

Earnings announcements and equity options

Andrew Dubinsky and Michael Johannes*

Graduate School of Business

Columbia University

First draft: November 2003.

This draft: September 2004.

Abstract

In asset pricing models, the uncertainty surrounding firm fundamentals plays a central role, driving expected returns, volatility, and valuation ratios. In this paper, we extract estimates of the uncertainty embedded in earnings announcements using option prices. To do this, we take seriously the fact that the timing of earnings announcements, although not the response of equity prices, is known in advance. We develop a no-arbitrage option pricing model incorporating jumps on earnings announcement dates. We estimate the uncertainty in a simple extension of the Black-Scholes model and in a more complicated stochastic volatility model. The uncertainty is large, has important pricing implications and interesting time-variation. Adding jumps on earnings announcement dates drastically reduces the model pricing errors. Not surprisingly, the estimates of the earnings uncertainty increase in periods of market stress, such as 2000 and 2001.

*Johannes and Dubinsky can be reached at mj335@columbia.edu and ald95@columbia.edu, respectively. Johannes is the corresponding author and can be contacted at Uris Hall #424, 3022 Broadway, NY, NY, 10025. We thank Blair Hull for a helpful formative discussion, Andrea Buraschi, Peter Carr, Joe Chen, Mike Chernov, Darrell Duffie, Paul Glasserman, Massoud Heidari, Neil Pearson, Allen Potesman, Tano Santos, Case Sprenkle, Suresh Sundaresan, and Liuren Wu for comments, and seminar participants at Columbia and Illinois for comments. All errors are our own.

1 Introduction

In asset pricing models, the uncertainty surrounding firm fundamentals plays a central role, driving expected returns, volatility, and valuation ratios. Characterizing and quantifying this uncertainty, however, is more difficult as it is not directly observed. For example, while current earnings are known, the uncertainty surrounding future earnings is not observed. In this paper, we develop reduced-form models that use option prices to extract information about the uncertainty embedded in the information released in earnings announcements.

On an earnings announcement date, firms release the prior quarter's firm financials (income statements, balance sheet, and cash flows), as well as "forward-looking statements," guidance based on the firm's current expectations of future business conditions and firm performance. Intuitively, investors revise their beliefs after this information is released and the uncertainty regarding firm performance is reduced, at least temporarily. To analyze the level and dynamics of this uncertainty around earnings dates, we consider option prices, the natural vehicle to learn about uncertainty or volatility.

To get a sense of the magnitudes of the uncertainty, consider the following example for Intel Corporation. On July 15, 1997, Intel released earnings after the close of the market. The Black-Scholes implied volatility of the July at-the-money call option was 71.15 percent prior to the announcement. For a comparison, the implied volatility of the August at-the-money call option was 45.19 percent. The day after the announcement, the implied volatility of the same July call fell drastically to 42.96 percent. Clearly, the high implied volatility before and the drastic decline in implied volatility after the earnings announcement provides information regarding the uncertainty embedded in the information released in the earnings announcement. This pattern holds more generally for other earnings announcement dates and for other firms.

On the theoretical side, the goal of this paper is to develop tractable reduced form models incorporating jumps on earnings announcement dates and to use these models to quantify the uncertainty surrounding earnings announcements. The key to our approach is that, unlike traditional option pricing models, we take seriously the timing of earnings announcements. Earnings announcements are events whose timing is known in advance. We therefore model equity prices as a process with randomly sized jumps at the time of the earnings release. To price the options in a no-arbitrage setting, we construct an equivalent martingale measure. Ignoring technical conditions, jumps at deterministic times add only

one additional constraint: that the expected jump size in the stock price at a deterministic time must be zero. This intuitively implies that there can be no expected capital gains over an instant.

A simple extension of the Black-Scholes model incorporating deterministic jumps provides the essence of our approach. In addition to the usual Brownian motion component, assume there is a single jump at time τ_j , the time of an earnings release. The size of the jump, Z_j , is log-normally distributed with a volatility of $\sigma_j^{\mathbb{Q}}$ where \mathbb{Q} is an equivalent martingale measure. If there is an option maturing at time $T > \tau_j$, then the moment before an earnings announcement, the Black-Scholes implied volatility is given by $\sigma_{\tau_j-}^2 = \sigma^2 + \frac{(\sigma_j^{\mathbb{Q}})^2}{T-\tau_j}$, where σ is the diffusive volatility. After the announcement, the implied volatility falls to $\sigma_{\tau_j}^2 = \sigma^2$. This generates the effect mentioned in the example above and moreover, it provides a means to estimate $\sigma_j^{\mathbb{Q}}$, the uncertainty embedded in earnings. In the Intel example above, the estimate of $\sigma_j^{\mathbb{Q}}$ based on the changes in implied volatility is 7.2 percent.

To quantify the uncertainty embedded in earnings announcements, we use a sample of 20 low-dividend firms with the most actively traded options from 1996 to 2002. Based on the extension of the Black-Scholes model described above, we first develop two different estimators of $\sigma_j^{\mathbb{Q}}$. The first uses only ex-ante information and relies on the term structure of option implied volatility. The intuition behind the estimator is that more of the total volatility of the shorter-to-maturity option is driven by the earnings jump. Since this estimate can be obtained prior to the announcement, it provides an ex-ante view of investor's expectations of the uncertainty present in the earnings announcement. The second estimator, the time series estimator, uses changes in implied volatility before and after an announcement.

The results indicate that option prices are very informative about the uncertainty embedded in earnings announcements. Across the sample of firms, the mean estimate of $\sigma_j^{\mathbb{Q}}$ is 10.4 percent for the term structure estimator and 8.5 percent for the time series estimator. The jump sizes vary both by firm and across time. For some firms and earnings announcement dates, estimates of $\sigma_j^{\mathbb{Q}}$ exceed 15 percent. It is important to recognize that $\sigma_j^{\mathbb{Q}}$ is a risk-neutral parameter, and due to risk premiums, it is not necessarily the volatility of the jumps under the objective measure. However, these large jump sizes are not out of line with casual observations: equity prices often react violently to earnings announced above or below expectations.

We can also use the estimates and the underlying equity returns to investigate risk premiums, the abnormality of returns around earnings announcement dates, specification, and the informational content of earnings jump volatility. Based on the observed returns after earnings, we cannot reject that jumps sizes are mean-zero, which implies there is no evidence for a mean jump risk premium. We do, however, find some evidence of a volatility risk premium: based on the ex-ante estimates of $\sigma_j^{\mathbb{Q}}$, the volatility of jumps sizes under \mathbb{Q} is greater than the observed volatility under \mathbb{P} : $\sigma_j^{\mathbb{Q}} > \sigma_j^{\mathbb{P}}$. This is consistent with evidence from index options and should not be surprisingly, given that it is not possible to hedge continuously distributed jumps with a finite number of instruments. The estimates of $\sigma_j^{\mathbb{Q}}$ based on the time series of implied volatility are lower which implies that the risk premium, if present, is smaller. We find that returns, scaled by option implied volatility, appear to be normally distributed, which is consistent with our assumption of normally distributed jumps. This implies that returns after an earnings announcement, while often extremely large, are in no way ‘abnormal,’ at least in the statistical sense. We also find that jump volatility under \mathbb{Q} is informative about return volatility under \mathbb{P} : firms with high option implied $\sigma_j^{\mathbb{Q}}$ tend to have high observed variability of returns on earnings announcement dates. Finally, the estimates of jump volatility tend to increase in 2000 and 2001, consistent with prior research indicating there was an increased uncertainty regarding earnings in this period.

Next, to quantify the mispricing in models without jumps on earnings dates, we consider stochastic volatility models with and without jumps on earnings announcement dates. We estimate the models using multiple option maturities, sampled daily, from 1996 to 2002. Jumps on earnings dates primarily affect the expected volatility of stock returns, and we therefore focus our empirical work on the term structure and time series of at-the-money option prices. Due to the extreme computational burdens of estimating a model using daily option prices over a long sample, we estimate the stochastic volatility model for five of the twenty firms in our sample. The firms include the three most actively traded firms, and one firm with both low and high earnings jump volatility.

In the pure stochastic volatility model, we find that there are systematic pricing errors before earnings announcements and that there are predictable movements in implied spot variance, V_t , around earnings dates. The pure stochastic volatility model cannot simultaneously price short dated options (which require a very high variance state) and longer maturity options (which do not require a high variance state). We find the extension with

jumps on earnings dates provides a substantial improvement in model performance. Around earnings dates, the pricing errors in the extended model are roughly half of those in a pure stochastic volatility model. Over the whole sample and for all maturities, the pricing errors fall substantially, especially for short dated options. To frame this result, Bakshi and Cao (2004) find no pricing improvement for at-the-money options when adding three additional factors (jumps in returns, jumps in volatility or stochastic interest rates). The stochastic volatility model, in an attempt to fit option prices around earnings announcements and the rest of the year, fits both periods poorly. In the model with earnings jumps, the jump component captures the movements around earnings announcements, freeing the stochastic volatility components to fit option prices during the rest of the year much better.

The paper is outlined as follows. Section 2 reviews an extensive literature that analyzes issues related to deterministic jumps and asset prices. Section 3 introduces a general deterministic jump model for option pricing and a simple extension of Black-Scholes incorporating earnings announcements, discusses the implications of earnings announcements and derives near-closed form option prices for a model incorporating earnings announcements. Section 4 investigates the implications and Section 5 concludes.

2 Related Literature

Before describing our modelling approach, it is important to recognize that there are a number of papers that address issues related to earnings announcements and asset prices. In this section, we briefly review some of the major contributions.

A number of papers use time series data to analyze how scheduled announcements effect the level and volatility of asset prices. For individual firms, Ball and Brown (1968), Foster (1977), Morse (1981), Kim and Verrecchia (1991), Patell and Wolfson (1984), Penman (1984) and Ball and Kothari (1991) analyze the response of equity prices to earnings or dividend announcements, focusing on the speed and efficiency with which new information is incorporated into prices. Patell and Wolfson (1984) is of particular interest. They study the response of individual equity prices to earnings announcements using transaction data and find that most of the price response occurs in the first few minutes after the release. This is important because we later argue that earnings announcements can be reasonably modeled by a discontinuous component in the price process.

In a time series model with state-dependent jumps, Maheu and McCurdy (2003) find that many of the jumps they statistically identify occurred on earnings announcement dates. For example, they report that 23% of the jumps for Intel Corporation occurred on earnings dates. They introduce a model with randomly timed jumps and assume the jump intensity increases on earnings dates. In the general model developed below, the variance of jump sizes on earnings dates can change across earnings dates, and this implies that their estimates of the impact of earnings announcements (based on a model with constant variances) is a lower bound.

In this paper, we are primarily interested in the implications of earnings announcements on option prices. Patell and Wolfson (1979, 1981) provide early descriptive work on the time series behavior of implied volatility around earnings announcements. They find that Black-Scholes implied volatility increases before and decreases after earnings announcements. Other papers that apply the Patell and Wolfson's approach to different equity markets include Donders and Vorst (1996), Donders, Kouwenberg, and Vorst (2000), and Isakov and Pérignon (2001). Whaley and Cheung (1982) argue that the informational content of earnings announcements is rapidly incorporated into option prices.

There are also a number of papers that analyze the impact of scheduled announcements on non-equity options. Ederington and Lee (1996) analyze the response of options on Treasury, Eurodollar, and foreign exchange futures to a number of different macroeconomic announcements using an approach similar to Patell and Wolfson (1979, 1981). They find that implied volatility increases on days without announcements and decreases after a wide range of macroeconomic announcements. Bailey (1988) analyzes the response of S&P 500, gold, Treasury bond, and foreign exchange futures prices to weekly money supply announcements and finds evidence that the announcements are important. Beber and Brandt (2004) find that the risk-neutral skewness and kurtosis embedded in Treasury bond futures options change around scheduled macroeconomic announcements, in addition to documenting that implied volatility decreases after the announcements.

Our paper is closely related, at least on an intuitive level, to a growing literature using accounting variable-based asset pricing models. The original models in Ohlson (1995) and Feltham and Ohlson (1999) assume that the current equity prices were a linear function of accounting variables such as abnormal current income. Ang and Liu (1999) extend these models to general discrete-time affine processes, while Pastor and Veronesi (2003) build a continuous-time model assuming geometric (as opposed to arithmetic) growth in the

accounting variables. In Pastor and Veronesi (2003), investors learn about mean profitability over time and the uncertainty regarding their forecasts is priced. If $\hat{\sigma}_t$ is the current uncertainty, then

$$\log(M_t/B_t) = \alpha'X_t + \beta\hat{\sigma}_t^2$$

where M_t is the market value of equity, B_t is the book value of equity and X_t includes constants, accounting variables and forecasts. In Pastor and Veronesi (2003), $\hat{\sigma}_t$ decreases deterministically, but in a more general model it would be random and it is not unreasonable to assume that most of the updating regarding $\hat{\sigma}_t$ occurs on earnings announcement dates. This implies that $\hat{\sigma}_t$, and in turn prices, jump on earnings dates and then there is a relatively close relationship between Pastor and Veronesi (2003) and our model. Pastor and Veronesi (2003) proxy uncertainty regarding profitability using firm age. Our empirical work below extracts a market based estimate of the uncertainty at earnings announcements, thus providing an alternative source of information about firm fundamental uncertainty.

3 Earnings announcements and option pricing models

Existing option pricing models assume that stochastic volatility and randomly timed jump components drive equity returns. On $(\Omega, \mathcal{F}, \mathbb{P})$, these models assume that the asset price, S_t , and its stochastic variance, V_t , jointly solve:

$$d \log(S_t) = \left(r_t + \mu_t - \frac{1}{2}V_t \right) dt + \sqrt{V_t}dW_t^s + d \left(\sum_{j=1}^{N_t} Z_j^s \right) \quad (1)$$

$$dV_t = \kappa_v(\theta_v - V_t) dt + \sigma_v\sqrt{V_t}dW_t^v + d \left(\sum_{j=1}^{N_t} Z_j^v \right) \quad (2)$$

where $W_t = (W_t^s, W_t^v)$ is two-dimensional Brownian motion, N_t is a counting process with stochastic intensity λ_t , τ_j are the jump times, μ_t is the equity risk premium, $Z_j^s \sim \Pi_s$ are the jumps in returns, $Z_j^v \sim \Pi_v$ are the jumps in volatility, and r_t is the spot interest rate.¹ Duffie, Pan and Singleton (1999) develop the general affine class of models. Most applications of these models focus on equity indices or options on equity indices (see, e.g., Andersen, Benzoni, and Lund (2001), Bates (2000), Pan (2002), Eraker, Johannes, and

¹We do not consider Levy driven models, although it is clear that it is possible to incorporate deterministic jumps into this class. The only complication occurs in time-changed models. In these models, we

Polson (2003), or Eraker (2004)). To our knowledge, the only formal study that considers options on individual equities is Bakshi and Cao (2004).

The response of equity prices to earnings announcements is different from the unpredictable events in the model above because the timing of the information release is known in advance, although the response of the underlying price to the event is not. Thus we assume that equity prices have a deterministically timed jump occurring at the earnings release. With discretely recorded prices, it is impossible to say with certainty if a given movement is a jump, however, we feel this assumption is warranted for three reasons. First, it is consistent with the recent literature. Existing work either explicitly assumes movements generated by announcements are jumps (Piazzesi (2004) and Beber and Brandt (2004)) or finds statistical evidence that announcements can be identified as jumps in the context of a jump-diffusion model (Johannes (2004) and Barndorff-Nielson and Shephard (2004)). Second, since the early 1990s, almost all of the earnings announcements are released after the close of the equity and options market. These announcements generate a visible discontinuity in trading time: the market open the following morning is often drastically different than the market close before the announcement. Third, even if earnings were announced during trading hours, prices react very rapidly. Patell and Wolfson (1984) find that for earnings announced during trading hours in the late 1970s, the bulk of the response occurs in the first few minutes. Even if the effect lingered up to an hour, for the sake of argument, from the perspective of pricing options expiring in weeks or months this is still a very short time period and modeling these movements as jumps seems a reasonable approximation. Our assumption of a jump is in contrast to Patell and Wolfson (1979, 1981)) who assume that diffusive volatility is higher throughout the day of the announcement.

To formally model deterministically timed events, we assume there is a deterministic counting process, N_t^d , counting the number of predictable events that occur up to time t : $N_t^d = \sum_j 1_{[\tau_j \leq t]}$ where $\{\tau_j\}_{j \geq 1}$ are increasing predictable stopping times. Intuitively, a predictable stopping time is a phenomenon that “cannot take us by surprise: we are

can alter the activity rate by assuming that

$$T_t = \int_0^t A_s ds + \sum_{j=1}^{N_t^d} Z_j$$

where A_s is a square-root diffusion process. The characteristic function of T is available in closed form and the characteristic function of the asset prices is available by recursively solving ordinary differential equations. We thank Peter Carr and Liuren Wu for helpful discussions related to this.

forewarned, by a succession of precursory signs, of the exact time the phenomenon will occur” (Dellacherie and Meyer (1978), *p.* 128). An inaccessible or random stopping time is just the opposite: there are no precursory signs and thus the arrival is a complete surprise. Unlike accessible stopping times, inaccessible stopping times and their associated point processes have a continuous compensator and admit an intensity (a process λ_t is a stochastic intensity of N_t if for a suitable regular function c , $E_0 \left[\int_0^t c_s dN_s \right] = E_0 \left[\int_0^t c_s \lambda_s ds \right]$ and $\int_0^t \lambda_s ds < \infty$).

The stochastic volatility model that we consider is given by

$$\begin{aligned} dS_t &= S_t [r_t + \eta_s V_t] dt + S_t \sqrt{V_t} dW_t^s + d \left(\sum_{j=1}^{N_t^d} S_{\tau_{j-}} [e^{Z_j} - 1] \right) \\ dV_t &= \kappa_v (\theta_v - V_t) dt + \sigma_v \sqrt{V_t} dW_t^v, \end{aligned} \quad (3)$$

where $Z_{\tau_j} | \mathcal{F}_{\tau_{j-}} \sim \pi(Z_{\tau_j}, \tau_{j-})$, $cov(W_t^s, W_t^v) = \rho t$, and N_t^d counts the number of earnings announcements.² Throughout, we assume the interest rate is constant, assume that the Feller condition holds ($\theta_v \kappa_v > \sigma_v^2/2$), and ignore dividends for notational simplicity. Between jump times, the stock price and volatility diffuse, that is, they have continuous sample paths with Brownian shocks. At a jump time, the stock price jumps by a random size: $\Delta S_{\tau_j} \triangleq S_{\tau_j} - S_{\tau_{j-}} = S_{\tau_{j-}} (e^{Z_j} - 1)$. The jump sizes Z_j can be most easily interpreted as the jump sizes to log-returns: $\log(S_{\tau_j}/S_{\tau_{j-}}) = Z_j$.

Our model does not include randomly timed jumps in prices or in volatility for a number of reasons. First, we are primarily interested in the impact of earnings announcements on option prices and, as we show below, the first-order effects of deterministically timed jumps are on the term-structure of at-the-money implied volatility. These options are not particularly sensitive to randomly timed jumps as randomly timed jumps in returns primarily impact short dated out-of-the-money options and jumps in volatility have little effect on the cross-section of option prices (see Broadie, Chernov, and Johannes (2004)). Bakshi and Cao (2004) find similar evidence with individual equity options. They find that neither jumps in returns nor jumps in volatility have any impact on pricing at-the-money options, across the term structure. Thus, we focus on at-the-money options and ignore randomly timed jumps. Second, at-the-money options are less subject to microstructure effects as

²We do not consider other predictable events such as mid-quarter earnings updates or stock splits, although these do have implications for option prices.

they tend to trade more heavily than out-of-the-money options for a given maturity. All option prices contain non-trivial bid-ask spreads, but the bid-ask spreads of out-of-the-money options are an order of magnitude higher than the spreads of at-the-money options. Third, as we discuss below, estimation of models with deterministic jumps requires daily data on multiple option prices over reasonably long time spans. This is extremely computationally burdensome and economizing on parameters, by excluding randomly timed jumps, is important.

Finally, there is little evidence for extreme non-normalities in the unconditional distribution of returns based on historical time series of equity returns. Unlike equity index returns which have a very high kurtosis and skewness (for the S&P 500 index, around 50 and -3), Appendix A shows that the individual equities that we consider have no noticeable negative skewness and only a modest amount of kurtosis (with the exception of Apple). These levels of kurtosis can be generated by a stochastic volatility model. The explanation for the lack of non-normalities is intuitive: with annualized volatility between 50 and 75 percent, it is easy to generate relatively large movements without randomly timed jumps. Moreover, Bakshi, Kapadia, and Madan (2003) document that individual equities have very little risk-neutral skewness, which shows that jumps in returns play a less prominent role for individual equities vis-a-vis the indices.

To price options, we construct a measure, \mathbb{Q} , under which the discounted gains are martingales, which implies the absence of arbitrage. The pricing approach is based on Piazzesi (2000). The martingale restriction requires the usual assumption that the drift of S_t under \mathbb{Q} is equal to $S_t r_t$ (ignoring, for the moment, dividends for simplicity). This assumption ensures that between deterministic jump times, the discounted gains process is a \mathbb{Q} -martingale. At a jump time, interest rate accruals do not matter,³ and thus for prices to be a martingale, we require that $E^{\mathbb{Q}} [S_{\tau_j} | \mathcal{F}_{\tau_j-}] = S_{\tau_j-}$ which is that the expected jump size in the asset price is zero ($E^{\mathbb{Q}} [\Delta S_{\tau_j} | \mathcal{F}_{\tau_j-}] = 0$). Given the jump specification above, this requires that $E^{\mathbb{Q}} [e^{Z_j} | \mathcal{F}_{\tau_j-}] = 1$ which implies that at a deterministic time, there can be no expected capital gains.

³If $\beta_t = \exp\left(\int_0^t r_s ds\right)$, then by the definition of the integral, $\beta_t = \beta_{t-}$ even if interest rates are a discontinuous function of time. This implies that $E^{\mathbb{Q}} \left[\frac{S_{\tau_j}}{\beta_{\tau_j}} | \mathcal{F}_{\tau_j^d-} \right] = \frac{S_{\tau_j-}}{\beta_{\tau_j-}}$ is equivalent to $E^{\mathbb{Q}} [S_{\tau_j} | \mathcal{F}_{\tau_j-}] = S_{\tau_j-}$.

If we define $\frac{d\mathbb{Q}}{d\mathbb{P}} = \xi_T$, the density process, ξ_t , solves

$$d\xi_t = -\varphi_t \xi_t dW_t + \xi_{t-} J_t^\xi dN_t^d,$$

or

$$\xi_t = \xi_0 \exp\left(-\frac{1}{2} \int_0^t \varphi_s \cdot \varphi_s ds - \int_0^t \varphi_s dW_s\right) \prod_{j=1}^{N_t^d} X_{\tau_j}^\xi,$$

where $\xi_0 = 1$, $\varphi_t = (\varphi_t^s, \varphi_t^v)$ are the prices of W_t^s and W_t^v risk, $\Delta\xi_{\tau_j} = \xi_{\tau_j} - \xi_{\tau_j-} = \xi_{\tau_j-} J_{\tau_j}^\xi$, and we define $X_{\tau_j}^\xi = \xi_{\tau_j-}^{-1} \xi_{\tau_j}$ as the jump in the pricing density. To ensure that ξ_t is a \mathbb{P} -martingale, φ and X^ξ must satisfy mild regularity conditions. For the diffusive components, we assume essentially affine risk premiums of the form $\varphi_t^s = \eta_s V_t$ and $\varphi_t^v = \frac{-1}{\sqrt{1-\rho^2}} \left(\rho \eta_s \sqrt{V_t} + \frac{\mu_t^{\mathbb{Q}} - \mu_t^{\mathbb{P}}}{\sigma_v \sqrt{V_t}} \right)$ where $\mu_t^{\mathbb{Q}} = \kappa^{\mathbb{Q}} (\theta^{\mathbb{Q}} - V_t)$ and $\mu_t^{\mathbb{P}} = \kappa (\theta - V_t)$. A sufficient condition for this to be valid is that the origin is not attainable under either \mathbb{P} or \mathbb{Q} (see, Cheridito, Filipovic, and Kimmel (2004)). Thus we do not require that the risk neutral and objective measure drifts share common parameters.

For the jump component, we require that $X_{\tau_j}^\xi > 0$ (to guarantee that $\xi_t > 0$) and that $E^{\mathbb{P}}[\xi_{\tau_j} | \mathcal{F}_{\tau_j-}] = \xi_{\tau_j-}$ or $E^{\mathbb{P}}[X_{\tau_j}^\xi | \mathcal{F}_{\tau_j-}] = 1$ (which guarantees that ξ_t is a \mathbb{P} -martingale at jump times). If we assume the jump sizes in the density process are equal to the ratio of jump size densities,

$$X_{\tau_j}^\xi = \frac{\pi^{\mathbb{Q}}(Z_{\tau_j}, \tau_j-)}{\pi^{\mathbb{P}}(Z_{\tau_j}, \tau_j-)},$$

then by construction $E^{\mathbb{P}}[X_{\tau_j}^\xi | \mathcal{F}_{\tau_j-}] = 1$. These intuitive conditions are extremely mild, only requiring that the jump densities have common support, since $\pi^{\mathbb{P}}$ and $\pi^{\mathbb{Q}}$ are both positive.

The change of measure for jump sizes occurring at deterministic times is extremely flexible. Unlike diffusion models where only the drift can change (subject to regularity conditions), in a jump model there are virtually no constraints other than common support. This implies that, for example, certain state variables could appear under one measure that are not under the other measure or the functional form of the distribution could change. We assume that the jump sizes are state independent and normally distributed under \mathbb{Q} : $Z_j \sim \pi^{\mathbb{Q}} = N\left(-\frac{1}{2}(\sigma_j^{\mathbb{Q}})^2, (\sigma_j^{\mathbb{Q}})^2\right)$. This flexibility has the cost that it does not require us to make assumptions about $\pi^{\mathbb{P}}$ and therefore breaks the close relationship (common in diffusion models) between the parameters indexing the stochastic differential equations under each measure and risk premiums.

Under \mathbb{Q} ,

$$\begin{aligned} dS_t &= S_t r_t dt + S_t \sqrt{V_t} dW_t^s(\mathbb{Q}) + d \left(\sum_{j=1}^{N_t^d} S_{\tau_{j-}} [e^{Z_j} - 1] \right) \\ dV_t &= \kappa_v^{\mathbb{Q}} (\theta_v^{\mathbb{Q}} - V_t) dt + \sigma_v \sqrt{V_t} dW_t^v(\mathbb{Q}) \end{aligned}$$

and it is clear that under the assumptions given above, discounted gains are a martingale for $t \in [0, T]$. For pricing at-the-money options, the total risk neutral variance of equity returns is important and it is given by the quadratic variation (QV): for a partition $\{t_j\}$ of $[0, T]$,

$$QV(T) = \lim_{\|\Delta_n\| \rightarrow 0} \sum_{j=1}^n \left| \log \left(\frac{S_{t_j}}{S_{t_{j-1}}} \right) \right|^2 = \int_0^T V_s ds + \sum_{j=1}^{N_T^d} Z_j^2.$$

The expected total variability is

$$E_0^{\mathbb{Q}} \left[\int_0^T V_s ds + \sum_{j=1}^{N_T^d} Z_j^2 \right] = \theta^{\mathbb{Q}} + \frac{V_0 - \theta^{\mathbb{Q}}}{\kappa^{\mathbb{Q}}} \left(e^{\kappa^{\mathbb{Q}} T} - 1 \right) + \sum_{j=1}^{N_T^d} (\sigma_j^{\mathbb{Q}})^2 + \left(\frac{1}{2} (\sigma_j^{\mathbb{Q}})^2 \right)^2. \quad (4)$$

From this, it is clear that jumps on earnings announcement dates allow for a very rich term structure of expected volatility. In contrast to a pure stochastic volatility which has either an upward or downward sloping term structure, deterministic jumps can generate a wider range of shapes, in particular, a hump-shaped term structure.

The equity price model generates an incomplete market, due to the earnings announcement jumps. The incompleteness arises due to the inability to hedge the continuously distributed jumps. In general, to perfectly hedge jumps, one requires as many hedging instruments as the cardinality of the jump size distribution. With normally distributed jumps, this requires an uncountably infinite number of hedging instruments. Due to the incompleteness, the measure \mathbb{Q} is not unique. In order to identify a measure consistent with the absence of arbitrage, we index the measure by the risk-neutral parameters of the process and then use option prices to estimate the parameters. This is the common approach in models with jumps.

3.1 Pricing Options

To price options, we need to evaluate the conditional transform of $\log(S_T)$. By the affine structure of the problem, we have that for a complex valued c ,

$$\begin{aligned}\psi(c, S_t, V_t, t, T) &= E_t^{\mathbb{Q}} [\exp(-r(T-t)) \exp(c \cdot \log(S_T))] \\ &= \exp(\alpha(c, t, T) + \beta(c, t, T) V_t + c \cdot \log(S_t))\end{aligned}$$

where $\beta(c, t, T)$ and $\alpha(c, t, T)$ are given by:

$$\begin{aligned}\beta_v(c, t, T) &= \frac{c(1-c) [1 - e^{\gamma_v(T-t)}]}{2\gamma_v - (\alpha_v - \kappa_v^{\mathbb{Q}}) [1 - e^{\gamma_v(T-t)}]} \\ \alpha(c, t, T) &= \alpha^*(c, t, T) - \sum_{j=N_t^d+1}^{N_T^d} \frac{c}{2} (\sigma_j^{\mathbb{Q}})^2 + \frac{c^2}{2} (\sigma_j^{\mathbb{Q}})^2\end{aligned}$$

where

$$\alpha^*(c, t, T) = r\tau(c-1) + \frac{-\kappa_v^{\mathbb{Q}}\theta_v^{\mathbb{Q}}}{\sigma_v^2} \left[(\alpha_v - \kappa_v^{\mathbb{Q}})\tau + 2 \ln \left(1 - \frac{\alpha_v - \kappa_v^{\mathbb{Q}}}{2\gamma_v} (1 - e^{\gamma_v\tau}) \right) \right],$$

$$\tau = T - t, \quad \gamma_v = [(\sigma_v\rho c - \kappa_v^{\mathbb{Q}}) + c(1-c)\sigma_v^2]^{1/2}, \quad \text{and } \alpha_v = \gamma_v + \sigma_v\rho c.$$

The transform of $\log(S_t)$ with deterministic jumps has a particularly simple structure under our assumptions. To see this, note that

$$\begin{aligned}\log(S_T) &= \log(S_t) + \int_t^T \left(r - \frac{1}{2} V_s \right) ds + \int_t^T \sqrt{V_t} dW_t^s + \sum_{j=N_t^d+1}^{N_T^d} Z_j \\ &= \log(\tilde{S}_T) + \sum_{j=N_t^d+1}^{N_T^d} Z_j\end{aligned}$$

where $\log(\tilde{S}_T)$ is the traditional affine component. If we assume that the deterministic jumps are conditionally independent of the affine state variables, then the transform of $\log(S_T)$ is just the product of the traditional affine transform and the transform of the

deterministic jumps:

$$\begin{aligned}
& E_t^{\mathbb{Q}} [\exp(-r(T-t)) \exp(c \cdot \log(S_T))] \\
&= E_t^{\mathbb{Q}} \left[\exp(-r(T-t)) \exp\left(c \cdot \log\left(\tilde{S}_T\right)\right) \right] E_t^{\mathbb{Q}} \left[\exp\left(c \sum_{j=N_t^d+1}^{N_T^d} Z_j\right) \right] \\
&= \exp[\alpha^*(t) + \beta(t) \cdot V_t + c \cdot \log(S_t)] \exp(\alpha^d(t))
\end{aligned}$$

where $E_t^{\mathbb{Q}} \left[\exp\left(c \sum_{j=N_t^d+1}^{N_T^d} Z_j\right) \right] = \exp(\alpha^d(t))$ for some state-independent function α^d , $\alpha^*(t) = \alpha^*(c, t, T)$, and $\beta(t) = \beta(c, t, T)$. This implies that only the constant term in the exponential is adjusted. Thus, option pricing with earnings announcements requires only minor modifications of existing approaches.

This pricing model has an additional implication of note. Since only the total number of jumps over the life of the contract matter, the exact timing of the jumps does not, provided that the distribution of jump sizes does not change. It is not hard to show that if, for example, there is a probability p that they announce on a given date and $(1-p)$ that they announce the following day, that the transform is unchanged provided the jump distribution does not change.

3.2 Black-Scholes with deterministic jumps

To gain intuition on the model, consider a simple modification of the Black-Scholes model incorporating deterministically timed jumps:

$$S_T = S_0 \exp \left[\left(r - \frac{1}{2} \sigma^2 \right) T + \sigma W_T(\mathbb{Q}) + \sum_{j=1}^{N_T^d} Z_j \right] \quad (5)$$

where $Z_j = -\frac{1}{2} (\sigma_j^{\mathbb{Q}})^2 + \sigma_j^{\mathbb{Q}} \varepsilon$ and $\varepsilon \sim N(0, 1)$. Under these assumptions, discounted prices are martingales. Notice that the prices are a finite, non-random mixture of normal distributions.

The price of a European call option struck at K , expiring at T , assuming a constant interest rate is given by:

$$BS(x, \sigma_T^2, r, T, K) = E^{\mathbb{Q}} \left[e^{-rT} (S_T - K)^+ | S_0 = x \right]$$

where BS is the usual Black-Scholes pricing function,

$$BS(x, \sigma_T^2, r, T, K) = x\Phi(z) - Ke^{-rT}\Phi\left(z - \sigma_T\sqrt{T}\right) \quad (6)$$

where

$$z = \frac{\log(x/K) + rT + \sigma_T^2 T/2}{\sigma_T\sqrt{T}},$$

and σ_T^2 is the annualized total volatility over the life of the option, $\sigma_T^2 = \sigma^2 + \frac{1}{T} \sum_{j=1}^{N_T^d} (\sigma_j^{\mathbb{Q}})^2$. By inspection, equation (6) implies that the Black-Scholes implied volatility is σ_T^2 . This extension of Black-Scholes, despite its simplicity, provides a number of interesting time series and option pricing implications that differ from traditional models and also provides the intuition for estimators of $\sigma_j^{\mathbb{Q}}$.

Deterministic jumps introduce a strong, rational predictability in implied volatility. To see this, assume that there is a single announcement at time, τ , $t < \tau < T$. The Black-Scholes implied volatility is given by $\sigma_t^2 = \sigma^2 + \frac{(\sigma_j^{\mathbb{Q}})^2}{T-t}$. From this, we can deduce three implications. First, the moment before an earnings release, annualized implied volatility is $\sigma_{\tau-}^2 = \sigma^2 + \frac{(\sigma_j^{\mathbb{Q}})^2}{T-\tau}$ and after the announcement it is $\sigma_{\tau}^2 = \sigma^2$. This implies there is a discontinuous decrease in implied volatility immediately following the earnings release. In Section 4.1 we use this implication to estimate $\sigma_j^{\mathbb{Q}}$ based on the changes in implied volatility before and after announcements. Second, if we analyze the behavior of implied volatility as a function of maturity, $(T-t)$, we see that volatility drastically increases leading into an announcement: it increases at rate $(T-t)^{-1}$ as the maturity decreases. In fact, the implied volatility just before an announcement will “blow-up” if the maturity is just after the earnings announcement. Third, there are also term structure implications. Holding the number of jumps constant, Black-Scholes implied volatility decreases as the maturity of the option increases. Thus longer dated options will have lower Black-Scholes implied volatilities than shorter dated options.

To see these effects, first consider the increase before and decrease after the earnings announcement. To get a general sense of the effect, Figure 1 displays Black-Scholes implied volatility extracted from at-the-money options on Intel Corporation from 1996 through 2002. The circles indicate dates on which earnings were announced. From this figure, it is clear that implied volatility dramatically increases prior to and falls drastically immediately following the release of quarterly earnings. Again, the magnitude of the increase and decrease depends on the maturity of the option relative to the earnings date. Patell and

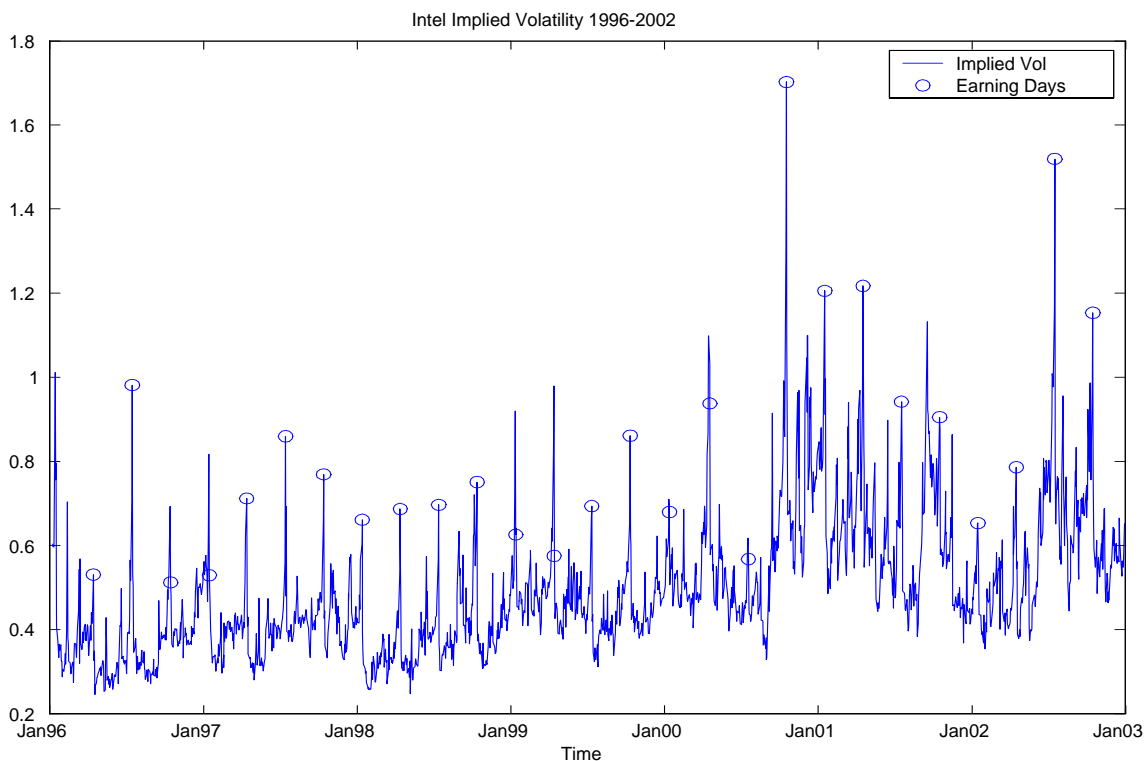


Figure 1: Black-Scholes implied for the nearest maturity at-the-money call option for Intel Corporation from January 1996 to December 2002. The circles represent days on which earnings announcements were released.

Wolfson (1979, 1981) first hypothesized this pattern and found evidence in support of its presence in the data.

To see the term structure implications, Figure 2 plots the term structure of Black-Scholes implied volatility assuming $\sigma = 30\%$, $\sigma_j^Q = 10\%$, and that a single earnings announcement occurs in one week. The figure plots $\sigma_t^2 = \sigma^2 + \frac{(\sigma_j^Q)^2}{T-t}$ as a function of $T - t$, and shows a very strong declining term structure of volatility prior to an announcement. The rapidly decreasing term structure before an announcement is a very strong testable implication and it will also provide a method to estimate σ_j^Q (see Section 4.1).

At this point, it is important to compare our model to the model in Patell and Wolfson (1979, 1981). Their argument relies on an observation in Merton (1973) that the Black-

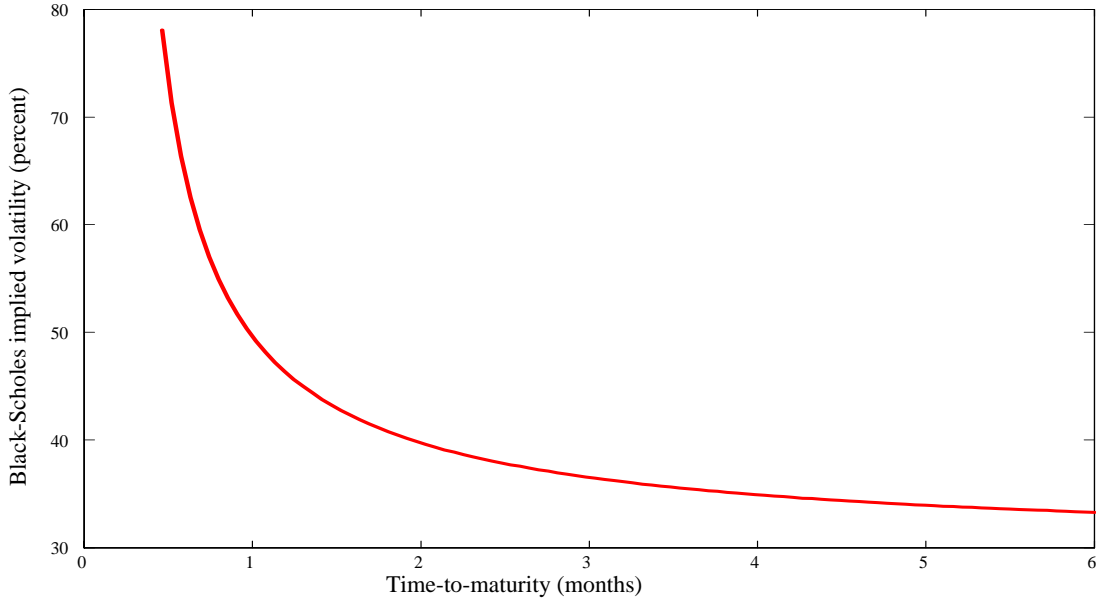


Figure 2: This figure shows the effect of a deterministic jump on Black-Scholes implied volatility. The figure plots σ_{BS} where $(\sigma_T^{BS})^2 = \sigma^2 + \frac{(\sigma_j^Q)^2}{T-t}$ for $\sigma = 30\%$, $\sigma_j^Q = 10\%$, $t = 1/52$ and for maturities from two weeks to six months.

Scholes model can handle deterministically changing diffusive volatility. Instead of assuming volatility is constant, they instead assume that volatility, $\sigma(t)$, is a non-stochastic function of time. The Black-Scholes implied volatility at time zero of an option expiring at time T is $(\sigma_T^{BS})^2 = \frac{1}{T} \int_0^T \sigma^2(s) ds$. Patell and Wolfson essentially decompose volatility into two components, assuming $\sigma^2(s) = \sigma^2 + \sigma_E^2 1_{[\tau_E \leq s \leq \tau_E + 1]}$, which implies that $(\sigma_T^{BS})^2 = \sigma^2 + \frac{1}{T} \sigma_E^2$. Clearly this delivers the result that annualized volatility increases prior to and decreases after an earnings release and that changes in implied volatility of the same contract before and after the announcement are informative about σ_E .

Despite the fact that Patell and Wolfson's model generates similar implications in a simple extension of the Black-Scholes model, there are crucial differences. Patell and Wolfson model asset prices as continuous functions of time with increased volatility around earnings announcements, whereas in our model, there is a discontinuity. Since earnings announcements are released after the market's close, it is clear that these movements will often lead to a jump in trading time. It also implies that Patell and Wolfson's model is a

complete market, where options can be perfectly hedged by trading in only the underlying equity and a money market account. These implications are clearly counterfactual given the large differences observed between market close and open prices subsequent to earnings announcements. Moreover, Patell and Wolfson's (1979, 1981) model appears to be in contrast to the findings in Patell and Wolfson (1984), which documents the reaction of the stock prices to earnings is extremely rapid.

Unlike Patell and Wolfson's model, it is straightforward to incorporate stochastic volatility into our model. An extension of Patell and Wolfson incorporating stochastic volatility requires deterministic timed jumps in stochastic volatility with deterministic sizes, but it is very difficult to price options in this model as the characteristic function must be computed recursively, as opposed to our model which possesses a closed form characteristic function. Finally, Patell and Wolfson's model does not allow for risk premiums associated with the earnings volatility, as it is a diffusive component. Our jump based model allows for flexible risk premium specifications, as the absence of arbitrage places few constraints on the jump distributions.

Next, consider the distributional features of returns under the objective measure. Assuming mean zero, normally distributed deterministically timed jumps, the distribution of the log-returns conditional on the parameters is normal,

$$\log\left(\frac{S_T}{S_0}\right) \mid \sigma^2, \{\sigma_j^2\}_{j=1}^{N_T^d} \sim N\left(\mu T, \sigma^2 T + \sum_{j=1}^{N_T^d} \sigma_j^2\right),$$

as a sum of normal random variables is normal. Clearly, deterministic jumps generate predictable heteroscedasticity. Also, since the earnings driven jump-volatility can vary over time ($\sigma_j^2 \neq \sigma_i^2$), this implies that, in the words of Piazzesi (2002), that time matters. This time-inhomogeneity contrasts with typical models which imply that the distribution of returns, conditional on current V_t is always the same shape.

Third, unlike models with jumps based on compound Poisson processes, the deterministic jump component does not necessarily generate conditional, distributional asymmetries or fat tails. For example, in Merton's (1976) model, the distribution of returns is a discrete mixture of normals, where the mixing weights are determined by the Poisson probabilities. Naturally, if the earning's jump volatility parameter were unknown or if the jump sizes were non-normal, then the distributions would generally be non-normal. This has strong implications for the findings in Beber and Brandt (2003).

Finally, as we show in Section 4.1, it is possible to estimate, ex-ante, $\sigma_j^{\mathbb{Q}}$ from option prices. This provides an ex-ante view of the uncertainty embedded in the announcement. In most studies of earnings announcements, or more generally macroeconomic announcements, high frequency data is used to analyze the response of prices to news. “News” is typically measured as standardized deviations from forecasts. This, while informative, is an ex post analysis and does not give a sense of what investors expect. It also requires assumptions on the forecast variance (typically assumed to be constant across news releases) and assumes the coefficients measuring the responses are constant across time.

3.3 Discussion

3.3.1 Extensions

It is straightforward to extend our model in a number of interesting directions. In this section, we briefly consider a few examples to show the flexibility of our modelling approach.

The most obvious way to generalize the model is with more flexible jump distributions. The normal distribution used in the previous section does not generate any conditional skewness or kurtosis. Discrete mixture distributions are the easiest way to introduce asymmetries and fat tails. To this end, consider a simple example with a mixture of two distributions where the jump size is given by

$$Z_j = 1_j Z_j^u + (1 - 1_j) Z_j^d$$

where 1_j is a Bernoulli random variable which equals one with probability $p_j^{\mathbb{Q}}$ and zero with probability $(1 - p_j^{\mathbb{Q}})$. When $1_j = 1$, interpreted as “good news” the random jump size is Z_j^u , and Z_j^d is the random jump size in the other state. Although the jump size distribution and Bernoulli probabilities could depend on j , we omit this subscript for notational simplicity.

For pricing purposes, we only require that the Laplace transform of the total jump can be easily computed either explicitly or numerically. The Laplace transform of a Bernoulli mixture is the probability weighted sum of the transforms of the underlying distributions,

$$\varphi_{Z_j}(c) = p^{\mathbb{Q}} \cdot \varphi_{Z_j^u}(c) + (1 - p^{\mathbb{Q}}) \cdot \varphi_{Z_j^d}(c),$$

where $\varphi_z(t)$ is the Laplace Transform of a random variable z , a for simplicity, we consider a real-valued c . A particularly convenient choice is a combination of exponential distributions which is parsimonious and delivers a closed form Laplace transform. For a positive

exponential distribution,

$$\varphi_Z(t) = \frac{1}{1 - c\beta_u^{\mathbb{Q}}}$$

where $\beta_u^{\mathbb{Q}} > 0$ is the mean of the jump size. A negative exponential jump has the transform $\varphi_Z(-c) = \frac{1}{1+c\beta_d^{\mathbb{Q}}}$ where $-\beta_d^{\mathbb{Q}} < 0$ is the mean of the negative exponential. Under \mathbb{Q} , the expected jump in the stock price must equal 1, $E^{\mathbb{Q}} [e^{Z_j} | \mathcal{F}_{\tau_j-}] = 1$, which is equivalent to $\varphi_Z(1) = 1$:

$$\varphi_Z(1) = p^{\mathbb{Q}} \cdot \frac{1}{1 - \beta_u^{\mathbb{Q}}} + (1 - p^{\mathbb{Q}}) \cdot \frac{1}{1 + \beta_d^{\mathbb{Q}}} = 1.$$

Since there are three free parameters, $(p^{\mathbb{Q}}, \beta_d^{\mathbb{Q}}, \beta_u^{\mathbb{Q}})$, this equation holds if, for example,

$$p^{\mathbb{Q}} = \frac{\beta_d^{\mathbb{Q}}(1 - \beta_u^{\mathbb{Q}})}{\beta_d^{\mathbb{Q}} + \beta_u^{\mathbb{Q}}}.$$

This binomial example is a special case of a more general multinomial distribution which allows for mixture of N distributions. More general mixtures could incorporate a chance that there is no jump as well.

The second extension that we consider incorporates jumps in square-root state variables at deterministic times. Consider the following variant of a model proposed by Duffie, Pan and Singleton (2000) and Pan (2002):

$$\begin{aligned} dS_t &= S_t [r_t - \delta_t] dt + S_t \sqrt{V_t} dW_t^s + S_{t-} (e^{Z_t} - 1) dN_t^d \\ dV_t &= \kappa_v (\theta_v - V_t) dt + \sigma_v \sqrt{V_t} dW_t^v + Z_t^v dN_t^d \\ d\theta_t &= \kappa_\theta (\theta_\theta - \theta_t) dt + \sigma_\theta \sqrt{\theta_t} dW_t^\theta + Z_t^\theta dN_t^d, \end{aligned}$$

where the long-run mean of stochastic volatility is now a square-root state variable. In a traditional affine framework, the jump distribution must be state independent and the jumps in V_t and θ_t have to be positive to insure the existence of a solution to the SDE. Since the jump times are unknown, even small negative jumps cannot be allowed because the jump could occur when V_t or θ_t are arbitrarily close to zero and the distribution of sizes is state independent. In a deterministic jump model, the jump distribution can be state dependent, depending on V_{τ_j-} or θ_{τ_j-} , which allows for negative and positive jumps. For example, provided that $V_{\tau_j}, \theta_{\tau_j} > 0$, all jump distributions are admissible. Since the distribution can vary over time, there could be periods in which the jumps are only positive

or only negative. Bakshi and Cao (2004) argue that there might be negative jumps in V_t . State-dependent jumps in volatility complicates option pricing only slightly as the loadings in the transform must be computed recursively as the jump distribution is not independent of the state variables.

This model is a special case of a more general model with regime-switches triggered on deterministic jump dates. Unlike traditional regime-switching models which commonly assume state-independent transition probabilities and jump sizes, a deterministically timed regime-switching model is far more flexible. This type of a specification, however, would likely be more useful in a term structure or foreign exchange setting.

3.3.2 Pricing and hedging with deterministic jumps

The model above has a number of interesting implications for pricing, hedging and risk premiums. Although we do not pursue them directly in this paper,

In asset pricing models, it is common to assume that the investors know the parameter values. One justification for this is that the investors have observed prices over a long time span and based on this data, they obtain accurate estimates of the parameters and therefore one can safely ignore estimation risk. However, in the setting of deterministic jumps, each earnings announcement has its own jump distribution and there is no reason to believe that the distribution or the parameters indexing the distribution are constant over time. If this is the case, it raises an interesting issue: how would investors learn about the parameters of the jump distribution? Option prices are informative regarding the risk-neutral jump parameters, but they do not provide information on objective measure parameters. Potential sources of information about these parameters are time series models of firm fundamentals and analyst forecasts.

Given that the usual justifications for known parameters do not hold for earnings announcements, how should investors price equities and options? Since there is only one earnings announcements to learn about the parameters indexing the jump distribution, there is no dynamic learning about the jump parameters over time. Thus, a Bayesian approach does not apply and it seems natural to price the stock and the options in a “robust” manner, following Andersen, Hansen, and Sargent (2003). In this case, investors are worried about worst-case scenarios and there are two dimensions along which investors can be robust: robust against parameter (σ_j^Q) uncertainty and robust against uncertainty

in the distribution of the jump sizes. Johannes and Williams (2004) provide results along these dimensions.

Earnings announcements and deterministic jumps provide an interesting laboratory to study the hedging of jumps. In diffusive models, options can be perfectly hedged with continuous trading in a small number of securities. In jump models with randomly timed arrivals, hedging of jumps requires hedging both the timing of the jumps and their sizes. In a deterministic jump model, the timing is not random and the focus is on hedging the discontinuity in the sample path. As in traditional jump-diffusion models (e.g., Merton (1976)), the jump distribution is continuous which implies that the jump sizes cannot be hedged with a finite number of instruments, despite the fact that the jump times are known. However, it is possible to derive hedge portfolios under common metrics (minimize variance, expected loss, etc.) and it is likely that deterministically timed jumps can be hedged reasonably well using both the underlying and a single other option contract.

4 Empirical Evidence

To analyze the effect of earnings announcements on options, we obtained closing prices on individual equity options from OptionMetrics for the period from the beginning of 1996 to the end of 2002. OptionMetrics reports prices for equity options traded on the Chicago Board of Options Exchange. A number of other papers have used this data source, see, for example, Carr and Wu (2004). A disadvantage of this data is that it is sampled only daily. High frequency, intradaily data would be preferred as it would allow one to analyze, for example, how quickly option prices adjust to the information embedded in earnings announcements. Unfortunately, since the close of the Berkeley Options Database in 1996, the CBOE time and sales data is not available and we have to settle for daily data.

The OptionMetrics data consists of closing prices for options and then converts these prices using a binomial tree to correct for early exercise and dividend payments into implied volatilities. We consider only call options because calls on individual equities are more heavily traded than puts and they minimize the American exercise feature. Moreover, we use the adjusted implied volatilities to convert the American prices to European prices and then analyze the European prices and/or their implied volatilities. Broadie, Chernov, and Johannes (2004) provide evidence that this provides an accurate correction for the

American feature in models with jumps and stochastic volatility.

Out of the universe of firms, we use the following criterion to select 20 firms for analysis. For the period from 1996 to 2002, we found the 50 firms with the highest dollar volume which traded in each year. Next, we filtered out firms with an average dividend rate of more than 0.35 percent. The focus on low dividend stocks provides a number of benefits: it minimizes the American feature, it avoids problems associated with pricing options on high dividend stocks, and low-dividend stocks will likely have high earnings uncertainty as they are “growth” stocks. Unlike equity indices whose dividend payments are usually modelled as continuous, for individual equities, dividends result in a jump in the stock price. For these remaining firms, we computed the average dollar volume of these remaining firms and took the twenty-highest remaining firms.⁴

The selection criterion resulted in the following firms, with their ticker symbols in parentheses: Apple Computer Inc. (AAPL), Adobe Systems Inc. (ADBE), Altera Corp. (ALTR), Applied Materials Inc. (AMAT), Amgen Inc. (AMGN), Cisco Systems Inc. (CSCO), Dell Computer Corp. (DELL), E.M.C. Corp. (EMC), Intel Corp. (INTC), KLA Tencor Corp. (KLAC), Microsoft Corp. (MSFT), Micron Technology Inc. (MU), Maxim Integrated Products Inc. (MXIM), Novellus Systems Inc. (NVLS), Oracle Corp. (ORCL), PMC Sierra Inc (PMCS), Peoplesoft Inc (PSFT), Qualcomm Inc. (QCOM), Sun Microsystems (SUNW), and Xilinx (XLNX). With the exception of AMGN which is a pharmaceutical company, all of the firms are in technology related industries. Apple, Dell, and Sun are computer makers; Adobe, Microsoft, Oracle and PeopleSoft are software companies; and Altera, Applied Materials, Intel, KLA Tencor, Micron, Maxim, Novellus, PMC Sierra, and Xilinx are semiconductor companies. The fact that the high volume, low-dividend stocks are technology stocks is not surprising.

We obtained earnings dates from Compustat and the exact timing of the release from First Call. The earnings date is defined as the last closing date before earnings are announced. If earnings are announced after hours or before the open of the following day, the earnings date is defined as the close of the previous day. There were only five announcements in our sample that occurred during the market hours. Most of the announcements were after the market close instead of before the market open on the following day.

⁴One of the firms in the top 20, AOL, was discarded. AOL had major merger and acquisition activity over the sample which has a prominent effect on implied volatilities, see Subramanian (2004). To avoid jointly modeling mergers and earnings announcements, we discarded AOL from the sample.

The data that we have provides the actual date of the release. For most of the firms, the dates occur in a very predictable pattern. For example, Intel announces earnings in the second week following the end of the quarter. Based on our data, it is not possible to generically confirm that the actual earnings dates were the exact expected date. However, there are three factors that lead us to believe this is not an issue. First, Bagnoli, Kross, and Watts (2002) find that from 1995 to 1998, there was an increase in the number of firms announcing on time and that large firms with active analyst coverage tend to miss less than smaller firms. For example, over all firms in 1998, more than 80 percent of the firms released earnings on the expected date. Second, for each firm, we searched in Factiva for each earnings announcement to find evidence of missed dates and did not find any evidence of reported missed earnings dates for our firms. Given our short sample and the large size of the firms in our sample, this is not a surprise. Third, as mentioned above, the exact timing does not matter if there is uncertainty over the date, but not the distribution of the jump sizes.

4.1 How important are earnings?

4.1.1 Estimates from a Black-Scholes analysis

Before analyzing a formal stochastic volatility model, we use the extension of the Black-Scholes model incorporating deterministic jumps to obtain estimates of $\sigma_j^{\mathbb{Q}}$. We use two different approaches to estimate $\sigma_j^{\mathbb{Q}}$: one based solely on ex-ante information in the term structure of implied volatility and the other based on the time series of implied volatilities around earnings announcement dates. These estimates are important for their simplicity: they do not require complicated estimation and can be obtained without large historical databases.

The term structure method uses the information in the implied volatility of two different maturities that both expire after a quarterly earnings announcement, but before the following quarter's announcement. With a single earnings announcement prior to maturity, the Black-Scholes implied volatility of an option with T_i days to maturity (measured in fractions of years) is $(\sigma_{T_i}^{BS})^2 = \sigma^2 + \frac{1}{T_i} (\sigma^{\mathbb{Q}})^2$, and for $T_1 < T_2$, we have that $(\sigma_{T_1}^{BS})^2 > (\sigma_{T_2}^{BS})^2$.⁵ This decreasing term structure implication was displayed in Figure 2. Under this condition,

⁵This is also robust to jumps in returns, provided the jumps in returns are i.i.d. To see this, note that in Merton's (1976) model, Black-Scholes implied volatility of an at-the-money option is constant and

we can solve for σ and $\sigma^{\mathbb{Q}}$. We denote this *term structure* estimator as $\sigma_{term}^{\mathbb{Q}}$ and it is given by

$$(\sigma_{term}^{\mathbb{Q}})^2 = \frac{(\sigma_{T_1}^{BS})^2 - (\sigma_{T_2}^{BS})^2}{\frac{1}{T_1} - \frac{1}{T_2}}.$$

We also report $\sqrt{T_1^{-1} (\sigma_{term}^{\mathbb{Q}})^2 / (\sigma_{T_1}^{BS})^2}$ as a measure of the proportion of total volatility due to the earnings release.

This estimator requires the implied volatility from two maturities prior to the earnings announcement. To obtain this, we select the two nearest-to-the-money call options for each of the three nearest expiration cycles. We then select the first two maturity cycles, discarding a maturity cycle that expires in less than five days. The liquidity of very short time-to-maturity options is low and the bid-ask spreads are relatively large, so we exclude those contracts. Contracts for which OptionMetrics has a zero implied volatility value or zero trading volume are also naturally excluded. For these maturity cycles, we take the two call options which are closest to maturity and average the two implied volatilities to obtain a composite implied volatility for each maturity. As noted in Bakshi, Kapadia, and Madan (2003), individual firms have very flat implied volatility curves so this has just guarantees that we have an implied volatility of the at-the-money if the current stock price is between the two closest strikes.

The time series estimator of $\sigma^{\mathbb{Q}}$ uses changes in implied volatility around the earnings announcement dates. Define σ_{t,T_i}^{BS} as the Black-Scholes implied volatility on date t of an option expiring in T_i days. If there is an earnings announcement after the close on date t (or before the open on date $t+1$), then the implied volatility j -days after the announcement is $(\sigma_{t+j,T_i-j}^{BS})^2 = \sigma^2$. The changes provide an estimator of the earnings jump variance based on the *time series*:

$$(\sigma_{time}^{\mathbb{Q}})^2 = T_i \left((\sigma_{t,T_i}^{BS})^2 - (\sigma_{t+1,T_i-1}^{BS})^2 \right),$$

where $\sigma_{time}^{\mathbb{Q}}$ denotes the estimator based on the time series changes. We report estimation results for $j = 1$, but we have also computed it for $j = 2$ and 5 and the results are similar. We also report the proportional of total volatility based on this estimate. Patell and Wolfson (1981) and Ederington and Lee (1996) use a related statistic to measure the drop

approximately equal to

$$\sigma^2 + \lambda (\mu_j^2 + \sigma_j^2) + \frac{1}{T_i} (\sigma^{\mathbb{Q}})^2$$

which is the total volatility.

in implied volatility that occurs after the announcement.⁶ We use the filtering procedure to generate option observations described in the previous paragraph.

The following example illustrates the estimators. On July 15, 1997 Intel released earnings after the market closed. The first three options expired 0.0198, 0.0992, and 0.2778 years (roughly 5, 25 and 70 business days) and the Black-Scholes implied volatilities were 71.15%, 45.19%, and 41.40%. In the late 1990s, options typically traded the first two months (serial months) and then the next maturity was the quarterly contract. In this example, there was a July, August and then October expiration. The term structure estimator is $\sigma_{term}^Q = 8.6\%$. The implied volatility of the short option falls to 42.96% the day after the announcement and the time series estimator is therefore $\sigma_{time}^Q = 7.2\%$. This example is very common with both estimators telling a similar story, even though the term structure estimator only uses ex-ante information while the time series estimator uses ex-ante and ex-post.

Both of the measures are imperfect if the simple extension of the Black-Scholes model is not a reasonable approximation. Even ignoring earnings announcements, it is clear that individual equities have time-varying and stochastic volatility. If volatility is very volatile, stochastic volatility creates obvious problems for the previous estimators. For the term structure estimators, stochastic volatility would generally result in an upward or downward sloping term structure depending on V_t and θ_v . This implies that different maturities have different Black-Scholes implied volatilities, irrespective of earnings announcements. Similarly, for the time series estimators, there are periods of time when volatility increases due to a large Brownian shock, and the estimate of $(\sigma_{time}^Q)^2$ will be negative. If, however, the effect of earnings announcements is very large, then the earnings effect swamps the potential effect of stochastic volatility.

For both metrics, about 1 out of 9 earnings announcements resulted in a negative estimate. In these cases, we zeroed out the estimator and for each company, we report the number of times this occurs. We have identified two issues which result in the inability to use the simple extension of Black-Scholes to estimate σ^Q : data problems (option expiration very close to the earnings announcement date) and other microstructure effects such as stock splits, mergers, and acquisitions. More than half of the zeroed out options occur because

⁶Patell and Wolfson (1981) also develop a time-series estimator to track the increase in implied volatility prior to the announcement, which, when properly scaled, could be used to deliver another estimate of σ^Q . We do not use this approach as it requires an assumption that diffusive volatility is constant over relatively long time spans, in their work, 20 business days, and the moneyness of the options do not change.

the short dated option gets filtered out as option expiration is very close to an earnings release. To see what happens, consider the following example, Intel around the July 13, 1999 earnings announcement. The shortest maturity option expired on July 16, so it was filtered out. The next two maturities were one month and three months with implied volatilities of 48.09% and 48.28%. Since $(\sigma_{T_1}^{BS})^2 \neq (\sigma_{T_2}^{BS})^2$, it is not possible to construct a positive estimate from the term structure method. The slight increase in implied volatility could be caused by stochastic volatility or other microstructure effects. An upward sloping term structure, especially at these relatively long maturities is not surprising and is consistent with a stochastic volatility model. The implied volatility of the second option fell to 43.92 the day after the announcement, resulting in a time series estimate of $\sigma_{time}^Q = 6.4\%$ which shows that the longer dated option still contains information about the volatility of the earnings jump.

Many of the companies (e.g., Apple, EMC, Intel, Novellus, and Sun) announce earnings in the second or third week after the end of the quarter which means that the nearest maturity option is very often filtered out and the nearest maturity option has more than three weeks to maturity. This results in options with relatively long maturities being used to estimate the earnings jump, and the situation of the previous paragraph occurs. If the true model is a stochastic volatility model, both the time series and term structure estimators work well if short-dated options are available. If one relies on longer dated options, the Black-Scholes based estimators can give poor estimates if V_i is drastically higher or lower than θ . It is important to note it is rarely the case (about 1 in 20 earnings dates) that we cannot estimate volatility if the short-dated option is available. The fact that it is possible to construct reasonable estimates in most cases points to the fact that the earnings effect is so large that it dwarfs any stochastic volatility effects.

There are two other causes of the inability to estimate σ^Q in the simple Black-Scholes model. First, many of the firms in the sample had stock splits which resulted in spikes in implied volatility for options expiring after the split. This is especially true in 1998, 1999, and 2000. For example, AMAT, INTC, and MSFT split 4 times, CSCO, ORCL, and SUNW split 5 times, and DELL split 6 times over the sample. Implied volatility increases after a stock split, as documented in Sheikh (1989), and this is related to a curious finding in Ohlson and Penman (1985), who find that after a stock split, the volatility of stock returns is higher than before the stock split. Based on Sheikh (1989), it appears that the option market correctly incorporates the fact that the underlying stock volatility increases

after the stock split, although it is difficult to motivate why this increase would occur in the first place.

Second, many of the firms were involved in mergers and acquisitions. As shown in Jayaraman, Mandelker, and Shastri (1991) and Subramanian (2004), pre-announced mergers and acquisition, and the risk they might be canceled, generate predictable behavior in implied volatility, with implied volatility falling after the merger. In our setting, this can result in longer dated options having a higher Black-Scholes implied volatility than shorter dated options that do not span the merger date.

Given these caveats, Tables 1 and Table 2 summarize the earnings jump volatility estimates for the 20 firms in our sample using the term structure and time series methods, respectively. For each firm, there were 28 earnings dates and we report the number of dates on which we could not estimate σ^{Q} and summary statistics of the estimates for each company over time (mean, median, quantiles, and fraction of total volatility explained). There are a number of notable results.

First, the estimates are quite large, both statistically and economically. For both approaches, the estimates are on the order of 10 percent. The 75 percent quantile implies that the expected volatility can be enormous: an estimate of 15 percent implies that an expected 3 standard deviation confidence band is ± 45 percent! Of course, this is a risk neutral parameter which could contain risk premiums and thus we may not see moves of this size in the actual time series of returns. The large estimates of earnings jump volatility can easily explain the spikes in Figure 2. Consider the following example. Assume the annualized diffusive volatility is 60 percent, which implies the daily volatility is about 3.75 percent. If the jump is 15 percent and there is an option expiring in five days, this implies that the total volatility over the life of the option is about 33.8 percent, or 6.77 percent per day. On an annualized basis, this implies that implied volatility of the short-dated option will be about 107 percent and will fall to 60 percent following the announcement.

Second, the two estimators deliver remarkably similar results, despite the fact that the term structure estimator uses only ex-ante information, while the time series estimator uses ex-ante and ex-post. Across firms, the correlation between the mean estimates is 83.53 percent and the correlation between the pooled observations is 71.87 percent. The high correlations indicate that both of the methods are capturing the same common effect. The term structure estimator is slightly higher on average and this is likely due to a term structure effect, which we can control for in a more sophisticated model with stochastic

Term	# Zero	Mean	Median	Std. Error	25%	75%	Av. Fraction
AAPL	3	10.44	10.02	0.75	7.70	12.73	48.92
ADBE	1	13.29	11.74	1.05	9.47	15.81	62.81
ALTR	4	11.73	10.38	1.15	8.55	13.26	54.38
AMAT	4	10.48	11.06	0.96	7.42	13.43	50.83
AMGN	1	6.91	6.38	0.46	5.27	8.29	50.33
CSCO	1	9.45	7.89	0.84	6.71	12.85	66.51
DELL	5	8.07	7.90	0.64	6.27	9.93	49.87
EMC	9	11.19	9.93	1.39	7.27	12.33	54.06
INTC	1	8.26	7.03	0.72	5.92	9.36	52.59
KLAC	6	9.63	8.77	1.12	6.43	11.49	46.71
MSFT	1	6.49	6.48	0.69	3.69	8.54	47.38
MU	3	13.13	11.44	1.32	7.53	16.66	59.05
MXIM	3	9.21	9.07	0.86	7.21	10.97	52.37
NVLS	6	11.22	10.61	1.27	8.04	14.71	56.97
ORCL	2	12.03	9.72	1.27	7.15	17.69	60.32
PMCS	0	12.85	13.78	1.17	8.29	15.89	48.99
PSFT	4	14.28	12.24	1.09	10.94	18.47	58.24
QCOM	2	8.95	9.51	0.75	6.61	11.65	49.01
SUNW	7	9.35	8.75	1.09	5.20	13.47	46.54
XLNX	1	11.28	11.29	1.00	7.63	15.05	51.12
Average	3.20	10.41	9.70	0.23	7.16	13.13	53.35

Table 1: Estimates of the jump volatility generated by earnings announcements using the term structure approach. The columns provide (from left to right), the mean estimates volatility across earnings dates, the median estimate, the standard error of the mean, the 25 percentile, the 75 percentile, and the average fraction of total volatility.

TS	# Zero	Mean	Median	Std. Error	25%	75%	Av. Fraction
AAPL	3	8.57	8.44	0.79	6.17	10.73	40.51
ADBE	3	11.07	9.93	0.86	8.81	12.90	52.46
ALTR	2	8.64	9.14	0.82	5.33	11.08	41.14
AMAT	2	10.49	11.02	0.80	8.32	12.96	50.19
AMGN	3	6.68	6.22	0.58	4.84	8.04	49.16
CSCO	1	7.98	7.85	0.63	5.60	9.12	57.40
DELL	2	7.82	7.95	0.46	6.09	9.38	47.86
EMC	3	8.04	7.47	1.07	4.94	9.14	42.67
INTC	4	6.95	6.48	0.58	5.09	8.24	45.23
KLAC	9	7.54	7.61	0.78	4.54	9.24	38.58
MSFT	2	6.83	5.88	0.56	4.79	8.44	48.17
MU	7	10.32	8.86	1.33	7.30	12.49	44.88
MXIM	5	6.86	6.01	0.78	4.87	7.84	40.12
NVLS	8	7.21	6.97	0.94	4.32	8.99	36.78
ORCL	5	10.13	9.44	0.77	7.89	12.75	53.04
PMCS	3	8.97	8.76	0.86	5.15	11.78	36.75
PSFT	4	11.44	11.14	0.92	8.67	14.14	48.09
QCOM	2	8.99	8.81	0.80	6.21	12.06	45.77
SUNW	6	7.98	7.33	0.69	5.70	10.59	43.09
XLNX	5	8.48	9.16	0.77	5.36	10.84	39.62
Average	3.95	8.55	8.22	0.18	6.00	10.54	45.08

Table 2: Estimates of the volatility of the jump generated by earnings announcements based on the time series of implied volatilities. The columns provide (from left to right), the mean volatility across time, the median volatility, the standard error of the mean, the 25 percentile, the 75 percentile, and the average fraction of total volatility.

volatility.

4.1.2 Time-variation, specification, and risk premiums

Given the estimates of $\sigma_j^{\mathbb{Q}}$, we can investigate a number of implications regarding jumps on earnings dates. First, we note that there is an interesting variation in the jump volatilities across time. Table 3 provides a year-by-year summary of the estimates using the term structure method for each firm in our sample. Across firms, we find that the expected, ex-ante uncertainty associated with earnings announcements was highest in 2000 and 2001 and was somewhat lower in 1996, 1997, 1998, 1999, and 2002. The magnitude of the effect is substantial: 2000 and 2001 are about 40 percent higher than the other years.

This result is related to the findings in Pastor and Veronesi (2004). They argue that the uncertainty regarding firm profitability was much higher during 2000 than in other periods and argue that this can rationalize observed valuations. In a time series analysis of the NASDAQ Composite index, they find that the implied uncertainty is an order of magnitude higher in 1999, 2000, and 2001 (see, e.g., $\psi = 1$ or $\psi = 2$ in their Figure 7). We also find that uncertainty over fundamentals, as measured by the implied jump variance, was higher during these years, although the magnitude was smaller than the magnitude found in Pastor and Veronesi (2004).

In order to investigate risk premiums, consider the return movements the day after the earnings announcement. If returns, for example, tend to be positive the day after the announcement, this would be evidence consistent with a positive risk premium for earning jump risk. Table 4 shows that the observed returns can be quite large as measured by the minimum and maximum and are very volatile (the column ‘Pvol’ gives the realized volatility). The column labeled ‘ t -test’ indicates that there is little evidence, however, for any predictable component, in the sense that one cannot reject the hypothesis that the mean return the day after the announcement is zero. There are two firms (MU and PMCS) for which there is some evidence of a non-zero response, but it is only marginally significant (just under the 5 percent level) and they are of different signs.⁷

Next, to analyze the evidence for a jump volatility risk premium, we can compare the observed variability of returns under \mathbb{P} with the ex-ante expected volatility of returns under

⁷Since we have at most 28 earnings announcements, we use critical values from the exact, finite-sample t -distribution to measure statistical significance.

Year	1996	1997	1998	1999	2000	2001	2002
AAPL	9.50	10.59	10.65	8.70	13.99	10.49	8.80
ADBE	15.37	10.98	13.47	12.47	15.89	15.41	10.52
ALTR	11.02	8.24	8.25	14.29	17.28	13.29	11.26
AMAT	14.27	10.52	8.87	9.80	13.15	10.34	7.49
AMGN	7.68	4.71	5.66	7.44	9.69	6.58	6.07
CSCO	7.12	9.91	5.26	5.49	10.44	12.37	14.63
DELL	8.27	9.21	7.64	8.55	10.11	5.48	5.44
EMC	8.18	22.55	8.54	7.40	9.37	13.76	11.20
INTC	8.84	6.87	5.23	5.85	10.41	11.00	9.03
KLAC	7.87	4.28	6.29	7.12	13.38	13.08	13.92
MSFT	4.49	7.09	5.01	5.77	10.93	7.99	6.75
MU	9.46	10.35	11.16	11.74	24.99	10.91	15.41
MXIM	11.97	4.31	6.89	9.72	9.89	10.67	9.37
NVLS	7.14	7.63	9.00	7.00	17.01	14.34	11.33
ORCL	6.21	7.28	11.59	13.01	14.88	17.33	11.28
PMCS	12.16	14.16	9.65	8.33	12.42	21.35	11.52
PSFT	16.17	13.38	7.94	12.90	15.40	18.82	16.45
QCOM	6.15	8.28	6.85	8.77	14.96	9.49	9.77
SUNW	6.33	7.56	6.01	8.10	12.79	14.40	11.84
XLNX	7.47	11.52	9.53	11.53	13.39	13.34	11.22
Pooled Av	8.97	9.42	8.25	9.22	13.46	12.76	10.66
Pooled Std	0.47	0.54	0.48	0.45	0.73	0.57	0.63

Table 3: Estimates of the volatility of the jump generated by earnings announcements based on the term structure across time for each firm. Each year, we average the earnings announcement jump size for each firm.

\mathbb{Q} . To do this, we compute the expected volatility under \mathbb{Q} (denoted as ‘Qvol’), realized volatility under \mathbb{P} (‘Pvol’), and also scaled standard deviations. This latter measure is motivated as follows. If we let $r_{\tau_{j+1}} = \log(S_{\tau_{j+1}}/S_{\tau_j})$ be the return on the day after the announcement, then define

$$J_{\tau_{j+1}} = \frac{r_{\tau_{j+1}}}{\sqrt{(\sigma_j^{\mathbb{Q}})^2 + \sigma^2/252}}.$$

Under the null of no risk earnings jump volatility risk premium ($\sigma_j^{\mathbb{Q}} = \sigma_j^{\mathbb{P}}$) and assuming that diffusive volatility is constant over the course of the day, then $J_{\tau_{j+1}}$ should be normally distributed with unit variance. The column titled ‘Std’ gives the standard deviation of $J_{\tau_{j+1}}$ for each firm and, in general, it is less than 1. Similarly, the ratio of realized volatility to expected volatility (the ratio of column 5 to 4) is, in every case but one, less than 1 (the two results are slightly different due to Jensen’s inequality). This would occur if $\sigma_j^{\mathbb{Q}} > \sigma_j^{\mathbb{P}}$, which is a form of a jump volatility risk premium. On average, the ratio of Pvol to Qvol is 0.74 while the average scaled ratio is 0.82, so that the volatility under \mathbb{Q} is about 20 to 30 percent higher than under \mathbb{P} . It is important to note that this effect is reduced, and largely eliminated, if we use the time series estimator. However, we are interested in the ex-ante expected volatility from options and the time series estimator uses ex-post information.

To place some economic significance on the risk premium, if we have an underlying stock with $\sigma = 0.30$ and if we assume that $\sigma_j^{\mathbb{Q}} = 1.25\sigma_j^{\mathbb{P}}$ and that $\sigma_j^{\mathbb{P}} = 8$ percent, then the value of a one month and two week option is \$5.86 and \$4.95 with the risk premium and \$5.34 and \$4.32 without the risk premium, respectively. This is economically significant and could be motivated as compensation to the option writers for their inability to hedge the earnings announcement jump. As a comparison, consider the risk premiums embedded in S&P 500 options. For example, typical estimates of the objective measure mean ($\mu^{\mathbb{P}}$) and volatility ($\sigma^{\mathbb{P}}$) of jump sizes are around -2 to -4 percent and 3 to 4 percent (see, Andersen, Benzoni, and Lund (2001) or Eraker, Johannes, and Polson (2003)), based on the time series of returns. Broadie, Chernov and Johannes (2004) estimate that $\mu^{\mathbb{Q}} \approx -5$ percent and $\sigma^{\mathbb{Q}} \approx 9$ percent. Viewed in this light, the risk premiums associated with $\sigma_j^{\mathbb{Q}}$ do not appear to be particularly large. This may be due to the fact that there is no timing risk in earnings announcements and because of this, it is easier to hedge options around earnings announcement dates.

The previous results indicated that it appears that $\sigma_j^{\mathbb{Q}} > \sigma_j^{\mathbb{P}}$. Another related issue

	Min	Max	Std	QVol	PVol	Skew	Kurt.	t-test	K-S	J-B
AAPL	-18.84	21.27	90.55	11.12	9.37	-0.13	2.92	-0.02	0.13	0.42
ADBE	-14.29	14.01	59.75	13.85	7.58	-0.63	2.84	1.60	0.24	1.70
ALTR	-22.47	12.97	68.96	12.51	8.06	-0.75	4.17	-0.43	0.11	0.85
AMAT	-9.78	14.42	75.26	11.35	6.44	-0.56	3.55	0.90	0.16	0.77
AMGN	-14.40	12.29	72.55	7.47	5.92	-0.68	2.55	1.08	0.19	1.85
CSCO	-14.05	21.82	67.18	10.00	7.00	0.23	2.72	1.17	0.17	3.08
DELL	-21.00	10.98	89.91	8.78	7.90	0.33	1.84	-0.09	0.19	0.93
EMC	-5.41	9.61	49.26	11.83	4.65	-0.16	2.48	0.53	0.18	1.70
INTC	-19.89	18.33	78.03	08.75	7.13	-0.25	3.17	0.50	0.15	2.64
KLAC	-11.66	14.18	63.95	10.74	6.76	0.24	3.11	1.70	0.25	0.28
MSFT	-7.09	17.87	90.81	6.99	5.92	-0.72	3.28	0.47	0.15	1.99
MU	-26.19	13.15	59.89	13.86	9.09	-0.11	2.15	-2.55*	0.21	0.74
MXIM	-30.31	10.60	74.38	10.07	7.81	-1.15	5.00	-1.02	0.19	37.92†
NVLS	-9.95	13.55	61.77	12.26	6.70	0.30	2.97	0.09	0.11	1.03
ORCL	-34.46	27.07	142.25	12.67	11.58	-2.56	11.32	-0.19	0.17	5.30
PMCS	-25.90	21.13	98.74	13.86	10.93	-0.94	4.56	2.18*	0.35†	4.78
PSFT	-26.53	22.92	107.47	15.02	12.59	-1.60	6.69	-0.50	0.11	0.64
QCOM	-17.34	32.72	132.91	9.80	10.13	1.05	5.11	1.31	0.19	3.50
SUNW	-31.09	7.13	78.66	10.17	8.51	-0.66	2.37	-1.14	0.20	24.18†
XLNX	-13.67	12.77	68.50	12.10	7.37	-0.09	2.08	-1.60	0.17	1.50

Table 4: Summary statistics (minimum, maximum, standard deviation, skewness, and kurtosis) of returns on the day after an earnings announcement. The first two columns are raw statistics, and the other columns are for returns scaled by ex-ante predicted volatility. The minimum, maximum, and volatilities are in percentage values. The last three columns provide a standard t -test for a zero mean, the Kolmogorov-Smirnov test for normality, and the Jarque-Bera test for normality, respectively. “*” indicates significance at the 5 percent level and “†” indicates significance at the 1 percent level. For the t -test, we use the exact t -distribution to obtain critical values.

is whether there is any predictive content to the information contained in options. For example, if $\sigma_j^{\mathbb{Q}}$ is larger than usual, does this imply that we should expect a large movement in the actual returns? It is difficult to analyze this in a time series context because $\sigma_j^{\mathbb{P}}$ can change from announcement to announcement and it is not possible to estimate $\sigma_j^{\mathbb{P}}$ based on the single observation occurring after the earnings announcement. Since this cannot be done in a time series analysis, we consider a cross-sectional analysis. If there is a predictive component in the options, we should see that firms with higher $\sigma_j^{\mathbb{Q}}$'s have higher realized volatilities on earnings dates. The across-firm correlation between the average $\sigma_j^{\mathbb{Q}}$ and the subsequent realized volatility (the correlation of columns labeled Qvol and Pvol) is 0.5386 which is strongly statistically different from zero, despite the very low number of observations (20). This provides evidence that the options data is informative about realized movements.

Finally, we can use the predicted jump volatilities and the realized returns to analyze the jump specification. As mentioned above, $J_{\tau_{j+1}}$ should be normally distributed if the jump distribution specification is correct. Table 4 provides evidence consistent with this assumption. Although the first two columns indicate, not surprisingly, that earnings announcements result in very large movements, there is little evidence of non-normalities. As indicated by the skewness and excess kurtosis, there appears only modest distributional abnormalities. As formal tests of non-normalities, we consider the Kolmogorov-Smirnov and Jarque-Bera tests. The Kolmogorov-Smirnov test uses the distance between the empirical distribution function and a normal distribution function, and the Jarque-Bera test combines the information in the skewness and kurtosis statistics. The tests find little evidence for non-normalities. The Kolmogorov-Smirnov and Jarque-Bera tests find significant departures from normality for one and three firms, respectively, but interestingly, there is no overlap in terms of the firms they identify. This is likely due to the small samples of earnings dates for which we have option data available. This evidence is reassuring regarding the jump specification as there is no statistical evidence that the jumps come from a non-normal distribution. Thus, the assumption that $Z_j = -\frac{1}{2}(\sigma_j^{\mathbb{Q}})^2 + \sigma_j^{\mathbb{Q}}\varepsilon$ does not generate any strong misspecification.

4.2 Stochastic volatility with deterministic jumps

The results in the previous section assumed that diffusive volatility was constant. In order to develop a better benchmark and to account for time-varying volatility, we consider the stochastic volatility model developed in Section 3.2 and estimate versions with and without deterministically timed jumps. In the models without jumps, we are interested in characterizing the misspecification around earnings dates. Specifically, the intuition from the previous section suggests that we expect to find that the SV model misprices short-maturity options around earnings and that V_t contains strong predictable behavior around earnings releases. In the models with jumps, we are interested in the magnitude of the implied jump volatilities in comparison to those based on the Black-Scholes model.

We use the entire time series of at-the-money call options from 1996 through 2002 to estimate the model. Unlike Bakshi and Cao (2004), who use a single option contract on each day, we use multiple maturities and the closest to-the-money call option for each maturity. In a stochastic volatility model, a short maturity at-the-money option provides information on V_t and the longer dated options provide information on the risk neutral parameters. This procedure imposes that the model parameters are constant from 1996 to 2002, in contrast to the usual calibration approach which re-estimates parameters every time period (daily, weekly, etc.). We estimate the parameters and volatility by minimizing scaled option pricing errors.⁸ Ideally, one would estimate the model using, in addition to option prices, the time series of returns. Existing approaches include EMM (Chernov and Ghysels (2000)), implied-state GMM (Pan (2002)), or MCMC (Eraker (2004) and Polson and Stroud (2002)). This approach is in principle statistically efficient, however the computational demands of iteratively pricing options for each simulated latent volatility path and parameter vector lead to implementations with short data samples and few options contracts (typically two at most).

To describe our approach, let $C(S_t, V_t, \Theta^{\mathbb{Q}}, \sigma_{\tau_n}^{\mathbb{Q}}, \tau_n, K_n)$ denote the model implied price of a call option struck at K_n and maturing in τ_n days, where $\Theta^{\mathbb{Q}} = (\kappa^{\mathbb{Q}}, \theta^{\mathbb{Q}}, \sigma_v, \rho)$ and

⁸We initially tried to follow Bates (2000) and impose time series consistency on the volatility process, by including a term in the likelihood incorporating the transition density of variance increments. This additional term penalizes the estimates if the volatility process is not consistent with its square-root dynamics. However, it was not possible to obtain reliable estimates due to the computational burdens involved in the optimization problem.

$\sigma_{\tau_n}^{\mathbb{Q}} = \{\sigma_j^{\mathbb{Q}} : t < j < t + \tau_n\}$. We maximize the objective function

$$\begin{aligned} \log [\mathcal{L}(\Theta^{\mathbb{Q}}, \sigma_{\tau_n}^{\mathbb{Q}}, V_t)] = \\ - \frac{TN}{2} \log(\sigma_{\varepsilon}^2) - \frac{1}{2} \sum_{t=1}^T \sum_{n=1}^N \left[\frac{C^{Mar}(t, \tau_n, K_n) - C(S_t, V_t, \Theta^{\mathbb{Q}}, \sigma_{\tau_n}^{\mathbb{Q}}, \tau_n, K_n)}{\sigma_{\varepsilon} S_t} \right]^2 \end{aligned}$$

where $C^{Mar}(t, \tau_n, K_n)$ is the market price of an option at time t , struck at K_n , and maturing at time τ_n . Since we use a long time series of option prices, normalizing by the stock price is important to impose stationarity. Without this constraint, the objective function would be concentrated on option values during periods when the stock price is relatively high.

Our objective function does weigh longer-dated options more than short-dated options, as longer dated options are more expensive. If this has an effect on our results, it tends to reduce the importance of earnings announcement jumps as the objective function is tilted toward longer-dated options. Alternatives would include minimizing implied volatility deviations or percentage pricing errors. We experimented with percentage pricing errors and found the differences were generally small.

Finally, we originally tried to estimate ρ , however, it is not possible to identify this parameter based on at-the-money options as it does not have a significant impact on option prices.⁹ It can be identified primarily from out-of-the-money options and from the joint time series of returns and volatility increments. We imposed the constraint that $\rho = 0$ throughout.

We require daily data, in order to track the performance of the models around earnings announcement dates. This, along with the fact that we impose that the parameters are constant through the sample, makes the optimization problem extremely computationally burdensome. In the general model, optimization occurs over more than 1500 variance states, 28 earnings jump volatilities and four static parameters. We start the optimization from numerous different starting values on multiple machines and randomly perturb the

⁹To see this, consider two option maturities, one and three months, and assume $\kappa_v = 1$, $\theta = 0.30^2$, $\sigma_v = 0.20$, and $V_0 = 0.30^2$. This implies that the current and long run mean of volatility is 30%. The price of a one month, at-the-money option if $\rho = -0.50, 0$, or $+0.50$ is 3.320, 3.321, and 3.323, respectively, and the Black-Scholes implied volatilities are 29.95, 29.96 and 29.97. For the three month option, the prices and implied volatilities are 5.563, 5.567, and 5.574 and 29.86, 29.88, and 29.92. Clearly, the effect is very small and, moreover, in an estimation procedure in which other parameters and volatility is estimated it is not identified based on at-the-money options.

variance and parameters in order to ensure that the algorithm efficiently searches. Due to the extreme computational burdens, we only consider five companies, Apple, Amgen, Cisco, Intel and Microsoft. The three largest and most actively traded companies are Cisco, Intel and Microsoft and then we chose one company with small average jump sizes (Amgen) and one with large average jump sizes (Apple).

4.3 Estimation Results

Estimation results for the five companies are in Tables 5, 6, and 7. Table 5 provides parameter estimates and likelihood function values for the pure square-root model (SV) and a version including deterministic jumps on earnings dates (SVDJ). We include standard errors based on the normal likelihood function to provide information on the local identification of each of the parameters. Although not reported, a likelihood ratio test overwhelmingly rejects the restrictions that the jump volatilities are zero.

All of the parameter estimates are plausible, although even with a relatively long time series, it is difficult to identify some of the parameters. For both models, the estimates of $\kappa_v^{\mathbb{Q}}$ are similar and in the range of two to three. These values are low relative to values obtained for index options, which implies that individual stock volatility is more persistent, although this could be strongly influenced by the sample period (our sample does not include, for example, the Crash of 1987). The estimates of $\theta_v^{\mathbb{Q}}$ imply plausible values for the long-run mean of volatility. The third column reports $\sqrt{\theta_v^{\mathbb{Q}}}$ which is the long run mean in volatility units (along with standard errors computed by the delta method) and the results imply long-run volatility in the range of 30 to 50 percent. In all cases, the long run volatility falls when earnings announcements are taken into account and the decrease is larger for firms with relatively large earnings jump volatilities. The standard errors imply that the objective function is very informative about these risk-neutral drift parameters.

In contrast to the risk-neutral drift parameters, σ_v is not well-identified with its standard error an order of magnitude larger than the estimate. This should not be surprising as we only use at-the-money options and do not consider the time series of volatilities. At-the-money option prices are driven primarily by expected future volatility and from (4) it is clear that this parameter does not affect expected future volatility. This parameter can most easily be identified by the time series of implied volatilities and, to a certain extent, from out-of-the-money options as this parameter contributes to the conditional kurtosis of

		κ_v^Q	θ_v^Q	$\sqrt{\theta_v}$	σ_v	σ_e	σ_E^Q	$L(\Theta, V_t)/NT$
AAPL	SV	2.3210	0.2721	0.5216	0.1132	0.0042	—	4.0537
		0.0347	0.0269	0.0258	2.1892	0.0027	—	
	SVDJ	1.6556	0.2460	0.4960	0.0774	0.0034	0.0811	4.2635
		0.0444	0.0289	0.0291	2.5406	0.0027	0.0024	
AMGN	SV	2.0113	0.1314	0.3625	0.0314	0.0030	—	4.3841
		0.0301	0.0190	0.0262	4.8507	0.0018	—	
	SVDJ	2.0662	0.1300	0.3606	0.1031	0.0029	0.0426	4.4239
		0.0311	0.0100	0.0139	0.8347	0.0019	0.0088	
CSCO	SV	2.6838	0.2151	0.4638	0.1156	0.0034	—	4.2625
		0.0333	0.0169	0.0182	1.6569	0.0021	—	
	SVDJ	2.7869	0.2038	0.4514	0.1042	0.0028	0.0723	4.4721
		0.0305	0.0113	0.0125	1.3579	0.0020	0.0034	
INTC	SV	2.6267	0.1252	0.3538	0.0953	0.0028	—	4.4551
		0.0286	0.0141	0.0199	1.5873	0.0013	—	
	SVDJ	2.1404	0.1042	0.3228	0.1325	0.0023	0.0565	4.6655
		0.0281	0.0131	0.0202	0.9143	0.0013	0.0017	
MSFT	SV	3.0981	0.1282	0.3580	0.0260	0.0022	—	4.7072
		0.0335	0.0054	0.0075	2.8651	0.0012	—	
	SVDJ	2.8748	0.1246	0.3530	0.0264	0.0020	0.0328	4.7944
		0.0346	0.0053	0.0075	2.6023	0.0013	0.0025	

Table 5: Parameter estimates and standard errors for Apple, Amgen, Cisco, Intel and Microsoft. For each firm and model, the first row contains the parameter estimate and the second row the estimated standard error. The standard errors for σ_e are multiplied by 100.

returns. A priori, it is not clear if σ_v would increase or decrease with deterministic jumps. On the one hand, one would think that V_t would become less volatile, which would imply that it would fall, however, since the volatility of variance increments is $\sigma_v\sqrt{V_t}$, and V_t falls in the deterministic jump model, the effect is unclear.

The sixth column of Table 5 provides the average estimate of $\sigma_j^{\mathbb{Q}}$, denoted $\sigma_E^{\mathbb{Q}}$, for each firm with the average standard error reported below. To frame the results, recall that the average jump volatility for Apple, Amgen, Cisco, Intel and Microsoft based on the time series estimator was 8.57, 6.68, 7.98, 6.95, and 6.83, respectively, whereas the full estimation resulted in 8.11, 4.26, 7.23, 5.65, and 3.28 percent for the same firms. The results are similar, although the jump sizes based on the full estimation are lower. The two estimators are highly correlated, for example, for Intel, the correlation between the two estimates is over 70 percent.

There are three reasons why the estimates of $\sigma_j^{\mathbb{Q}}$ differ. First, in the Black-Scholes model, a number of earnings dates resulted in zero jump volatility estimates. In the stochastic volatility model, this does not happen for any of the earnings dates, although some are relatively small. Thus, a direct comparison based on average estimates of $\sigma_j^{\mathbb{Q}}$ is not strictly valid. Second, the time series and term structure estimators of the previous section use one and two options, respectively, whereas the full estimation results use information in all options that are effected by earnings announcement jumps. This means that on each day at least three options are effected and an earnings announcement will have a significant impact on options for at least a month prior to the announcement. Third, the stochastic volatility model imposes that the parameters in the model are constant through time, whereas the term structure and time series estimators allow expected volatility to differ at each announcement. Due to this, the estimates based on the extension of the Black-Scholes model are less constrained and are less subject to potential misspecification.

Next, Table 6 provides the pricing errors in the two models in the days surrounding an earnings announcement. For each model, we report pricing errors for short maturity options (5 to 15 days), medium maturity options (15 to 35 days), and for long term options (more than 35 days). The columns indicate the days relative to the earnings announcement. For example, ‘0’ is the day of the announcement (which is released after the close on that day) and ‘-2’ is two days prior to the announcement. For a number of days and firms, there are fewer than five total option prices available in the short maturity category for any earnings announcements and we denote these days by a ‘—’. This lack of data is due to the timing of

the earnings announcements and the expiration calendar. It is common for the short-dated option on Microsoft to expire in the week prior to them releasing earnings. Cisco is the only company that has options available over the entire window as they typically release earnings late in the cycle.

For all of the firms, there is a major pricing difference between the SV and SVDJ models, especially for short-dated options. In the week leading up to the earnings announcement, the reduction in pricing errors is on the order of 50 percent. The effect is largest for Cisco and Intel and smallest for Amgen and Microsoft, which have relatively small jump sizes. As an example, the mean-absolute pricing errors for Cisco fall in the three days leading up to the earnings announcement from 0.3328, 0.2680 and 0.4142 to 0.1041, 0.0898, and 0.1705 in the SVDJ model. For most firms and days, there is also a noticeable improvement in the pricing of the long-dated options also.

The SV model cannot fit the short, medium and long dated options with only V_t , and so it generally underprices the short dated options and overprices the long-dated options. To price the short dated options around earnings dates, the SV model requires a very high V_t , but this results in a drastic overpricing of the longer maturities. The SV model cannot simultaneously fit both of these features. By introducing jumps on earnings announcements, the SVDJ model allows $\sigma_j^{\mathbb{Q}}$ to capture the behavior of the short-dated options and then V_t can jointly fit the other options with greater accuracy. The SV and SVDJ models perform similarly for the day after the announcement, although again there is a modest improvement in the SVDJ model.

Table 7 provides overall mean absolute pricing errors for the entire sample.¹⁰ There is clearly a substantial pricing improvement for all of the firms and for all of the maturities, with the exception of Amgen. Amgen is a low volatility, low earnings uncertainty firm, so this should not be surprising. For the other firms, the pricing improvement, especially in short-dated options, is large. This is somewhat surprising given that earnings announcements occur only four times per year. The rather large improvements occur because in the SVDJ model, spot V_t and the parameters are not forced to fit both earnings announcement effects and the rest of the year. Although earnings announcements affect primarily options for about 2 weeks per cycle, they substantially reduce overall pricing. This pricing reduction is in contrast to Bakshi and Cao (2004) who find that jumps in returns, jumps in volatility, and stochastic interest rates have no noticeable pricing impact on at-the-money

¹⁰We also computed root-mean-squared errors which result in similar conclusions.

			-5	-4	-3	-2	-1	0	+1
AAPL	Short	SV	0.2040	0.2570	0.2236	0.3705	—	—	—
		SVDJ	0.1229	0.1520	0.1538	0.2111	—	—	—
	Med	SV	0.0943	0.0701	0.0827	0.0959	0.1157	0.1245	0.0850
		SVDJ	0.1109	0.0856	0.1083	0.1106	0.1069	0.1224	0.0989
	Long	SV	0.1263	0.1272	0.1160	0.1415	0.0925	0.0878	0.0600
		SVDJ	0.0868	0.0890	0.0674	0.0993	0.0766	0.0809	0.0668
AMGN	Short	SV	0.2547	0.2196	0.2308	0.2165	—	—	—
		SVDJ	0.1842	0.1123	0.1895	0.0755	—	—	—
	Med	SV	0.1319	0.1246	0.1601	0.1658	0.1607	0.1590	0.1267
		SVDJ	0.1205	0.1083	0.1345	0.1471	0.1449	0.1556	0.1141
	Long	SV	0.1009	0.0927	0.1172	0.1001	0.1070	0.1054	0.0867
		SVDJ	0.0945	0.0892	0.1167	0.1029	0.1137	0.1097	0.1262
CSCO	Short	SV	0.2621	0.2955	0.3328	0.2680	0.4142	0.3827	0.1227
		SVDJ	0.1065	0.1072	0.1041	0.0898	0.1705	0.1956	0.1236
	Med	SV	0.0919	0.1006	0.1000	0.0919	0.0641	0.0597	0.0509
		SVDJ	0.0787	0.0788	0.0713	0.0736	0.0518	0.0692	0.0935
	Long	SV	0.0975	0.1125	0.1067	0.1117	0.1812	0.1754	0.0824
		SVDJ	0.0645	0.0663	0.0510	0.0542	0.0759	0.0883	0.1574
INTC	Short	SV	0.3746	0.4022	0.4012	0.5994	0.7515	—	—
		SVDJ	0.1539	0.1866	0.1818	0.2839	0.4308	—	—
	Med	SV	0.0785	0.0894	0.0885	0.1115	0.1217	0.1407	0.0972
		SVDJ	0.0724	0.0733	0.0852	0.1029	0.1218	0.1190	0.1099
	Long	SV	0.1715	0.1822	0.1808	0.2251	0.2326	0.1361	0.0734
		SVDJ	0.0811	0.1019	0.0992	0.1427	0.1442	0.1000	0.0791
MSFT	Short	SV	0.2260	0.2700	0.4724	—	—	—	—
		SVDJ	0.1886	0.1654	0.3018	—	—	—	—
	Med	SV	0.1094	0.1374	0.1238	0.1682	0.2014	0.2179	0.1618
		SVDJ	0.1089	0.1277	0.1136	0.1522	0.1671	0.1989	0.1720
	Long	SV	0.1362	0.1586	0.1525	0.1361	0.1624	0.1369	0.1121
		SVDJ	0.0890	0.1201	0.1142	0.1172	0.1480	0.1271	0.1155

Table 6: Absolute pricing errors around earnings announcements. The columns are indexed relative to the earnings date (e.g., -2 indicates two days prior to an earnings announcement). The maturities are short (5 to 15 days to maturity), medium (16 to 35 days), and long (more than 35 days).

Maturity		$5 < \tau < 15$	$16 < \tau < 35$	$\tau > 35$
		MAE	MAE	MAE
AAPL	SV	0.1610	0.1063	0.0920
	SVDJ	0.1235	0.0925	0.0754
AMGN	SV	0.1683	0.1378	0.1191
	SVDJ	0.1609	0.1330	0.1178
CSCO	SV	0.1795	0.1310	0.1093
	SVDJ	0.1343	0.1105	0.0947
INTC	SV	0.2847	0.1962	0.1298
	SVDJ	0.1688	0.1093	0.0917
MSFT	SV	0.1932	0.1418	0.1294
	SVDJ	0.1762	0.1388	0.1189

Table 7: Overall mean absolute pricing errors broken down by firm and maturity.

options across the maturity spectrum.

Although common in the literature, we do not perform an out-of-sample pricing exercise. Since the jump distribution can change across earnings dates, this would imply that to price options out-of-sample, we would have to calibrate both V_t and $\sigma_j^{\mathbb{Q}}$ in the SVDJ model and just V_t in the SV model. It is clear that the SVDJ model would perform better as it has the same number of fixed parameters as the SV model. As noted in Bates (2002), these tests, in general, tend not to be useful for analyzing model specification: “*Perhaps the one test that does not appear to be especially informative is short-horizon “out-of-sample” option pricing tests...*” (p. 396. Bates (2003))

Finally, Figure 3 displays the median behavior of the implied variance state around earnings announcements for each firm and then the grand, pooled mean. It displays $\sqrt{V_{t+j}} - \sqrt{V_t}$ where V_t is the spot variance two days prior to the announcement and the volatilities are measured in annualized units. The figure shows that in the SV model, spot volatility decreases substantially after the announcement. There is also there is a modest decrease in volatilities for the SVDJ model. It is important to recall that the V_t ’s are estimated jointly from all of the option maturities, not just the short-dated option. The modest decrease

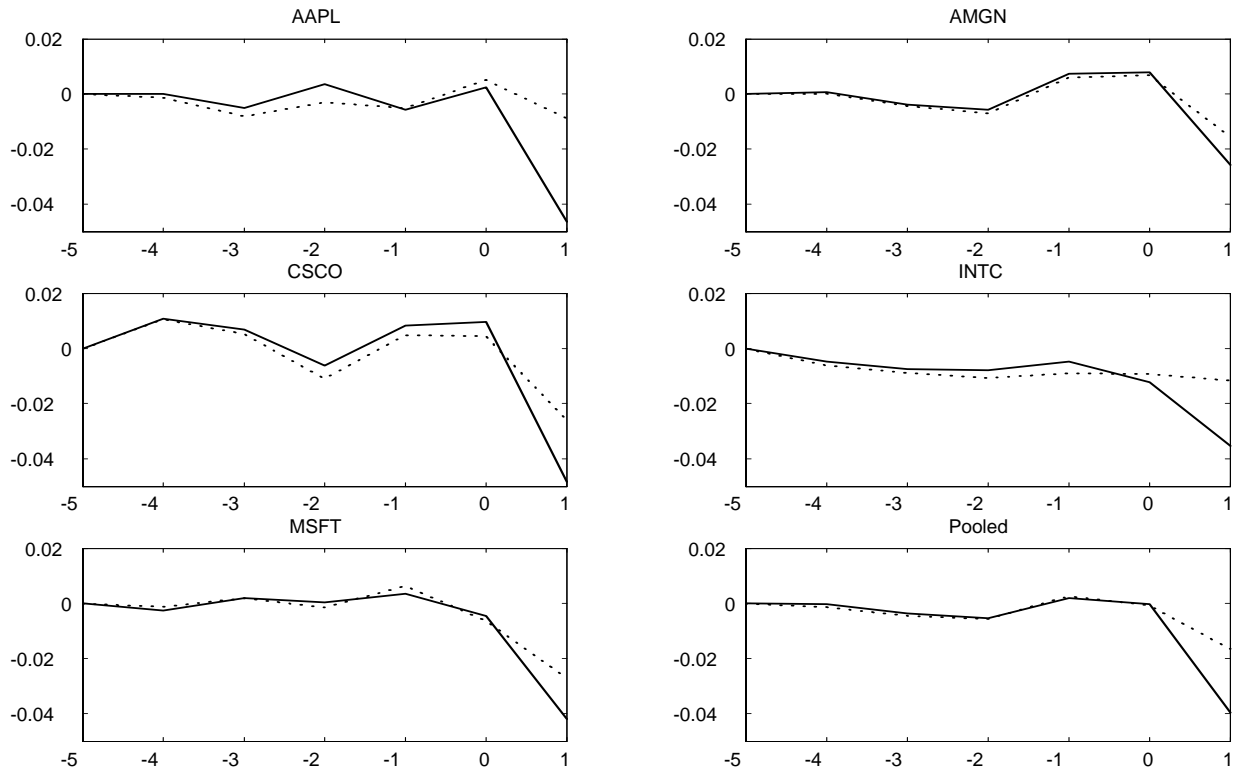


Figure 3: Changes in implied V_t around earnings dates.

in the SVDJ has a number of potential causes. First, as implied spot variance tends to be higher than its long-run mean just before the announcement, the decrease could be due to mean-reversion (we do not model the objective measure parameter so it is difficult to test this). It could also be due to model misspecification in the form of an incorrect jump distribution (which results in a decrease in variance after the announcement) or omitted negative jumps in variance. Bakshi and Cao (2004) argue that there may be negatively sized jumps in V_t . Finally, the objective function tends to place more weight on longer maturity options (as these are more expensive) and there are often substantive changes in option composition right around the earnings date. This could generate the effect by removing short dated options and adding long dated options.

5 Conclusions and extensions

In this paper, we develop models incorporating earnings announcements for pricing options and for learning about the uncertainty embedded in individual firms earnings announcement. We take seriously the timing of earnings announcements and develop a model and pricing approach incorporating jumps on earnings announcement dates. Jumps on earnings announcement dates are straightforward to incorporate into standard option pricing models. Based on these models, we introduce estimators of the uncertainty surrounding earnings announcements and discuss the general properties of models with deterministically timed jumps.

Empirically, based on a sample of 20 low-dividend firms, we find that earnings announcements are important components of option prices, we investigate risk premiums, and we analyze the underlying assumptions of the model. To quantify the impact on option prices, we calibrate a stochastic volatility model and find that accounting for jumps on earnings announcement dates is extremely important for pricing options. Models without jumps on earnings announcement dates have large and systematic pricing errors around earnings dates. A stochastic volatility model incorporating earnings jumps drastically lowers the pricing errors and reduces misspecification in the volatility process.

In the future, we plan to extend the analysis in a number of directions. First, we would like to incorporate additional predictable events such as stock splits and mid-quarter earnings updates into equity option pricing models. Anecdotally, both of these events appear to be significant, although not nearly as strong as quarterly announcements. In some cases, a firm will issue a warning before the formal earnings announcement date stating that earnings are going to be drastically higher or lower than expected. Second, we plan to extend the analysis to a broad panel of equities. There are two potential problems with this approach: high-dividend stocks tend to have relatively lower volume (both in the stock and the options), so it is more difficult to obtain good implied volatility data across the maturity spectrum and high-dividend stocks have less uncertainty embedded in earnings. Third, in order to better identify the parameters, it would be interesting to consider a likelihood penalty in the objective function and to add longer dated options. This would allow us to better identify σ_v and estimate the objective measure drift parameters.

Fourth, we are interested in analyzing the predictive information embedded in our ex-ante estimates of $\sigma^{\mathbb{Q}}$. Given the time variation that we document in this parameter, it

is interesting to see what information this parameter contains. For example, we find it is correlated with future volatility, but is this parameter more informative than the dispersion in analysts forecasts? Does it provide information about future returns? Fifth, there are a large number of papers study the response of fixed income securities or exchange rates to macroeconomic announcements using high frequency data (see, e.g., Ederington and Lee (1993), Fleming and Remolona (1999, 2000), Bollerslev and Andersen (1998), Balduzzi, Elton, and Green (2001), and Andersen, Bollerslev, Diebold, and Vega (2004)). Ederington and Lee (1996) analyze the response of options on Treasury, Eurodollar, and Deutschemark futures to a number of different macroeconomic announcements and find that the implied volatility of these contracts increasing into and decreases after an announcement. Balachandran, Dubinsky, and Johannes (2004), using a simple extension of Black’s model to incorporate deterministic jumps, provide estimates of $\sigma_j^{\mathbb{Q}}$ based on options on the note-future contract. In the context of affine term structure models, Chernov and Johannes (2004) analyze the effect of deterministic jumps on the time series of Treasury and swap rates. They find that deterministic jumps are more important than randomly timed jumps, and, moreover, that once deterministic jumps are taken into account, there is little evidence for stochastic volatility in Treasury or swap yield changes.

Sixth, many studies analyze the response of “news” on asset prices, for recent examples, see Balduzzi, Elton, and Green (2001), Beber and Brandt (2003) and Andersen, Bollerslev, Diebold, Vega (2003,2004). These papers define the news of an announcement of type k at time t as $S_{t,k} = (A_{t,k} - E_{t,k})/\sigma_k$ where $A_{t,k}$ is the value of the announcement k at time t , $E_{t,k}$ is the mean or median forecast for the announcement at time t , and σ_k is empirical standard deviation of $A_{t,k} - E_{t,k}$. As our models clearly show, there is no reason that news will have a homogeneous impact on prices throughout time and this implies that the potential volatility of news is time-varying and not equal to the historical standard deviation of $A_{t,k} - E_{t,k}$. Since most of these studies analyze very liquid markets with actively traded options, it would be straightforward to obtain an ex-ante measure of the uncertainty embedded using the term structure approach we developed in Section 4.1. These estimators have the advantage that they are ex-ante and based on the expectations of investors and not analysts. Finally, as mentioned in Section 3.2.2, deterministically timed jumps provide an interesting setting to study hedging and robust pricing.

References

- Andersen, Torben, Luca Benzoni and Jesper Lund, 2002, Towards an empirical foundation for continuous-time equity return models, *Journal of Finance* 57, 1239-1284.
- Andersen, Torben and Tim Bollerslev, 1998, Deutsche Mark-Dollar volatility: intraday activity, patterns, macroeconomic announcements, and longer run dependencies, *Journal of Finance* 53, 219-265.
- Andersen, Torben, Tim Bollerslev, Frank Diebold and Clara Vega, 2003, Micro effects of macro announcements: real-time price discovery in foreign exchange, *American Economic Review* 93, 38-62.
- Andersen, Torben, Tim Bollerslev, Frank Diebold and Clara Vega, 2004, Real-time price discovery in stock, bond and foreign exchange markets, working paper, Northwestern University, Duke University, University of Pennsylvania and University of Rochester.
- Anderson, Evan, Lars Hansen and Thomas Sargent, 2003, A quartet of semi-groups for model specification, detection, robustness and the price of risk, Working paper, University of Chicago.
- Ang, Andrew and Jun Liu, 2001, A general affine earnings valuation model, *Review of Accounting Studies* 6, 397-425.
- Bagnoli, Mark, William Kross, and Susan Watts, 2002, The information in management's expected earnings report date: A day late, a penny short, *Journal of Accounting Research* 40, 1275-1296.
- Bakshi, Gurdip, and Charles Cao, 2004, Risk neutral kurtosis, jumps, and option pricing: Evidence from 100 most active firms on the CBOE, Working paper, University of Maryland.
- Bakshi, Gurdip, Charles Cao and Zhiwu Chen, 1997, Empirical performance of alternative option pricing models, *Journal of Finance* 52, 2003-2049.

Bakshi, Gurdip, Nikunj Kapadia and Dilip Madan, 2003, Stock Return Characteristics, Skew Laws, and Differential Pricing of Individual Equity Options *Review of Financial Studies* 16, 101-143

Balachandran, Binu, Andrew Dubinsky and Michael Johannes, 2004, Which macroeconomic announcements are important: ex-ante evidence from the Treasury market, working paper, Columbia University.

Balduzzi, Pierluigi, Edward Elton, and Clifton Green, 2001, Economic news and bond prices: Evidence from the U.S. Treasury market, *Journal of Financial and Quantitative Analysis* 36, 523-543.

Ball, Ray and Phillip Brown, 1968, An empirical evaluation of accounting income numbers. *Journal of Accounting Research* 6, 159-178.

Ball, Ray and S.P Kothari, 1991, Security returns around earnings announcements, *The Accounting Review* 66, 718-738.

Barndorff-Nielson, Ole and Neil Shephard, 2004, Econometrics of testing for jumps in financial economics using bipower variation, working paper, Oxford University.

Bates, David, 1996, Jumps and stochastic volatility: Exchange rate processes implicit in Deutsche Mark options, *Review of Financial Studies* 9, 69-107.

Bates, David, 2000, Post-'87 Crash Fears in S&P 500 futures options, *Journal of Econometrics* 94, 181-238.

Bates, David, 2003, Empirical Option Pricing: A Retrospection, *Journal of Econometrics* 116, 387-404.

Beber, Alessandro and Michael Brandt, 2004, The effect of macroeconomic news on beliefs and preferences: Evidence from the options market, working paper, Duke University .

Broadie, Mark, Mikhail Chernov and Michael Johannes, 2004, Model specification and risk premiums: Evidence from futures options, working paper, Columbia University.

Carr, Peter and Dilip Madan, 1999, Option Pricing and the Fast Fourier Transform, *Journal of Computational Finance* 2, 61-73.

Carr, Peter and Liuren Wu, 2003, A simple test for the presence of jumps in index returns, forthcoming, *Journal of Finance* 58.

Cheridito, Patrick, Damir Filipovic, and Robert Kimmel, 2003, Market price of risk specifications for affine models: Theory and evidence, working paper, Princeton University.

Chernov, Mikhail and Eric Ghysels, 2000, A study towards a unified approach to the joint estimation of objective and risk neutral measures for the purpose of options valuation, *Journal of Financial Economics* 56, 407-458.

Chernov, Mikhail and Michael Johannes, 2004, What generates bond market volatility? The relative importance of jumps and stochastic volatility, working paper, Columbia University.

Dellacherie, Claude. and Paul Meyer, 1978, *Probabilities and Potential*, Vol. 1, North Holland, Vol. 2 1982.

Donders, Monique, Roy Kouwenberg and Ton Vorst, 2000, Options and earnings announcements: an empirical study of volatility, trading volume, open interest and liquidity, *European Financial Management* 6, 149-171.

Donders, Monique and Ton Vorst, 1996, The impact of firm specific news on implied volatilities, *Journal of Banking and Finance* 20, 1447-1461.

Duffie, Darrell, Jun Pan, and Kenneth Singleton, 2000, Transform analysis and asset pricing for affine jump-diffusions, *Econometrica* 68, 1343-1376.

Ederington, Louis and Jae Ha Lee, 1993, How market process information: new releases and volatility, *Journal of Finance* 48, 1161-1189.

Ederington, Louis and Jae Ha Lee, 1996, The creation and resolution of market uncertainty: the impact of information releases on implied volatility, *Journal of Financial and Quantitative Analysis* 31, 513-539.

Eraker, Bjørn, 2003, Do equity prices and volatility jump? Reconciling evidence from spot and option prices, forthcoming, *Journal of Finance*.

Eraker, Bjørn, Michael Johannes and Nicholas Polson, 2003, The impact of jumps in equity index volatility and returns, *Journal of Finance* 58, 1269-1300.

Feltham, George and James Ohlson, 1995, Valuation and clean surplus accounting for operating and financial activities, *Contemporary Accounting Research* 11, 689-731.

Fleming, Michael and Eli Remolona, 1999, Price formation and liquidity in the U.S. Treasury market: The response to public information, *Journal of Finance* 54, 1901-1915.

Fleming, Michael and Eli Remolona, 2000, What moves bond prices?, *Journal of Portfolio Management* 25, 28-38.

Foster, George, 1977, Quarterly accounting data: time series properties and predictive ability results, *The Accounting Review*, 1-21.

Isakov, D. and Perignon, Christophe, 2001, Evolution of market uncertainty around earnings announcements, *Journal of Banking and Finance* 25, 1769-1788.

Jayaraman, Narayan, Gershon Mandelker and Kuldeep Shastri, 1991, Market anticipation of merger activities: an empirical test, *Managerial and Decision Economics* 12, 1991, 439-448.

Johannes, Michael, 2004, The statistical and economic role of jumps in interest rates, *Journal of Finance* 59, 227-260.

Johannes, Michael and Noah Williams, 2004, Robust pricing of options with announcement effects, working paper, Columbia University.

Kim, Oliver and Robert Verrecchia, 1991, Market reaction to anticipated announcements. *Journal of Financial Economics* 30, 273-309.

Lee, Roger, 2004, Option pricing by transform methods: extensions, unification, and error Control, *Journal of Computational Finance* 7.

- Maheu, John and Thomas McCurdy, 2003, News arrival, jump dynamics and volatility components for individual stock returns. *Journal of Finance*. forthcoming.
- Merton, Robert, 1973, Theory of rational option pricing, *Bell Journal of Economics and Management Science*, 4, 141-183.
- Merton, Robert, 1976, Option pricing when the underlying stock returns are discontinuous, *Journal of Financial Economics* 3, 1235-144.
- Morse, D., 1981, Price and trading volume reaction surrounding earnings announcements: A closer examination. *Journal of Accounting Research* 19, 374-383.
- Ohlson, James and Stephen Penman, 1985, Volatility increases subsequent to stock splits: An empirical aberration, *Journal of Financial Economics* 14, 251-266.
- Pan, Jun, 2002, The jump-risk premia implicit in options: evidence from an integrated time-series study, *Journal of Financial Economics* 63, 3-50.
- Patell, James and Mark Wolfson, 1979, Anticipated information releases reflected in call option prices, *Journal of Accounting and Economics* 1, 117-140.
- Patell, James and Mark Wolfson, 1981, The ex ante and ex post price effects of quarterly earnings announcements reflected in option and stock prices, *Journal of Accounting Research* 19, 434-458.
- Patell, James and Mark Wolfson, 1984, The intraday speed of adjustment of stock prices to earnings and dividend announcements, *Journal of Financial Economics* 13, 223-252.
- Pastor, Lubos and Pietro Veronesi, 2003, Stock valuation and learning about profitability, *Journal of Finance* 58, 1749-1789.
- Pastor, Lubos and Pietro Veronesi, 2004, Was there a Nasdaq bubble in the late 1990s?, working paper, University of Chicago.
- Penman, Stephen, 1984, Abnormal returns to investment strategies based on the timing of earnings reports, *Journal of Accounting and Economics* 1984, 165-84.

Piazzesi, Monika, 2000, Essays on monetary policy and asset pricing, unpublished Ph.D. dissertation, Stanford University.

Piazzesi, Monika, 2002, Affine term structure models, prepared for the *Handbook of Financial Econometrics*, edited by Yacine Ait-Sahalia and Lars Hansen.

Piazzesi, Monika, 2004, Bond yields and the Federal Reserve, forthcoming *Journal of Political Economy*.

Polson, Nicholas and Jonathan Stroud, 2003, Bayesian inference for derivative prices, *Bayesian Statistics 7* (Bernardo et al., eds.), Oxford University Press, 641-650.

Sheikh, Aamir, 1989, Stock splits, volatility increases, and implied volatilities, *Journal of Finance* 44, 1361-1372.

Subramanian, Ajay, 2004, Option pricing on stocks in mergers and acquisitions, *The Journal of Finance* 59, 795-829.

Whaley, Robert, and Joseph Cheung, 1982, Anticipation of quarterly earnings announcements: a test of option market efficiency, *Journal of Finance of Accounting and Economics* 4, 57-83.

Appendix A

We only considered pure stochastic volatility models and did not consider models with randomly timed jumps in returns. Prima facie evidence for jumps in returns is often an asymmetry or excess kurtosis in the distribution of equity returns. For example, it is common for broad equity indices such as the S&P 500 to have significant negative skewness and positive kurtosis, indicative of rare jumps that are very negative. Table 6 provides the distributional properties of returns for the stocks that we consider.

Table 8 indicates that there are not strong unconditional non-normalities in the stocks that we consider, with the possible exception of Apple. This should not be surprising. The average daily volatility across firms is about four percent, which implies that a three standard deviation confidence band is ± 12 percent. Since volatility is also stochastic, suppose that volatility is high, say, eight percent per day. In this case, the confidence band is ± 24 percent which just about covers the average minimum and maximum moves for the stocks. This is in strong contrast to equity indices which has relatively low daily volatility (for the S&P 500, less than one percent) but has very large relative moves relative to this volatility historically (Crash of 1987). This is consistent with the observation in Bakshi, Kapadia, and Madan (2003) that implied volatility for individual equities are very flat, relative to those for aggregate indices.

Appendix B

The discounted log stock transform below is the key piece in transform based option pricing methods. In a two-factor stock price model in an affine setting we know the form includes two loading functions for each of the factors.

$$\psi(c, S_t, V_t, t, T, r) = \exp(-r(T-t) + \alpha(c, t, T) + \beta(c, t, T)V_t + c \cdot \log S_t)$$

where c is complex-valued. Duffie, Pan, Singleton (2000) and Pan (2001) price call options by breaking up the claims into two components, the all or nothing option minus the binary option. Pan (2001) describes methods of bounding the truncation and sampling errors involved with numerical inversion of transform integrals for these claims. Instead we follow Carr-Madan (1999) and Lee (2003) and compute the Fourier transform of the call option which reduces the problem to one numerical inversion and improves the characteristics of the integrand thus reducing sources for error and computational demands.

We briefly describe Carr-Madan's results. Let $C(k)$ be the call option with a log strike k . We introduce the dampened call price, $c(k)$ with a dampening coefficient $\alpha > 0$ which forces the square integrability of the call price transform. We also require $E[S^{\alpha+1}] < \infty$ which can be verified with the log stock price transform, we find $\alpha = 2$ performs well. If we let the dampened call price be given by $c(k) \equiv \exp(\alpha k)C(k)$, the Fourier transform of $c(k)$ is defined by

$$\psi_c(v) = \int_{-\infty}^{\infty} \exp(i\alpha v) c(k) dk \tag{7}$$

The Fourier transform of $c(k)$ is given by

$$\psi_c(v) = \frac{\psi(v - i(\alpha + 1), S_t, V_t, t, T, r)}{\alpha^2 + \alpha - v^2 + i(2\alpha + 1)v} \tag{8}$$

where some of the arguments are suppressed on the left hand side for notational simplicity. To invert the dampened call price to get the call price, we use the inversion formula.

$$C(k) = \frac{\exp(-\alpha k)}{\pi} \int_0^{\infty} \mathbf{Re}[\exp(-i\alpha k)\psi_c(v)]dv. \tag{9}$$

Obviously in practice we must truncate this indefinite integral and the log stock price transform can be used again to find an appropriate upper limit. Carr and Madan (1999) show the following the inequalities.

$$|\psi_c(v)|^2 \leq \frac{E[S^{\alpha+1}]}{(\alpha^2 + \alpha - v^2)^2 + (2\alpha + 1)^2 v^2} \leq \frac{A}{v^4} \quad (10)$$

and

$$|\psi_c(v)| \leq \frac{\sqrt{A}}{v^2}. \quad (11)$$

The integral tail can be bounded by the right hand side which is

$$\int_a^\infty |\psi_c(v)| dv < \frac{\sqrt{A}}{a}. \quad (12)$$

If we set $A = E[S^{\alpha+1}]$ the upper limit a can be selected for a general ε truncation bound.

$$a > \frac{\exp(-\alpha k) \sqrt{A}}{\pi \varepsilon} \quad (13)$$

Once an upper limit is selected, any numerical integration method can be used. We use an adaptive quadrature algorithm that uses Simpson's Rule with one step of Richardson extrapolation and the integral grid is iteratively changed until the value converges where the improvements are less than a specified value, which controls the error. We find that this provides accurate prices and is computationally attractive.

	Minimum (%)	Maximum (%)	Std Dev (%)	Skewness	Kurtosis
AAPL	-73.12	28.69	65.60	-2.8285	60.7688
ADBE	-35.32	21.49	66.40	-0.5902	9.9567
ALTR	-31.56	22.46	77.38	-0.0918	5.0666
AMAT	-15.10	22.82	66.86	0.2684	4.1175
AMGN	-14.40	12.95	46.82	0.0574	4.8421
CSCO	-14.54	21.82	57.32	0.1332	5.9096
DELL	-21.00	16.37	58.19	-0.2223	4.8211
EMC	-32.95	22.20	66.43	-0.3543	7.5851
INTC	-24.89	18.33	52.96	-0.3844	7.4161
KLAC	-18.62	22.39	76.87	0.2470	4.0450
MSFT	-16.96	17.87	41.07	-0.1065	7.0007
MU	-26.19	21.72	75.61	0.0101	4.4972
MXIM	-30.31	20.89	69.32	0.0983	4.9814
NVLS	-35.05	28.77	77.93	0.2181	6.1082
ORCL	-34.46	27.07	65.44	-0.1845	9.1158
PMCS	-25.90	29.61	93.89	0.2260	4.9687
PSFT	-39.56	22.92	77.96	-0.2770	8.2753
QCOM	-18.45	32.72	70.14	0.3664	6.4615
SUNW	-31.09	26.03	65.34	-0.1299	6.5136
XLNX	-23.69	16.61	74.37	-0.1188	4.1875
Pooled	-28.16	22.69	67.30	-0.1832	8.8319

Table 8: Summary statistics for the underlying returns for the firms in our sample for the period 1996 to 2002. The standard deviations are annualized and in percentages. The skewness and kurtosis statistics are raw statistics, and not excess skewness or excess kurtosis. The pooled numbers are the averages of the statistics across firms.