmark contamination. Because standard event studies are cross-sectional, their use of market models for prediction is justified to some extent by the fact that the mean cross-sectional abnormal return can be interpreted as that of an equally-weighted portfolio. A consequence of this diversification is reduced volatility, which is not the case with a single stock, where noise dominates. In addition, the equal-weight portfolio has been found to be in fact nearly efficient (cf. DeMiguel et al., 2009). We should point out that even for stock portfolios, the empirical evidence of the standard predictive models has been seriously challenged (see, e.g., Ang and Bekaert, 2007; Welch and Goyal, 2008) as has the methodology of the popular Fama–French model (Black, 1995). An additional complication regarding regression models for the estimation of expected daily return is that of data inclusion/exclusion as we need to remove days that may be associated with event windows and thus significantly reduce the number of observations. Given our focus on daily returns, for which mean returns are significantly smaller than volatility and near zero, we chose the constant benchmark of zero expected returns. In fact, we tested a market model for return generation with three proxies: S&P 500 index, a value-weighted market portfolio, and an equal-weighted market portfolio (all three sourced from CRSP). As an example (see end of Section 3.3), for all three cases we obtained statistically insignificant intercepts and statistically significant sensitivities, with R^2 of approximately 0.3. However, not only did our model not detect any structural break, the event did not even have an impact.

Our model estimates the length of each regime by Gibbs sampling, finds maximum likelihood estimators (MLEs) of direction and volatility for each regime by the Monte-Carlo expectation–maximization (MCEM) method and produces the marginal likelihood of each model (associated with a pre-specified number of regimes) to find a Bayes factor that evaluates the model's performance relative to the others. The statistical methods used to analyze estimates of the change-point model are described more fully in Section 3.

2.1. Estimation of change points

To ease notational burden, we omit firm and key development/event identifiers. A sample event period of abnormal returns associated with a key development is split into S states (or regimes) changing at unknown times $\tau_1 \leqslant \tau_2 \leqslant \ldots \leqslant \tau_{S-1}$. Let s_t denote the regime at time t and $S_T = \{s_t; t = 1, \ldots, T\}$ be the regime set specifying a regime for each date in the event window. Here, both S and T are fixed a-priori. With the convention that $\tau_0 \equiv 0$, we assume that for each regime $s \in \{1, \ldots, S\}$, the abnormal returns $\{a_t : \tau_{s-1} \leqslant t \leqslant \tau_s - 1\}$ are distributed with mean μ_s and variance σ_s^2.

Let $f(a_t | \mu_s, \sigma_s^2)$ denote the probability density for the abnormal return a_t when the regime s_t at time t is s. This function need not

be explicit. The Markov chain Monte Carlo (MCMC) algorithm we apply will generate the associated distribution as the stationary limit of a Markov chain. Following Chib (1998), the random sequence $s_1, s_2, \ldots, s_T$ is assumed to be a Markov Chain, distinct from the MCMC Markov chain, with transition probabilities satisfying, without loss of generality,

$$P(s_{t+1} = s + 1 | s_t = s) = 1 - P(s_{t+1} = s | s_t = s) \text{ if } s \in \{1, 2, \ldots, S - 1\} \tag{1}$$

and $P(s_{t+1} = S | s_t = S) = 1$. Define $p_{ij} = P(s_t = j | s_{t-1} = i)$ and let $P = \{p_{ij}\}_{1 \leqslant i,j \leqslant s}$ denote the corresponding transition probability matrix. Since $p_{s,s+1} = 1 - p_{s,s}$, for $1 \leqslant s \leqslant S - 1$, and $p_{SS} = 1$, it is clear that P is completely determined once its diagonal terms are fixed. Therefore the estimation of P is tantamount to that of $\{p_{s,s}; s = 1, \ldots, S - 1\}$.

Let $\theta_s = (\mu_s, \sigma_s^2)$ for $s \in 1, \ldots, S$. For our model we need to estimate the joint posterior distribution of the parameter set $\Theta = \{\theta_s; 1 \leqslant s \leqslant S\}$ and transition probability matrix P, denoted $\pi(\Theta, P | A_T)$, where $A_T = \{a_1, a_2, \ldots, a_T\}$, as well as the posterior probabilities $p(s_t | A_T), 1 \leqslant t \leqslant T$, for the regime sequence $S_T = \{s_1, s_2, \ldots, s_T\}$. Since the latter is unobservable, we adopt the Bayesian paradigm by specifying conjugate priors. More explicitly, using given hyper-parameters to be detailed later, we employ the following standard prior distributions:

$$\mu_s | \sigma_s^2 \sim \mathcal{N}\left(\mu_0, \frac{\sigma_s^2}{\kappa_0}\right), \quad \sigma_s^2 \sim \mathcal{IG}\left(\frac{v_0}{2}, \frac{\sigma_0^2}{2}\right), \quad p_{ss} \sim \mathcal{B}(a_0, b_0),$$
$$s = 1, \ldots, S, \tag{2}$$

where $\mathcal{N}, \mathcal{IG}$, and $\mathcal{B}$ stand for the normal, inverse gamma, and beta distributions, respectively. By Bayes theorem, $\pi(\Theta, P | A_T) \propto \pi(\Theta, P) f(A_T | \Theta, P)$. Note that, as is common, we use the same label (π) for prior and posterior probabilities when there is no risk of confusion. Since Θ depends on the unobserved regimes $s_1, s_2, \ldots, s_T$, we work with the augmented posterior distribution $\pi(P, \Theta, S_T | A_T)$. We then use a Gibbs sampler to generate posterior realizations of the augmented parameters (P, Θ, S_T) by simulating in turn the full conditional distributions $\pi(P, \Theta | S_T, A_T)$ and $\pi(S_T | \Theta, A_T, P)$, with conditioning on the most recent values. Given the reasonable independence assumption between P and Θ, the former is the product of the corresponding marginals and our Gibbs sampling proceeds according to the following three steps:

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1. Generate $P \sim \pi(P | S_T, A_T)$
2. Generate $\Theta \sim \pi(\Theta | S_T, A_T)$
3. Generate $S_T \sim \pi(S_T | \Theta, A_T, P)$

Step 1: Generation of P. Given S_T, for each $s \in S_T$, we can trivially determine m_{ss}, the number of successive dates the system remains in the same regime s given that $s_t = s$ for the corresponding t in $\{1, 2, \ldots, T\}$. Clearly, $m_{ss} = \sum_{t=1}^T I(s_t = s)$, where $I(\cdot)$ is the indicator function. With the beta prior for p_{ss}, its posterior is then:

$$p_{ss} | S_T \sim \mathcal{B}(a_0 + m_{ss}, b_0 + 1), \text{ for } s = 1, \ldots, S - 1, \tag{3}$$

where we recall $p_{SS} = 1$ by assumption.

Step 2: Generation of Θ. Given S_T and A_T, the posterior distribution of Θ is obtained by first noticing that

$$\mu_s | \sigma_s^2, S_T, A_T \sim \mathcal{N}\left(\mu_m, \frac{\sigma_s^2}{\kappa_m}\right) \sigma_s^2 | S_T, \quad A_T \sim \mathcal{IG}\left(\frac{v_m}{2}, \frac{\sigma_m^2}{2}\right), \quad s = 1, \ldots, S, \tag{4}$$

where $m := m_{ss}, \mu_m = \kappa_0 \kappa_m \mu_0 + \frac{m}{\kappa_m} \bar{a}_s, \kappa_m = \kappa_0 + m, v_m = v_0 + m, \ \sigma_m^2 = \sigma_0^2 + (m-1)S_s^2 + \frac{\kappa_0}{\kappa_m}(\bar{a}_s - \mu_0)^2$, and with $\bar{a}_s$ and S_s^2 denoting the sample mean and variance respectively, of a_t values such that $s_t = s$. The posterior of $\theta_s = (\mu_s, \sigma_s^2)$ is then retrieved as

$$\pi(\mu_s, \sigma_s^2 | S_T, A_T) = \pi(\mu_s | \sigma_s^2, S_T, A_T)\pi(\sigma_s^2 | S_T, A_T).$$

Step 3: Generation of S_T. We break down the posterior distribution of S_T as

$$\pi(S_T | A_T, \Theta, P) = \prod_{t=2}^{T-1} \pi(s_t | A_T, S^{t+1}, \Theta, P), \tag{5}$$

where $S^t := \{s_t, \ldots, s_T\}$. We omit the $\pi(s_T | A_T, \Theta, P)$ and $\pi(s_1 | A_T, S^2, \Theta, P)$ terms because $p(s_T = S) = 1$ and $p(s_1 = 1) = 1$ by construction. Then generating the posterior distribution of S_T reduces to generating $\pi(s_t | A_T, S^{t+1}, \Theta, P), t = T - 1, \ldots, 2$, by recursively taking their product. Chib (1996) shows that

$$\pi(s_t = k | A_T, S^{t+1}, \Theta, P) = \frac{\pi(s_t = k | A_t, \Theta, P)\pi(s_{t+1} | s_t, P)}{\sum_{l=1}^{S-1} \pi(s_t = l | A_t, \Theta, P)\pi(s_{t+1} | s_t = l, P)}, \tag{6}$$

where s_{t+1} is known from the previous iteration. Given $S^T = s_T = S$, then $s_{T-1}, s_{T-2}, \ldots, s_2$ are generated through (8) as follows:

- $s_{T-1} \sim \pi(s_{T-1} | A_T, S_T = S, \Theta, P)$
- $s_{T-2} \sim \pi(s_{T-2} | A_T, S^{T-1}, \Theta, P)$
- $\vdots$
- $s_2 \sim \pi(s_2 | A_T, S^3, \Theta, P)$

As shown in (7), the right hand side of (6) requires knowing $\pi(s_t = k | A_t, \Theta, P)$ and $\pi(s_{t+1} | s_t, P)$. The latter can be determined through the conditional Markov transition probability given S_T from Step 1. To find the former, we consider another recursive calculation. Because we know $\pi(s_1 = 1 | A_1, \Theta, P) = P\{s_1 = 1\} = 1$, we can evaluate

$$\pi(s_t = k | A_t, \Theta, P) = \frac{\pi(s_t = k | A_{t-1}, \Theta, P) f(a_t | \theta_k)}{\sum_{l=1}^{S-1} \pi(s_t = l | A_{t-1}, \Theta, P) f(a_t | \theta_l)}, \tag{7}$$

where

$$\pi(s_t = k | A_{t-1}, \Theta, P) = \sum_{l=1}^{S} \pi(s_{t-1} = l | A_{t-1}, \Theta, P) p_{lk}. \tag{8}$$

Through the Gibbs sampler, we can simulate the posterior distribution of regimes as:

$$\pi(s_t = k | A_T) = \int \pi(s_t = k | A_{t-1}, \Theta, P)\pi(\Theta, P | A_T)d(\Theta, P)$$
$$\approx \frac{1}{M}\sum_{m=1}^{M} \pi(s_t^{(m)} = k | A_{t-1}^{(m)}, \Theta^{(m)}, P^{(m)}), \tag{9}$$

where M is the number of iterations of the Gibbs sampler and superscripts are used for sample identification.

2.2. Estimation of direction and volatility

The Gibbs sampling above enables us to estimate the probabilities of regime switches and, if desired, the posterior estimates for the mean returns (directions) and volatilities for each regime. However, given our interest in computing the marginal likelihood to compare different regime-switching models and following the

recommendation of (Chib, 1998, pp. 229–230), we estimate parameters via maximum likelihood (see also Section 2.3). Since the likelihood function is intractable with unobservable regimes, we follow a Markov chain expectation–maximization (MCEM) algorithm (Robert and Casella, 2005). Iterating on an index i, the MCEM algorithm proceeds as follows:

Step 1: Find the expectation of the log-likelihood of the entire data

$$E_{\Theta_{(i)}}\big(\ln f^c(A_T, S_T | \Theta)\big):$$
$$= \sum_{s_1}\sum_{s_2}\cdots\sum_{s_T}\ln f(A_T, S_T|\Theta)\pi(S_T|A_T, \Theta^{(i)}) \tag{10}$$

In each iteration $(i), i = 1, \ldots, I$, with I large enough, we generate M sample regime sets $S_T^{(1)}, S_T^{(2)}, \ldots, S_T^{(M)}$ where for $m = 1, \ldots, M, S_T^{(m)}$ is generated according to $\pi(S_T | A_T, \Theta^{(i)})$. We then obtain the following expectation estimate:

$$E_{\Theta_{(i)}}\Big(\ln f(A_T, S_T|\Theta^{(i)})\Big) \approx \frac{1}{M}\sum_{m=1}^M \ln f(A_T, S_T^{(m)}|\Theta^{(i)})$$
$$= \frac{1}{M}\sum_{m=1}^M\Big\{\ln f(A_T|S_T^{(m)}, \Theta) + \ln f(S_T^{(m)}|P)\Big\}. \tag{11}$$

The second term $f(S_T^{(m)}|P)$ is fixed because $f(s_1^{(m)} = 1|P) = f(s_T^{(m)} = T|P) = 1$ and

$$\hat{p}_{ss} = \frac{\sum_{m=1}^M m_{ss}^{(m)}}{\sum_{m=1}^M (m_{ss}^{(m)} + 1)}, \quad s = 1, \ldots, S, \tag{12}$$

where $m_{ss}^{(m)}$ is the number of times the system remains in regime s during the mth iteration.

Step 2: Find the maximum likelihood estimator of Θ^*. From (11),

$$\Theta^* = \text{argmax}_\Theta \frac{1}{M}\sum_{m=1}^M\Big\{\ln f(A_T|S_T^{(m)}, \Theta)\Big\}. \tag{13}$$

It is now straightforward to find the maximum likelihood estimator Θ^* because we know the posterior distributions of direction and volatility. The MLE of mean direction for the sth regime is:

$$\mu_s^* = \frac{1}{M}\sum_{m=1}^M \bar{a}^{(m)} = \frac{1}{M}\sum_{m=1}^M\left[\frac{1}{m_{ss}^{(m)}}\sum_{t=1}^T a_t I(s_t^{(m)} = s)\right], \quad s = 1, \ldots, S, \tag{14}$$

as a consequence of the normal posterior distribution of the direction parameter. Similarly, given the gamma posterior distribution of the variance of abnormal returns the variance estimate for the sth regime is:

$$\sigma_s^{2*} = \frac{1}{M}\sum_{m=1}^M\left[\frac{1}{m_{ss}^{(m)}}\sum_{t=1}^T I(s_t^{(m)} = s)(a_t - \bar{a}_s^{(m)})^2\right], \quad s = 1, \ldots, S, \tag{15}$$

where $\bar{a}_s^{(m)}$ is defined in (14). For the simulation, the sample size M and I are set large enough so that the difference between two successive estimates is negligible.

2.3. Model selection via Bayes factors

The number of regimes in our model is set a priori and a natural question is how to determine it optimally. In this section we use the Bayes factor criterion for pairwise model comparison. Following Chib (1996), the marginal likelihood for abnormal returns in a change-point model $\mathcal{M}_r$ with r regimes can be expressed as:

$$m(A_T|\mathcal{M}_r) = \frac{f(A_T|\mathcal{M}_r, \Theta^*, P^*)\pi(\Theta^*, P^*|\mathcal{M}_r)}{\pi(\Theta^*, P^*|A_T, \mathcal{M}_r)}, \tag{16}$$

where the densities are as previously defined with now an explicit reference. Theoretically, the estimation method for $\{\Theta^*, P^*\}$ does not affect the result. Since we already have them, we use MLE estimates from the previous section. With this marginal likelihood we can compare two models $\mathcal{M}_r$ and $\mathcal{M}_s$ by using the Bayes factor defined as:

$$B_{rs} := \frac{m(A_T|\mathcal{M}_r)}{m(A_T|\mathcal{M}_s)}, \tag{17}$$

or equivalently compare the log of both marginal likelihoods,

$$\ln B_{rs} = \ln m(A_T|\mathcal{M}_r) - \ln m(A_T|\mathcal{M}_s). \tag{18}$$

From Jeffreys (1961), a large value of $\ln B_{rs}$ indicates that the data support $\mathcal{M}_r$ over $\mathcal{M}_s$. We can further express the log-scale marginal likelihood as follows:

$$\ln m(A_T) = \ln f(A_T|\Theta^*) + \ln \pi(\Theta^*) + \ln \pi(P^*) - \ln \pi(\Theta^*|A_T) - \ln \pi(P^*|A_T, \Theta^*). \tag{19}$$

Note that when there is no risk of confusion we suppress the model term $\mathcal{M}$ in our notation. The first term on the right side can be made more explicit as follows:

$$\ln f(A_T|\Theta^*) = \sum_{t=1}^T \ln f(a_t|\theta^*)$$
$$= \sum_{t=1}^T \ln\left(\sum_{s=1}^S f(a_t|\Theta^*, s_t = s)\pi(s_t = s|A_{t-1}, \Theta^*)\right), \tag{20}$$

where $\pi(s_t = s|A_{t-1}, \theta^*)$ is given in (8). The second and third terms in (20) can be easily found by plugging MLE estimates of direction and volatility. For the fourth term, we again use simulation estimates:

$$\pi(\Theta^*|A_T) = \sum_{s_1}\sum_{s_2}\cdots\sum_{s_T}\pi(\Theta^*|A_T, S_T)\pi(S_T|A_T)$$
$$\approx \frac{1}{G}\sum_{g=1}^G \pi\Big(\Theta^*|A_T, S_T^{(g)}\Big), \tag{21}$$

where $S_T^{(g)}$ is the gth draw from $\pi(S_T|A_T)$, as described at the end of Section 2.1. The fourth term is similarly estimated:

$$\pi(P^*|A_T, \Theta^*) = \sum_{s_1}\sum_{s_2}\cdots\sum_{s_T}\pi(P^*|S_T)\pi(S_T|A_T, \Theta^*)$$
$$\approx \frac{1}{G}\sum_{g=1}^G \pi\Big(P^*|S_T^{(g)}\Big), \tag{22}$$

where $S_T^{(g)}$ is the gth draw from $\pi(S_T|A_T, \Theta^*)$, as described above. In each case, we have

$$\pi(P^*|S_T^{(g)}) \sim \mathcal{B}(a_0 + m_{ss}^{(g)}, b_0 + 1). \tag{23}$$

3. Empirical analysis

3.1. Data

We randomly select 273 firms from the Russell 3000 list of the year 2008 and categorize them by the Global Industry Classification Standard (GICS) into industry sectors, large/small market capitalizations, and high/mid/low book-to-market ratios. For our sample, all cells contain the same number of firms. The upper/lower market capitalization categories are separated at the 50th percentile, and the book-to-market ratio categories are separated at the 30th and 70th percentiles. The source for both categories is the Compustat fundamentals annual data set in calendar year
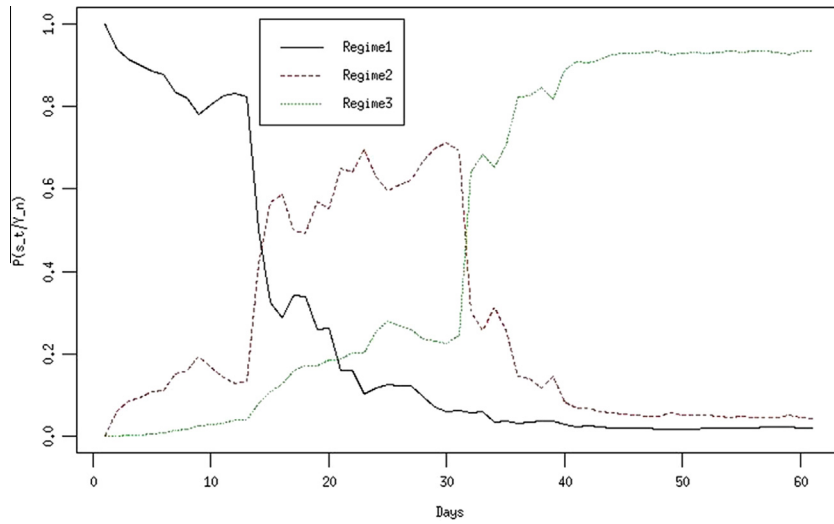
Fig. 1. Posterior probabilities for a three-regime model over a 60-day window. Firm: J.C. Penney; event date: April 6, 2006 (day 30). Two announcements on that day: (i) reiteration of Q1 Earnings-Per-Share (EPS) guidance, and (ii) S&P raised J.C. Penney's credit rating.
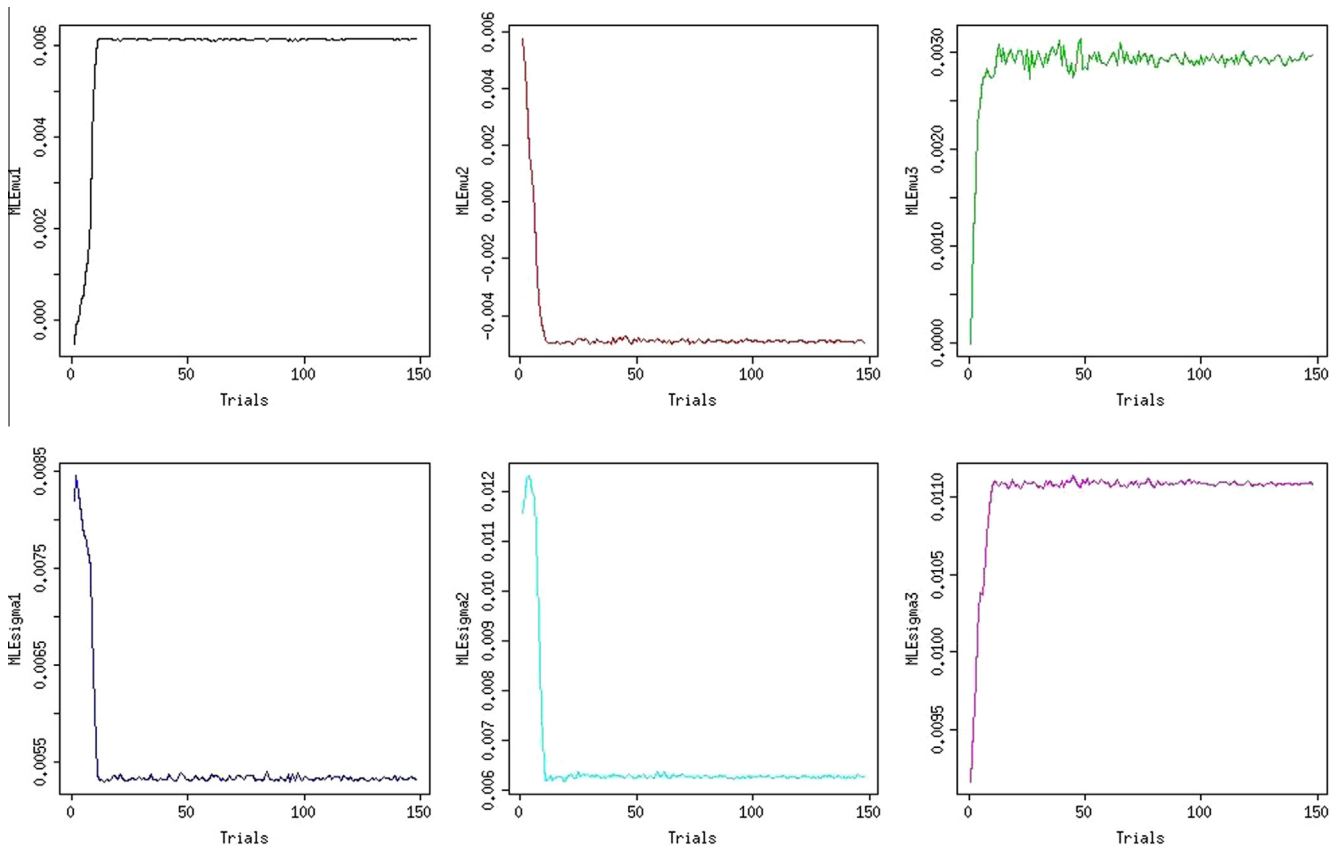

Fig. 2. MLE convergence of μ_s^* and σ_s^* in MCEM. Firm: J.C. Penney; event date: April 6, 2006. Two announcements on that day: (i) reiteration of Q1 Earnings-Per-Share (EPS) guidance, and (ii) S&P raised J.C. Penney's credit rating.

2006, and the percentiles are based on Russell 3000. We chose only domestic firms that reported consolidated financial statements, with no stock-split or stock-dividend in calendar year 2006 to make equity prices consistent.

Based on the sampled firms, we then use ReutersKnowledge (2006) to search for 'High' (i.e., significant) developments reported from 2004 to 2006. As a result, 273 firms have one or more significant developments, and 26 firms have more than 30 significant

developments from a total of 4,114 developments. The Reuters Knowledge website gives the specific time of each announcement and sometimes expresses the inter-arrival time of key developments in minutes.

The parameters for the prior distribution of direction are set as $\mu_0 = \bar{a}$ and $\kappa_0 = 1$, where $\bar{a}$ is the sample mean of a_t over $t = 1, \ldots, T$. The parameters for the prior distribution of volatility are set as $\nu_0 = 10$ and $\sigma_0^2 = S^2(\nu_0 - 2)\kappa_0$, where S^2 is the sample
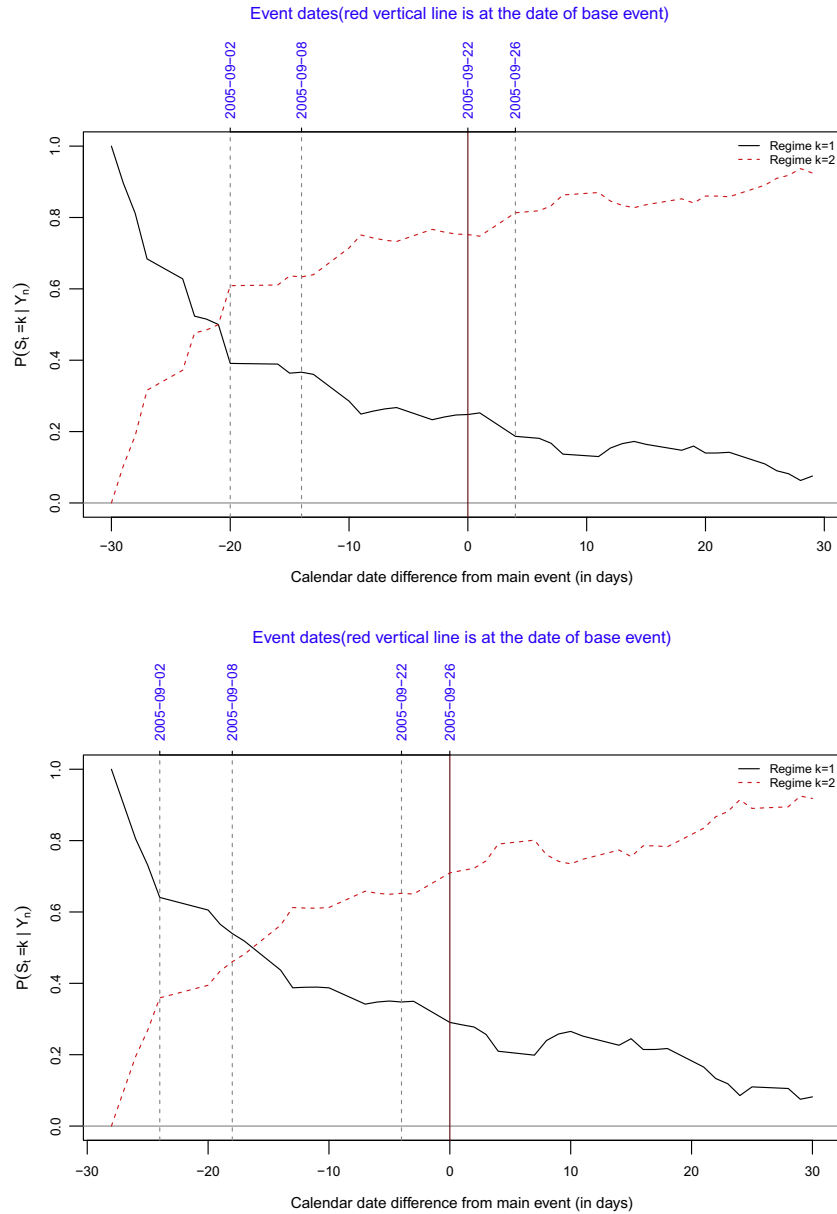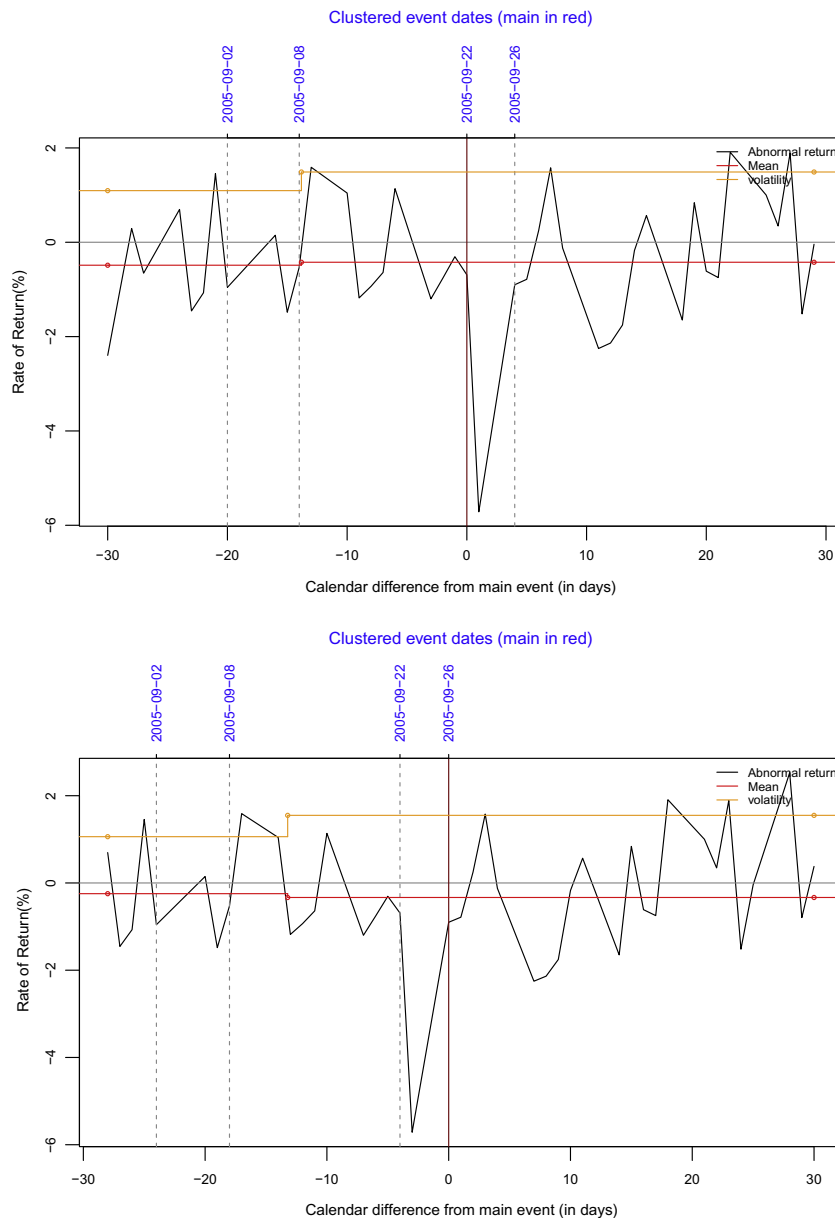
Fig. 3. Posterior probabilities for two two-regime models associated with two close events over their respective 60-day windows. On September 22, 2005, Alcoa made a negative earnings pre-announcement. Four days later, on the 26th of September, it announced the purchase of the remaining stake in a Russian facility from minority shareholders.

variance of a_t. The parameters for prior transition probability P_{ss} are set at $\alpha_0 = 20$ and $\beta_0 = 1$. We choose arbitrary, large values for v_0 and α_0 to make the prior inverse gamma and beta distributions as flat as possible, therefore minimizing bias in prior parameters. Furthermore, this setup enables us to achieve faster convergence in running the Gibbs sampler and MCEM with $E(\mu_0|\sigma_0^2) = \bar{a}$ and $E(\sigma_0^2) = S^2$ because it avoids starting points too far from the sample mean and variance. The prior parameter α_0 for the transition probability reflects the belief that the expected duration of each regime is 20 days. Since the length of our abnormal data time series is 61 days, we fit prior parameters based on a change-point model with two regimes. As observed by Chib (1998, p. 233), the effect of choosing different prior expected durations is minimal in practice. The Gibbs sampler to find break-points is iterated 500 times after 150 transient iterations and the MCEM algorithm to find maximum likelihood estimators is iterated 150

times, with each iteration taking 50, 100 and 200 sub-iterations to find the sample mean in (14) and variance in (15).

3.2. Estimation of change points, direction, and volatility

The methodology presented in Sections 2.1 and 2.2 produces posterior distribution $\pi(S_T|A_T)$ for regime set S_T and maximum likelihood estimates of direction (μ_s^*) and volatility (σ_s^*). As an example, Fig. 1 shows the marginal posterior probability P_{ss} given abnormal returns $\{a_{nkt}\}$ over a 60-day event window. The event date is April (ReutersKnowledge, 2006), and the firm is J.C. Penny. We have two key developments on that day: one is that J.C. Penney reiterated Q1 Earnings-Per-Share (EPS) guidance and the other is that S&P raised J.C. Penney's credit rating. Clearly, Regime-2 probabilities show that information may have been anticipated by investors about 15 days before the announcement. Prior to April

Fig. 4. Mean and volatility of returns for two two-regime models associated with two close events over their respective 60-day windows. On September 22, 2005, Alcoa made a negative earnings pre-announcement. Four days later, on the 26th of September, it announced the purchase of the remaining stake in a Russian facility from minority shareholders.

6, 2006, the most recent key development about J.C.Penny was announced on March 2nd, more than a month earlier. Therefore it is not likely that regime 2 is a result of the previous news. Fig. 2 presents a set of convergence graphs of MLE estimates for $\{\mu_s\}$ and $\{\sigma_s\}$ from MCEM with the same data as in Fig. 1. The top panel plots $\{\mu_s\}$ and the second plots $\{\sigma_s\}$, for $s = 1, 2, 3$, consecutively. It is evident from these graphs that the MLE estimates converge quickly. Observe that in regime 2 (middle plot in upper panel), direction is negative and that in regime-3 direction is almost 50% lower than that in regime 1 despite the apparent good announcement. Volatility doesn't vary much between regimes 1 and 2. However, in regime 3, it jumps 80% higher than the value in regimes 1 and 2. This result implies that the market overvalued the equity before the announcement and that the post-announcement period shows higher volatility with a drop in direction compared to the pre-announcement interval.

3.3. Change-point model selection

So far, the number of regimes in the change-point model is fixed a priori. In order to pick the best, we consider models with 1, 2, 3, or 4 regimes and select that which has the highest Bayes factor relative to all the others. This approach is empirical and is only meant to suggest good, plausible regime-switching models. To get statistically meaningful results, we restrict our data to the 30 most recent key developments and their associated abnormal data for 26 firms in the year 2004–2006.

Let B_{rs} denote the Bayes factor for a model with r regimes relative to another with s regimes. A change-point model with r regimes will be the best if it attains the largest value of $\ln B_{rs}$ for all values of s in $\{1, 2, 3, 4\}$. Jeffreys (1961) suggests that a model $\mathcal{M}_r$ with r regimes must satisfy $\ln B_{rs} > 2$ for all s in order to be considered among the best. From Table 1, 179 events, about 23% of the

Table 1

Selection of the best change-point model. This table reports the number of best change-point models based on the Gibbs sampler results out of a total 776 events for the 26 firms having a significant number of events from ReutersKnowledge (2006). For a given event the best change-point model with r regimes has the largest (log-) Bayes factor value $\ln B_{rs}$ and satisfies $\ln B_{rs} > 2$ when compared to all s-regime models (Jeffreys, 1961). If no model satisfies such a condition, the event is labeled indeterminate. Columns labeled $\mathcal{M}_r$, $1 \le r \le 4$, indicate the counts of best change-point models with r regimes.

Ticker	Events	Indeterminate	$\mathcal{M}_1$	$\mathcal{M}_2$	$\mathcal{M}_3$	$\mathcal{M}_4$
AA	30	4	2	6	7	11
AEP	30	6	1	4	9	10
BIIB	30	8	3	5	5	9
BSX	30	2	2	6	7	13
CAT	30	9	1	4	10	6
CELG	30	6	1	1	8	14
EGN	30	8	4	3	7	8
FDX	30	7	4	4	9	6
FL	30	10	1	6	10	3
GCO	30	4	2	3	7	14
JCP	29	8	3	3	5	10
KFT	28	5	1	4	7	11
MGM	30	9	0	6	5	10
MON	30	7	3	4	7	9
PDX	30	2	0	2	12	14
PG	30	8	2	8	4	8
PLCE	30	9	2	6	3	10
PTRY	29	8	3	3	7	8
QCOM	30	7	3	4	7	9
S	30	9	1	2	12	6
T	30	7	2	4	4	13
TMO	30	5	1	4	7	13
TSN	30	6	0	4	7	13
UNH	30	8	1	4	9	8
VZ	30	8	3	1	8	10
WYE	30	9	2	5	6	8
Total	776	179	48	106	189	254

Table 2

Number of regimes and marginal likelihood. Event Date: 2005-09-22. Alcoa (AA) issues Q3 EPS guidance below analysts' estimates.

Number of regimes	Marginal likelihood
2	398
3	395
4	392
5	404
6	404
7	388
8	324
9	385
10	396
11	408
12	237
13	253
14	235
15	400

Table 2. As an illustration of a two-regime occurrence in the presence of clustered events, we contrast next two events that appeared in succession for Alcoa. On September 22, 2005, the company announced that it expected 2005 Q3 income from continuing operations to be in the range of $0.27 to $0.31 per diluted share, that is below the consensus estimate of $0.44 per share. Alcoa cited lower aluminum prices and higher input costs, particularly for energy and raw materials, as the primary reasons for the discrepancy. Four days later, on September 26th, Alcoa announced that it had begun an offer to purchase all remaining outstanding shares of OJSC Belaya Kalitva Metallugical Plant (BKMPO) that were not acquired by Alcoa from Rusal in January 2005. Alcoa held an 82% supermajority position in the Belaya Kalitva aluminum facility in Russia, while approximately 43 million shares of BKMPO, or 18% of the shares outstanding, were held by minority shareholders. Fig. 3 displays the posterior probabilities of the two-state regimes associated with these two different events.The fact that both events result in the same number of regimes appears coincidental. In either case, there seems to have been effects on the both the mean and volatility of returns long before the official event announcements as displayed in Fig. 4. Though one might be inclined to think that the negative announcement took investors by surprise due to the drop on the first announcement, the volatility increase that occurred with the regime switch leads to a wider expected range of returns, as would be computed with expected mean ± three standard deviations, say. With this perspective, the market did react negatively but not as dramatically as one would think without the volatility increase. The subsequent correction is likely due to the combined effect of mean reversion and the second regime associated with the second, more positive event.
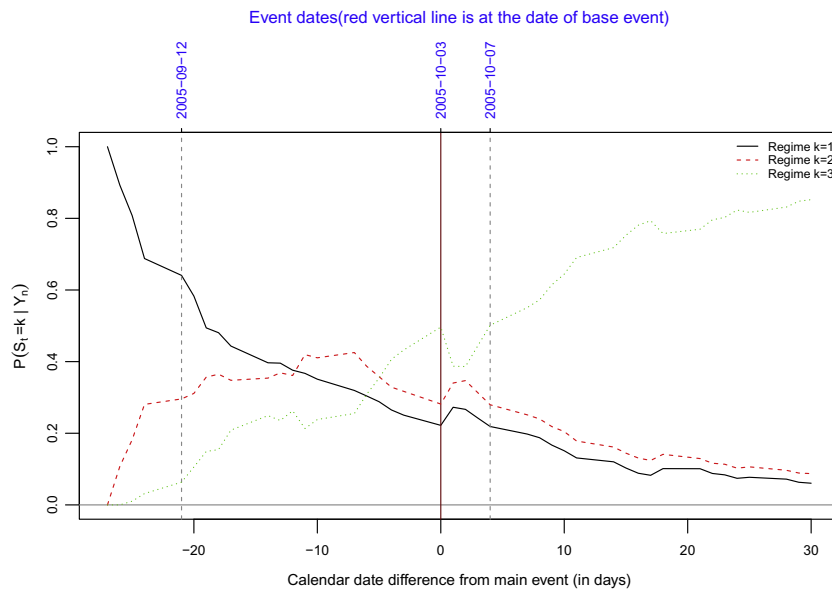
A more pronounced regime switch is illustrated for the global insurance concern ACE Limited. On October 3rd, 2005, it announced its intention to commence a public offering of $1.25 billion of its ordinary shares plus up to an additional $187.5 million of ordinary shares that would be subject to a 30-day option granted to its underwriters. Four days later, it also announced that it had

total 776 events, are found as indeterminant. These may have either two- or three-regime models as potentially the best, but neither is prevalent. A one-regime event clearly cannot reveal any change in either direction or volatility throughout the event window.

As illustrated in Table 1, the number of regimes for the best change-point models varies for each firm. There are clearly a number of reasons for this. Events differ according to the complexity of their interpretation, the acquisition of private information changes from one event to another, and exogenous liquidity conditions not captured by market returns that may affect specific abnormal returns.

Though we computed marginal likelihoods for a large number of regimes, we only considered those that were economically significant and thus restricted our attention to no more than four regimes. In fact, we considered first up to 15 possible regimes but observed that though the marginal likelihood changed with the number of regimes, its range did not differ from that captured by models with up to four regime, as shown, for example, in

Table 3

Regime lengths in the best change-point models. $\hat{m}_{ss}$ is the average of the expected durations (days) in the same regime s across all events. Associated 95%-confidence limits of two-sided t-tests are listed as well. The first two columns show the number of events where the best model is $\mathcal{M}_r$, with r regimes.

Best model	Events	$\hat{m}_{11}$	$\hat{m}_{22}$	$\hat{m}_{33}$	$\hat{m}_{44}$
$\mathcal{M}_2$	106	18.55 (16.77, 20.33)	42.45 (40.67, 44.23)		
$\mathcal{M}_3$	189	18.81 (17.44, 20.17)	11.07 (10.32, 11.81)	31.13 (29.77, 32.49)	
$\mathcal{M}_4$	254	14.13 (13.39, 14.88)	11.70 (11.15, 12.25)	10.34 (9.82, 10.86)	24.83 (23.82, 25.84)

Event dates(red vertical line is at the date of base event)

Fig. 5. Posterior probabilities for a three-regime model associated with a main event surrounded by others over a 60-day window. On October 3rd, 2005, the financial concern ACE Limited announced its intention to commence a public offering of $1.25 billion of its ordinary shares plus up to an additional $187.5 million of ordinary shares that would be subject to a 30-day option granted to its underwriters. Four days later, it also announced that it had launched ACE Energy, a new retail business unit that would focus on serving the property and casualty needs in the U.S. energy marketplace.

Clustered event dates (main in red)
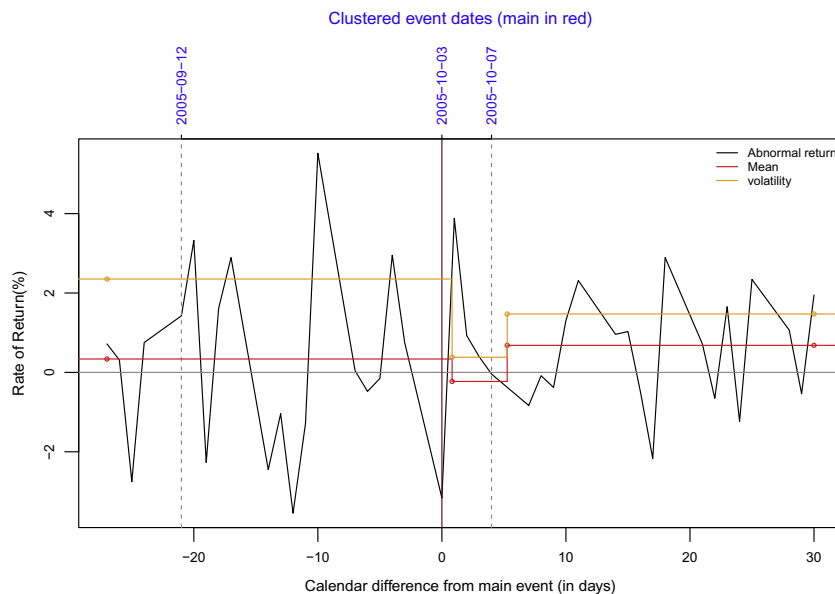
Fig. 6. Mean and volatility of returns for a three-regime model associated with a main event surrounded by others over a 60-day window. On October 3rd, 2005, the financial concern ACE Limited announced its intention to commence a public offering of $1.25 billion of its ordinary shares plus up to an additional $187.5 million of ordinary shares that would be subject to a 30-day option granted to its underwriters. Four days later, it also announced that it had launched ACE Energy, a new retail business unit that would focus on serving the property and casualty needs in the U.S. energy marketplace.

launched ACE Energy, a new retail business unit that would focus on serving the property and casualty needs in the U.S. energy marketplace. In contrast to the Alcoa case discussed above, where the switch from regime 1 to regime 2 occurs more or less at the same time as the probability of the former regime drops below that of the latter, Figs. 5 and 6 show that there is a switch in probabilities long before the actual regime switch, which occurs immediately following the announcement. The probability switch is very suggestive of the anticipation of the event, which is not that unusual in the context of public offerings. To a certain degree, the drop in volatility can be interpreted as the market having settled on this

offering, especially given the reputation of the company. The associated drop in mean return (direction) on the other hand is not surprising given the size of the offering (dilution effect). On the other hand, the subsequent event conveyed the message that the company was looking for growth opportunities, which means increased risk and higher expectations.

Finally, we argued earlier (beginning of Section 2) that we opted for benchmark expected returns of zero due to the high level of noise in daily observations and the difficulty of specifying a good predictive model for expected returns in general. As an illustration of the noise in the context of our approach, consider the following

case: In relation to the JCP event regarding Fig. 1, three different market models based on S&P 500 returns, a value-weighted market portfolio, and an equal-weighted market portfolio, resp. had mixed statistical significance regarding their regression estimates and when used in our implementation of the Chib model resulted in no regime detection and no event impact.

3.4. Estimation of regime length

Traditional event studies assume that the event window is fixed in $(-1, 0)$ (i.e. up to one day before the announcement). Since the event date is known exogenously, it is assumed that the equity price adjusts immediately to incorporate the key development on the event date. However, that may not be the case in a semi-strong efficient market because informed traders who acquire some information earlier or who have more precise information can exploit their advantage. For example, in Fig. 1, regime 2 is likely to have begun about 15 days before the news is announced while regime 3 begins right after the news is announced. We can suspect that up to 15 days before the announcement, price adjustments in the market may have already begun. From Table 3, the best model with two regimes ($\mathcal{M}_2$) shows that the announcement occurs during the second regime on average. For 3-regime models ($\mathcal{M}_3$) the announcement date is typically between the second and third regimes. For 4-regime models ($\mathcal{M}_4$), the announcement date is likely in the third regime. These observations indicate that equity prices doe not adjust instantly at the announcement date, but gradually throughout the event window. The confidence intervals are narrow enough for us to see that regime lengths do not differ much by events.

We may reasonably label the regime containing the announcement date as "transition regime" and call the others "stable." If the market is informationally efficient, regardless of the certainty with which an announcement affects the related equity price, the transition regime should begin immediately following the announcement and should be infinitesimally short. Table 3 shows that is not the case: there are no announcement dates located between adjacent regimes and all the regimes are at least 10 days long.

A possible explanation for an announcement date not necessarily causing a regime switch is that the impact of the information content may last a very short time (e.g., thirty minutes) and by the end of the trading day the impact has been neutralized by other news affecting the price. Since our study is based on end-of day observations, we may not be able to detect such impact. However, it is still possible in this case that the regime switch is not due to an event. Thus we cannot explain why those specific regime lengths are estimated with relatively narrow confidence intervals without any impact from the event announcement. An alternative reasonable explanation is that informed traders trade on the information before the announcement and the transition regime begins when they start trading. It is then entirely plausible that the early information for these trades is in fact about anticipated direction following the transition regime during which the information is formally disclosed. On the other hand, the direction of a transition regime reflects the reaction of uninformed traders to informed trading.

This idea is particularly useful under the assumption of a semi-strong form market in that the number of regimes and their lengths around the key developments measure the informational efficiency of the market. The number of regimes around key developments capture the degree of certainty of new information. If new information content introduces new price levels every trader can agree on, then the number of regimes will be smaller because the incorporation of new information will not require too many adjustments (regimes). Regime lengths around the key development indicate the sensitivity of uninformed traders to informed

trading. If the uninformed traders detect informed trading and react quickly assuming sufficient liquidity, regime lengths will be smaller because the price disparity between informed and uninformed traders will converge fast.

4. Summary and discussion

Conventional event studies only deal with three fixed sub-event windows: pre-event, event, and post-event windows. We introduce a change-point model based on Gibbs sampler that estimates variable sub-event windows associated with latent regimes and their corresponding directions and volatilities of abnormal returns. We then evaluate models with various regimes and select the best with the highest relative Bayes factor. We present evidence that not all key developments produce regime switches although our data suggest that a 60-day event window is more likely to consist of three or four regimes. An analysis of average regime lengths indicates that breakpoints may not necessarily coincide with announcement dates, implying that price adjustments due to key developments may occur prior and continue after some event dates.

One potential issue with classical event studies is their reliance on event dates as reported in common data sources such as Eventus (Cowan, 2007; ReutersKnowledge, 2006). In turn, the latter get their information from other sources, the reliability of which may sometime be questioned, potentially affecting these studies. Alternatively, determining uncertain event dates and finding structural break only from return data may be more reasonable in this regard (cf. Ball and Torous, 1988). In this respect, our approach is better tailored than the standard event studies and directly tackles the issue of the fuzzy nature of an event date. As further extension we can incorporate liquidity-induced changes by analyzing intraday data in event periods in a manner similar to observing the adverse selection component in bid-ask spreads as in Krinsky and Lee (1996) or observing regime changes in realized volatility as in Liu and Maheu (2008).

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