Earnings announcements and equity options

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Abstract

This paper uses option prices to learn about the uncertainty surrounding firm fundamentals. When firms announce earnings every quarter, they reveal current fundamentals (earnings, cash flows, sales, taxes, etc.) which were, to varying extents, unknown to investors prior to the announcement. This information revelation is why stock prices often react violently after earnings announcements. This paper develops estimators of the uncertainty associated with information revealed in earnings announcements and investigates. On the theoretical side, we develop no-arbitrage option pricing models in the presence of earnings announcements; and we develop and justify estimators of the earnings uncertainty using option prices. Empirically, we first nonparametrically test for the importance of earnings announcements on option prices and then implement the estimators. We analyze their time series behavior and test for the presence of risk premia. Finally, we quantify the impact that earnings annoucements have on formal option pricing models.

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1 Introduction

When firms announce earnings every quarter, they reveal current fundamentals (earnings, cash flows, sales, taxes, etc.) which were, to varying extents, unknown to investors prior to the announcement. This revelation is why stock prices often react violently after earnings announcements. While it is often possible to obtain measures of investor's expectations of fundamentals prior to announcements (from, for example, analysts forecasts, etc), it is far more difficult to obtain ex-ante estimates of the uncertainty of fundamentals. This uncertainty over fundamentals plays a prominent role in many asset pricing models (see Pastor and Veronesi (2003, 2005)), although little is known about it.

This paper uses option prices to learn about the uncertainty surrounding firm fundamentals. Since Patell and Wolfson (1979, 1981), it is well know that option prices embed ex-ante information about earnings announcements. The uncertainty associated with the stock price response to the release of earnings generates a distinctive time series pattern in implied volatilities, as implied volatility increases prior to and decreases subsequent to an earnings announcement. Figure 1 displays a graphical view of the phenomenon for Intel Corporation, using data from 1996 to 2003.[1]

The goal of this paper is to *quantify* the uncertainty associated with earnings announcements using option prices. This is distinct from documenting that option prices contain information about earnings announcements. To do this, we first develop formal no-arbitrage models incorporating announcements on prescheduled earnings dates. In the context of these models, we develop estimators of the earnings uncertainty, analyze the robustness of these estimators, investigate the informational content of these estimates, and quantify the importance of accounting for earnings announcements using standard option pricing models.

We model earnings announcements as a jump or path discontinuity at the time of an earnings release. In our model, the distribution of price jump sizes functions as a reduced

[1] It is common to see these implications reported in the popular press. For example, see the following quote taken from the Options Report in the *Wall Street Journal* on June 27, 2005: "Option buyers ran with athletic footwear and apparel giant Nike ahead of the company's fourth-quarter report today. The volatility implied by the Beaverton, Ore., company's short-term options rose to about 29% from 22% a week ago[...]. Today brings the potential stock catalyst of earnings, which likely accounts for the rise in Nike's expected stock volatility." (Scheiber, 2005).

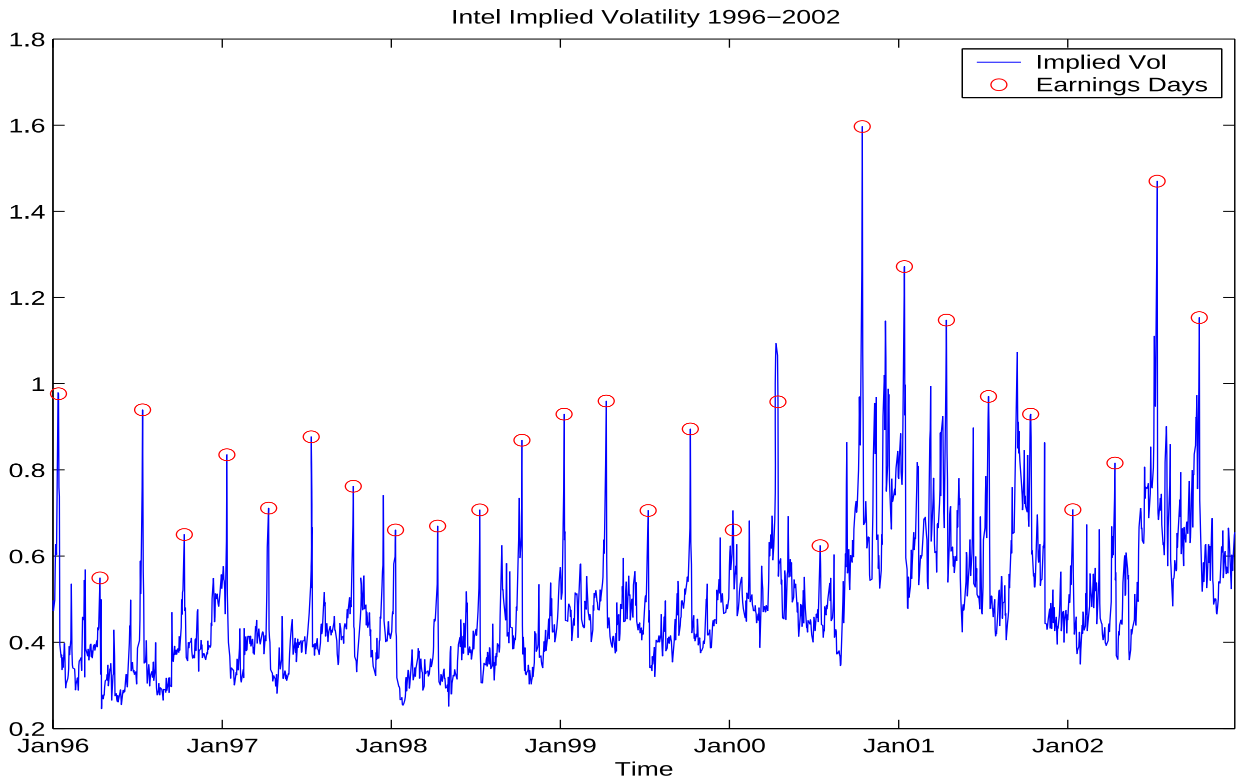

Figure 1: Black-Scholes implied volatility for the nearest maturity at-the-money call option for Intel Corporation from January 1996 to December 2002. The circles represent days on which earnings announcements were released.

form model, translating shocks to firm fundamentals into shocks in equity prices. The absence of arbitrage implies that the risk-neutral jump size has mean zero, and therefore the central parameter of interest in our model is the risk-neutral earnings price jump volatility. This parameter is one measure of informational uncertainty, capturing anticipated uncertainty in firm fundamentals.

We model earnings announcements as a jump or path discontinuity at the time of an earnings release. In our model, the distribution of price jump sizes functions as a reduced form model, translating shocks to current and future expected earnings into shocks in equity prices. The absence of arbitrage implies that the risk-neutral jump size has mean zero, and therefore the central parameter of interest in our model is $\sigma_j^{\mathbb{Q}}$, the risk-neutral volatility of price jumps due to earnings announcements. This parameter is one measure of informational uncertainty, capturing the anticipated uncertainty for the equity price embedded in an earnings announcements.[2]

Our main contribution is to develop and implement estimators of this parameter using option prices. We introduce two main estimators, one based on the time series of implied volatilities, the other based on the term structure of implied volatilities. Both estimators are easy to compute, as they only require Black-Scholes implied volatilities on different dates or for different maturities. The first, the term structure estimator, is based on ex-ante information contained in two ATM options of different maturities. The second, the time series estimator, is based on changes in IVs around earnings announcements.

In theory, the two estimators will perform very differently in the presence of stochastic volatility or microstructure noise. The time series estimator, as it depends on implied volatilities on multiple dates, will generally be a noisier estimator than the term structure estimator. Because of this, we primarily focus rely on the term structure estimator but are careful to compare the two estimators where appropriate.

For our empirical work, we use a sample of 20 firms with the most actively traded options from 1996 to 2002 and choose low dividend firms, as we expect them to have relatively high-earnings uncertainty. Based on this sample, we have a number of empirical results. First, we provide nonparametric tests to document the importance of earnings anounncements on option prices. We use test statistics related to those in Patell and Wolfson (1979, 1981) and also test an additional implication that is important for the term structure estimator. These tests are important because our model and estimators requires that earnings announcements have a strong impact on implied volatilities. While casual data observation such as Figure 1 are re-assuring, formal tests are required. Using nonparametric tests, we find overwhelmingly strong evidence for all of the tested implications.

Next, we implement our estimators of the earnings uncertainty, $\sigma_j^{\mathbb{Q}}$, for each firm and earnings cycle using the term structure and time series estimators. Across firms and time, the average jump volatility estimate using the term structure (time series) estimator is 11.31 (9.11) percent, which is both statistically and economically significant. The estimates are highly correlated: the correlation of firm means for the two estimators is about 80 percent and the pooled correlation of the two estimates for all of the earnings events is 71 percent.

[2]Pastor and Veronesi (2003, 2005), Jiang, Lee and Zhang (2004) or Zhang (2005) use alternative, indirect proxies for fundamental uncertainty using variables such as firm age, return volatility, firm size, analyst coverage, or the dispersion in analyst earnings forecasts.

Together, this points to a very large and consistent effect. As we discuss in greater detail below, large symmetric or positively skewed shocks in volatility would result in the time series estimator being biased slightly downwards, generating the lower average estimates when compared to the term structure estimator.

We document that the jump volatilities vary across firms and time. For some firm/quarter combinations, estimates of $\sigma_j^{\mathbb{Q}}$ are quite large, around 20 percent. These large sizes are not inconsistent with stock price movements, as prices often react violently to announced earnings. The estimates also vary over time: earnings uncertainty increases in 2000 and 2001 during the recession and bursting of the dot-com bubble.

With the estimates of $\sigma_j^{\mathbb{Q}}$, we can use historical returns to investigate the informational content of earnings jump volatility, risk premia, and the abnormality of returns around earnings dates. The first issue is informativeness, which is the extent to which a high estimate of $\sigma_j^{\mathbb{Q}}$ forecasts a subsequent large movement in the stock prices. We find that the correlation across firm averages are positive and above 50 percent. This implies that our estimator is informative about futures movements.

Regarding risk premia, we cannot reject that realized standardized returns on earnings dates are mean zero, which implies there is no evidence for a mean jump risk premium. We do find evidence for a jump volatility risk premium: the volatility of jumps sizes under $\mathbb{Q}$ is greater than the observed volatility under $\mathbb{P}$, consistent with evidence from index options. On the one hand, this result is surprising given that there is little evidence for an overall volatility/jump risk premium embedded in individual equity options based on the differences between realized and implied volatilities (see, e.g., Carr and Wu 2005; Driessen, Maenhout, and Vilkov 2005; and Battalio and Schultz 2004). On the other hand, a risk premium is plausible given that it is not possible to hedge continuously distributed jumps with a finite number of instruments. We also find that standardized returns appear to be normally distributed, consistent with our model.

To quantify the importance of announting for earnings announcements when pricing individual equity announcements, we estimate stochastic volatility model with and without jumps on earnings dates. We find that adding jumps on earnings dates provides a substantial improvement in model performance as dollar pricing errors on short-dated options fall by about 50 percent. Firms with high earnings uncertainty naturally have a greater improvement by incorporating jumps on earnings dates. To frame our results, Bakshi and Cao (2004) find no pricing improvement for ATM options when adding randomly-timed jumps in prices or volatility.

Finally, we discuss the implications of our results for empirical option pricing research. Most papers do not account for earnings announcements, and we document

2 Pricing options on individual equities

Compared to index options, the extant literature on pricing individual options is quite small. For index options, there is a reasonable agreement on a general class of models that provide an accurate fit to both the time series of index returns and the cross-section of option prices.[3] The results indicate that factors such as stochastic volatility, jumps in prices, and jumps in volatility are present. The main debate focuses over the magnitude and causes of risk premia.[4]

The literature on pricing individual equity options is less advanced. Most of the work analyzes the behavior of the IV smile and term structure vis-à-vis the index option literature (see, e.g., Dennis and Mayhew 2002; Bakshi, Kapadia, and Madan 2003; Bollen and Whaley 2004; Dennis, Mayhew, and Stivers 2005). The main conclusions are that IV curves are flatter for individual equities than for index options and that gap between realized and IV is smaller for individual equities (Carr and Wu 2005; Driessen, Maenhout, and Vilkov 2005; Battalio and Schultz 2004). To our knowledge, the only paper analyzing formal pricing models for individual equities is Bakshi and Cao (2004).

The first step in pricing options on individual equities is modeling earnings announcements. Huang (1985a) provides an intuitive way to motivate model specification via continuous-time information structures. Huang (1985a) argues that a "continuous" information structure, such as those generated by Brownian motions, is one in which "no events can take us by surprise" (p. 61). Under mild regularity on preferences, prices with "continuous" information structures will have continuous sample paths.

Events such as macroeconomic or earnings announcements are canonical examples of

[3]See, e.g., Bates (2000), Andersen, Benzoni, and Lund (2001), Pan (2002), Chernov, Ghysels, Gallant, and Tauchen (2003), Eraker, Johannes, and Polson (2003), Eraker (2004) and Broadie, Chernov, and Johannes (2005).

[4]Bollen and Whaley (2004) and Garleanu, Pedersen, and Poteshman (2005) provide evidence that demand based pressures contribute to the risk premium embedded in options.

events that take market participants by surprise, thus information structures are not continuous in the sense of Huang (1985a). These informational discontinuities immediately translate, under mild regularity on preferences, into discontinuities in the sample path of prices at the points in time when the information is released. Thus prices are necessarily discontinuous with announcements.[5]

To formally model earnings announcements, we assume there is a deterministic counting process, N_t^d, counting the number of predictable events occurring prior to time t: $N_t^d = \sum_j 1_{[\tau_j \leq t]}$ where the τ_j's are an increasing sequence of predictable stopping times.[6] Intuitively, a predictable stopping time is a phenomenon that "Cannot take us by surprise: we are forewarned, by a succession of precursory signs, of the exact time the phenomenon will occur" (Dellacherie and Meyer 1978, 128). An inaccessible or random stopping time is just the opposite: there are no precursory signs and thus the arrival is a complete surprise.

The assumption of a discontinuity in the sample path is consistent with existing work analyzing announcement effects (Beber and Brandt 2004 and Piazzesi 2005), and with statistical evidence identifying announcements as jumps in the context of jump-diffusion models (Johannes 2004 and Barndorff-Nielson and Shephard 2006), and is intuitively appealing. Since earnings announcements occur either after market close (AMC) or before market open (BMO), earnings announcements will generate a visible discontinuity in economic or trading time: the market open the following morning is often drastically different than the market close before the announcement.[7] Further evidence consistent with a jump is in Patell and Wolfson (1984), who find that for earnings announced during trading hours in the late 1970s, the bulk of the response occurs within the first few minutes. We provide a test of this implication in Section 3 using close-to-open returns.

We augment Heston's (1993) SV model with randomly-sized jumps at earnings announcements. The advantage of the square-root specification is that option prices are easy to compute using standard numerical integration routines. Prices and volatility jointly

[5]We generally ignore dividends, which naturally introduce a discontinuity on lump-sum ex-dividend dates, see, Huang (1985b).

[6]Piazzesi (2000) introduced deterministic jumps on macroeconomic announcement dates in the context of bond pricing and we extend her approach to pricing equity and equity options with deterministic jumps.

[7]There is a limited after hours market for trading stock, although the characteristics of the market are not well known (see Barclay and Henderschott 2004). Anecdotally, volume is low and bid-ask spreads are much larger than during trading hours. It is important to note that there is no after-hours trading of individual equity options; trading ends at 4:02 p.m. EST.

solve the following stochastic differential equations

$$dS_t = (r_t + \eta_s V_t) S_t dt + \sqrt{V_t} S_t dW_t^s + d\left(\sum\nolimits_{j=1}^{N_t^d} S_{\tau_j -}\left[e^{Z_j} - 1\right]\right) \tag{1}$$
$$dV_t = \kappa_v (\theta_v - V_t) dt + \sigma_v \sqrt{V_t} dW_t^v,$$

where all random variables are defined on the probability measure $\mathbb{P}$, $\log\left(S_{\tau_j}/S_{\tau_{j-}}\right) = Z_{\tau_j}$, $Z_{\tau_j}|\mathcal{F}_{\tau_j -} \sim \pi\left(Z_{\tau_j}, \tau_j -\right)$, $cov\left(W_t^s, W_t^v\right) = \rho t$, and N_t^d counts the number of earnings announcements.[8] The variable Z_j is the jump in prices due to "earning surprises." Throughout, we assume the interest rate is constant and that the Feller condition holds ($\theta_v \kappa_v > \sigma_v^2/2$), and we ignore dividends for notational simplicity. Appendix B derives the characteristic function and discusses numerical option pricing in the stochastic volatility model with jumps on earnings dates.

The jump distribution $\pi(Z_j, \tau_j -)$ serves as a reduced form, earnings-based asset pricing model. On EADs, firms reveal the current quarter's earnings per share E_{τ_j} and also provide forward-looking information. The jump size Z_j is a shock translating this fundamental information into equity prices and is similar to the common approach in accounting and finance of computing the "earnings response coefficient" (Ball and Brown 1968). Here, stock price changes are regressed on current quarter earnings' surprises:

$$Z_j = \log\left(\frac{S_{t_j}}{S_{\tau_j -}}\right) = \alpha + \beta\left(E_{\tau_j} - E^f_{\tau_{j-}}\right) + \varepsilon_{\tau_j}$$

where 'f' stands for a forecast, based either on analysts or a statistical model of earnings.

This approach assumes that all of the reaction in the stock prices is due to learning about current earnings, E_{τ_j}, ignoring the forward-looking information. Ang and Zhang (2005) find that forward-looking statements are as important, if not more so, than current earnings in explaining stock price movements after earnings. Our focus is on pricing options, and we are especially interested in the behavior under the pricing measure $\mathbb{Q}$, although our approach does not rule out predictable components under $\mathbb{P}$. For option pricing, the central parameter of interest is the volatility, or uncertainty, of Z_j.

Our specification is intentionally chosen to be parsimonious, as we do not include other potential factors such as randomly-timed jumps in prices or in volatility. We do this for

[8] We do not consider other predictable events such as mid-quarter earnings updates, stock splits, or mergers and acquisitions although these do have implications for option prices.

two 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 ATM implied volatility. ATM options are not particularly sensitive to randomly-timed jumps (see Broadie, Chernov, and Johannes 2005 for index options or Bakshi and Cao 2004 for individual stocks). Second, unlike equity indices, there is little *prima facie* evidence for the importance of randomly-timed jumps based on either option prices or the time series of returns. The existing option pricing literature (cited above) documents that IV curves (for a fixed maturity) are much flatter for individual equities, implying that jumps in returns are not likely to be very important for individual equities. The time series of individual equity returns provides similar intuition: unlike indices, which have strong evidence for conditional non-normalities (for the S&P 500 index, around 50 and minus three), we show that the individual equities we consider have no noticeable negative skewness and only a modest amount of kurtosis (with the exception of one firm in our sample).

Before proceeding, we briefly review the existing literature that deals with the impact of earnings announcements on equity and equity option prices.

2.1 Comparison to existing literature

Our paper relates to a number of different literatures in accounting and finance. First, a number of papers use time series data to analyze how scheduled announcements affect 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 argue that earnings announcements can be reasonably modeled by a discontinuous component in the price process.

In terms of descriptive time series analysis, there is little relevant work on earnings announcements and equity price volatility. The one paper, to our knowledge, that deals with these issues is Maheu and McCurdy (2004), who analyze discrete-time GARCH models with state-dependent jumps. They find that many of the jumps they statistically identify occurred on EADs. 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.

Our paper is primarily motivated by Patell and Wolfson (1979, 1981), who provide early descriptive work on the time series behavior of IV around EADs. They develop a model without jumps that uses a specification with deterministically changing volatility. They nonparametrically test that volatility increases prior, and decreases subsequent, to earnings announcements. Patell and Wolfson (1979) find mixed evidence using a sample of annual earnings announcements from 1974 to 1978, while Patell and Wolfson (1981) find relatively stronger evidence using a sample of quarterly earnings announcements from 1976 to 1977. Donders and Vorst (1996), Donders, Kouwenberg, and Vorst (2000), and Isakov and Pérignon (2001) apply Patell and Wolfson's approach to European options markets. Whaley and Cheung (1982) argue that the informational content of earnings announcements is rapidly incorporated into option prices.

Our theoretical and empirical work is quite different from Patell and Wolfson's. The main overlap is the nonparametric tests for the importance of earnings announcements. There are at least four important differences. First, we model earnings announcements as jumps, introducing a discontinuity into the sample path. We provide empirical evidence, based on close-to-open returns, consistent with a jump in economic time. Patell and Wolfson's model has a continuous sample path, which has major implications for market completeness, risk premia, hedging, and pricing. Second, we analyze additional implications, most notably the downward-sloping term structure of implied volatility, and test for its presence. Third, and most importantly, we develop and implement estimators of $\sigma_j^{\mathbb{Q}}$. Fourth, we analyze the evidence for risk premia, informativeness, and quantify the pricing impact in the context of formal option pricing models.

Ederington and Lee (1996) and Beber and Brandt (2004) analyze announcement effects in the options on Treasury bond futures market. Ederington and Lee document that IV falls after announcements. Brandt and Beber analyze the implied pricing density in options around announcements and find that, in addition to IV falling, the skewness and kurtosis change after announcements. In the context of our model, this implies that the risk-neutral jump distribution in the Treasury market is asymmetric with fat tails. Beber and Brandt (2004) relate these changes to news about the economy and argue that this effect is consistent by time-varying risk aversion.

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 (1995) assume that the current equity prices are a linear function of accounting variables such as abnormal current income. Ang and Liu (2001) extend these models to general discrete-time affine processes, while Pastor and Veronesi (2003, 2005) build continuous-time models assuming log-normal (as opposed to linear) growth in the accounting variables. The uncertainty over firm fundamentals (earnings, profitability, etc.) impacts prices and is important for valuation (see Pastor and Veronesi 2005). Pastor and Veronesi (2003) use firm age as a proxy for the uncertainty in profitability while Jiang, Lee and Zhang (2004) and Zhang (2005) use variables such as firm age, return volatility, firm size, analyst coverage, or the dispersion in analyst earnings forecasts. Our empirical work below extracts a market-based estimate of the uncertainty at earnings announcements, thus providing an alternative source of information about the uncertainty regarding a firm's fundamentals.

2.2 Equivalent martingale measures

To price options, we construct an equivalent martingale measure, which implies the absence of arbitrage. The pricing approach extends Piazzesi (2000) to equities and equity options. We ignore dividends for simplicity.

Under the equivalent martingale measure, $\mathbb{Q}$, discounted prices are a martingale, which requires that they be a martingale between jump times and that the pre-jump expected value of the post-jump stock price is equal to the pre-jump stock price. Between jump times, this requires that the drift of S_t under $\mathbb{Q}$ is equal to $r_t S_t$. At a jump time, interest rate accruals do not matter.[9] For prices at jump times to be a $\mathbb{Q}-$martingale, we require that $E^{\mathbb{Q}}\left[S_{\tau_j}|\mathcal{F}_{\tau_j-}\right] = S_{\tau_j-}$, which implies that there can be no expected capital gains at a deterministic jump time, $E^{\mathbb{Q}}\left[\Delta S_{\tau_j}|\mathcal{F}_{\tau_j-}\right] = 0$. Given the jump specification above, this requires that $E^{\mathbb{Q}}\left[e^{Z_j}|\mathcal{F}_{\tau_j-}\right] = 1$.

[9] If $\beta_t = \exp\left(\int_0^t r_s ds\right)$, 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 $E^{\mathbb{Q}}\left[S_{\tau_j}|\mathcal{F}_{\tau_j-}\right] = S_{\tau_j-}$.

To construct the measure, we define $\frac{d\mathbb{Q}}{d\mathbb{P}} = \xi_T$ and assume the density process, ξ_t, is given by the stochastic exponential

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

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 $\xi_{\tau_j} = \xi_{\tau_j-} X_{\tau_j}^{\xi}$ is 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 premia of the form $\varphi_t^s = \eta_s V_t$ and $\varphi_t^v = -\left(1-\rho^2\right)^{-1/2}\left(\rho\eta_s\sqrt{V_t} + \frac{\mu_t^{\mathbb{Q}} - \mu_t^{\mathbb{P}}}{\sigma_v\sqrt{V_t}}\right)$ where $\mu_t^{\mathbb{Q}} = \kappa_v^{\mathbb{Q}}\left(\theta_v^{\mathbb{Q}} - V_t\right)$ and $\mu_t^{\mathbb{P}} = \kappa_v\left(\theta_v - V_t\right)$. A sufficient condition for this to be a valid change of measure is that the Feller condition holds under both measures (see, Collin-Dufresne, Goldstein, and Jones 2005 or Cheridito, Filipovic, and Kimmel 2004).

To guarantee that ξ_t is positive and a $\mathbb{P}-$martingale at jump times we require that $X_{\tau_j}^{\xi} > 0$ and $E^{\mathbb{P}}\left[\xi_{\tau_j} | \mathcal{F}_{\tau_j-}\right] = \xi_{\tau_j-}$ or $E^{\mathbb{P}}\left[X_{\tau_j}^{\xi} | \mathcal{F}_{\tau_j-}\right] = 1$, respectively. These conditions are satisfied assuming

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

This intuitive condition is extremely mild, requiring only 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 do not appear under the other measure or the functional form of the distribution could change. Throughout, we assume for simplicity that the jump sizes are state independent and normally distributed under $\mathbb{Q}: Z_j \sim \pi^{\mathbb{Q}} = N\left(-\frac{1}{2}\left(\sigma_j^{\mathbb{Q}}\right)^2, \left(\sigma_j^{\mathbb{Q}}\right)^2\right)$. This implies that there is a single parameter indexing the jump distribution and estimating $\sigma_j^{\mathbb{Q}}$ is the primary focus of the paper. We make no assumptions about the behavior of $\pi^{\mathbb{P}}$, which, in particular, implies that the volatility of jump sizes under $\mathbb{P}$ could be different.

Under $\mathbb{Q}$,

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

For pricing ATM options, the total, annualized, expected risk-neutral variance of continuously compounded returns is important and it is given by

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

Our model is incomplete, as jumps cannot be hedged with a finite number of securities. In general, to perfectly hedge jumps, one requires as many hedging instruments as the cardinality of the jump size distribution. Due to this 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.

2.3 Black-Scholes with deterministic jumps

Consider next an extension of the Black-Scholes model incorporating deterministically-timed jumps:

$$S_T=S_0\exp\left[\left(r-\frac{1}{2}\sigma^2\right)T+\sigma W_T(\mathbb{Q})+\sum_{j=1}^{N_T^d} Z_j\right], \tag{3}$$

where $Z_j=-\frac{1}{2}\left(\sigma_j^{\mathbb{Q}}\right)^2+\sigma_j^{\mathbb{Q}}\varepsilon$ and $\varepsilon\sim N(0,1)$. Under these assumptions, discounted prices are martingales. Since $W_T(\mathbb{Q})$ and $\sum_{j=1}^{N_T^d} Z_j$ are normally distributed (a non-random mixture of normal random variables is normal), log returns are exactly normally distributed. This allows us to derive exact, closed-form prices.

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

$$BS\left(x,\sigma_T^2,r,T_i,K\right)=E^{\mathbb{Q}}\left[e^{-rT_i}\left(S_T-K\right)^+|S_0=x\right]=x\Phi(z)-Ke^{-rT_i}\Phi\left(z-\sigma_T\sqrt{T_i}\right),$$

where BS is the usual Black-Scholes pricing formula,

$$z=\frac{\log(x/K)+rT_i+\sigma_{T_i}^2T_i/2}{\sigma_T\sqrt{T_i}}, \tag{4}$$

and the Black-Scholes IV is $\sigma_{0,T_i}^2=\sigma^2+T_i^{-1}\sum_{j=1}^{N_{T_i}^d}\left(\sigma_j^{\mathbb{Q}}\right)^2$.[10] The results in Hull and White (1987) indicate that if there is stochastic volatility, then under certain conditions $\sigma_{T_i}^2$ is

[10]For simplicity, we often refer to implied variance and implied volatility as IV.

the expected variance to maturity. In the case of square-root stochastic volatility, σ^2 is replaced by

$$T_i^{-1} E_0^{\mathbb{Q}} \left[\int_0^{T_i} V_s ds \right] = \theta_v^{\mathbb{Q}} + \frac{V_0 - \theta_v^{\mathbb{Q}}}{\kappa_v^{\mathbb{Q}} T_i} \left(e^{-\kappa_v^{\mathbb{Q}} T_i} - 1 \right).$$

Since we use Black-Scholes IV to estimate $\sigma_j^{\mathbb{Q}}$ (see Section 3.2.1), we will discuss the implications of stochastic volatility in greater detail below. This extension of Black-Scholes, despite its simplicity, provides a number of time series and option pricing implications that differ from traditional models.

Deterministic jumps introduce a strong predictability in implied volatility. To see this, assume that there is a single announcement at time, τ_j, $t < \tau_j < t + T_i$. The Black-Scholes IV is $\sigma_{t,T_i}^2 = \sigma^2 + T_i^{-1} \left(\sigma_j^{\mathbb{Q}} \right)^2$, which generates three testable implications. First, the moment before an earnings release, annualized IV is $\sigma_{\tau_j -, T_i}^2 = \sigma^2 + T_i^{-1} \left(\sigma_j^{\mathbb{Q}} \right)^2$, and after the announcement it is $\sigma_{\tau_j, T_i}^2 = \sigma^2$. This implies there is a discontinuous decrease in IV immediately following the earnings release. Second, IV increases leading into an announcement at rate T_i^{-1} as the maturity decreases. Third, holding the number of jumps constant, the term structure of Black-Scholes IV decreases as the maturity of the option increases. We use these three implications to nonparametrically test for the presence of an earnings announcement effect in option prices and as a basis to estimate $\sigma_j^{\mathbb{Q}}$.

At this point, it is important to contrast our model to the model in Patell and Wolfson (1979, 1981). Their model relies on an observation in Merton (1973) that the Black-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 IV at time zero of an option expiring at time T is $\left(\sigma_{T_i}^{BS} \right)^2 = T_i^{-1} \int_0^T \sigma^2(s) \, ds = \sigma^2 + T_i^{-1} \sigma_E^2$. Clearly, this delivers the result that annualized volatility increases prior to, and decreases after, an earnings release.

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 is in contrast to the findings in Patell and Wolfson (1984), who document the rapid reaction of the stock prices to earning announcements.

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 deterministically-timed jumps in stochastic volatility with deterministic sizes, and it is far more 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 σ_E to change across measures (as it is in the diffusion coefficient). 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 $\mathbb{P}$. Assuming mean zero and normally-distributed jumps, the distribution of the log-returns conditional on the parameters is normal, because 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 ($\sigma_j \neq \sigma_i$), this implies that, in the words of Piazzesi (2000), 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.

Finally, 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. For example, Beber and Brandt (2005) find that the distributional shape changes after announcements, which implies in the context of our model there is an asymmetric jump distribution in the T-bond futures market.

2.4 Earnings jump estimators

In this section, we develop two estimators motivated by the extension of the Black-Scholes model in the previous section: an ex-ante measure based on the term structure of implied volatilities and an ex-post measure based on the time series changes of implied volatility.

The term structure estimator uses the differential information in the implied volatilities of two maturities expiring after a quarterly earnings announcement. With a single earnings announcement prior to maturity, the Black-Scholes IV of an ATM option at time t, with T_i days to maturity (measured in annualized units) is $\left(\sigma_{t,T_i}^{BS}\right)^2 = \sigma^2 + T_i^{-1}\left(\sigma^{\mathbb{Q}}\right)^2$, and for $T_1 < T_2$, we have that $\left(\sigma_{t,T_1}^{BS}\right)^2 > \left(\sigma_{t,T_2}^{BS}\right)^2$. Provided the term structure is downward sloping, we can solve for $\sigma^{\mathbb{Q}}$,

$$\left(\sigma_{term}^{\mathbb{Q}}\right)^2 = \frac{\left(\sigma_{t,T_1}^{BS}\right)^2 - \left(\sigma_{t,T_2}^{BS}\right)^2}{T_1^{-1} - T_2^{-1}},$$

which we label the *term structure* estimator. We also report $\sqrt{T_1^{-1}\left(\sigma_{term}^{\mathbb{Q}}\right)^2 / \left(\sigma_{t,T_1}^{BS}\right)^2}$ as a measure of the proportion of total volatility due to the earnings release.

The time series estimator uses changes in IV around the EADs. If there is a single earnings announcement after the close on date t (or before the open on date $t+1$), then the IV the day after the announcement is σ^2, provided there are no other announcements prior to option maturity. Solving for $\sigma^{\mathbb{Q}}$, we define the *time series* estimator,

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

We report estimation results for one day time differences, but we have also computed time series estimators for greater lengths, (two, three and five days). The results are similar, although there is far more noise in the estimates for longer time-intervals. We also report the proportion of total volatility based on this estimate.

In order to understand the estimators, we revisit the Intel example from the introduction. On April 18, 2000, Intel released earnings AMC. The first two options expired in 0.0159 and 0.0952, years (roughly four and 24 days) and the Black-Scholes implied volatilities were 95.80% and 65.89%, respectively. In this example, we use the July and August expirations. The term structure estimator is 9.60%. The IV of the short-dated option falls to 55.31% the day after the announcement and the time series estimator is therefore 9.86%. This example is common with both estimators pointing to a common effect, even though the term structure estimator uses only ex-ante information, while the time series estimator uses both ex-ante and ex-post information.

Both of these estimators are technically correct only our model in (3) holds. Under certain conditions on stochastic volatility, the results of Hull and White (1987) and Bates

(1995) indicate that $\left(\sigma_{t,T_i}^{BS}\right)^2 = T_i^{-1} E_t^{\mathbb{Q}}\left[\int_t^{T_i} V_s ds\right] + T_i^{-1}\left(\sigma^{\mathbb{Q}}\right)^2$, which implies that the estimator is robust to stochastic volatility.[11] The Hull and White (1987) procedure formally requires that the shocks to the volatility process are independent of those to prices, that is, it rules out leverage effects. Recent research has shown (Jones 2003 and Chernov 2005) that the impact of correlation on the validity of the Hull and White procedure is negligible, at least for index options. Since index options have a much larger leverage effect than individual stocks (about five times as large, see Dennis, Mayhew, and Stivers 2005), this implies that any bias from using Black-Scholes IV as a proxy for expected variance due to correlation is negligible.[12]

In Appendix C, we provide a detailed discussion of the performance of the two estimators in the presence of square-root stochastic volatility. We argue that the term structure estimator is more robust as it is an ex-ante measure, relying only on expectations of future average variance. For example, in the context of the stochastic volatility model above, σ_v or the realized Brownian shocks have no impact on the term structure estimator. The time series estimator relies also on the shock realizations over the next day. Large Brownian shocks or jumps in volatility could introduce a significant amount of noise into the time series estimator. Moreover, the time series estimator also has a strong directional asymmetry: increases in IV downward-bias estimates more than decreases in IV upward-bias estimates. Although we report both, we expect the time series estimator to be quite noisy.

For both estimators, there are occasionally days for which the estimate is negative, as either the term structure was not decreasing or IV did not fall. We report how often this occurs, and we discuss this issue in greater detail below.

[11] As noted by Merton (1976) and Bates (1995), Black-Scholes implied volatility also provided expected total volatility in the presence of jumps, provided that the mean jump size is small. This implies that for an ATM option,

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

where σ_J^2 is the variance of jump sizes. This indicates that randomly timed jumps will not adversely impact the estimators. Dubinsky and Johannes (2005) find that randomly-timed jump means for individual stocks are quite small.

[12] Our procedure also relies on the difference between two implied variances. If the Hull-White procedure introduced a level bias, it would not affect our estimators as it would be differenced out.

3 Empirical Evidence

We obtained closing option prices from Ivy DB OptionMetrics for the period beginning in 1996 and ending in 2002. OptionMetrics records the best closing bid and offer price for each equity option contract traded on all U.S. exchanges. One disadvantage of this data source is that it relies on close prices instead of transaction prices. Unfortunately, this is the only widely-available source of option price data. 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. OptionMetrics is now the common data source for research on individual equity options and has been used in a number of recent papers (e.g., Ni, Pearson, and Poteshman 2005, Carr and Wu 2005, Driessen, Maenhout, and Vilkov 2005).

Out of all possible firms, we use the following criterion to select 20 firms for analysis. For the period from 1996 to 2002, we found the initial 50 firms with the highest dollar volume which traded in every year. Next, we eliminated 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 any American early-exercise premium and avoids problems associated with pricing options on high-dividend stocks. Unlike equity indices, whose dividend payments are usually modeled as continuous, dividends on individual equities are "lumpy," resulting in jumps. For these remaining firms, we computed the average dollar volume of these remaining firms and took the twenty highest remaining firms.[13]

The selection criteria result 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

[13] One 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.

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 all technology stocks is not surprising.

We apply the following filters to the individual firm option files. We remove option strikes for which there is no volume; for which the bid price is zero; or for which OptionMetrics reports a 'NaN' or cannot compute an implied volatility. We then remove options with less than three days to maturity to avert potential issues arising in the final days of the options contract. OptionMetrics obtains closing midpoints for options and then converts these prices (using a binomial tree to correct for early exercise and dividend payments) into Black-Scholes implied volatilities using midpoints of the bid-ask spread. Broadie, Chernov, and Johannes (2005) provide evidence that the procedure of converting to European prices by using Black-Scholes implied volatilities adjusted for early exercise provides an accurate correction for the American feature in models with jumps and stochastic volatility. We consider only call options because calls on individual equities are more heavily traded than puts, and American calls have no early exercise premium for stocks without dividends. Dividends are a minor concern, as only three firms in our sample (ADBE, INTC, MU, and MXIM) had dividends over the sample period, and these were extremely small (the maximum dividend payout was less than 0.2 percent).

Earnings dates from Compustat were obtained as was the exact timing of the release from First Call. Because we found an alarmingly high percentage of date errors in Compustat (with respect to earnings dates) and timing errors in First Call (AMC versus BMO), all of the earnings dates and times were hand-checked using Factiva to confirm the exact timing of the announcement.[14] The earnings date is defined as the last closing date before earnings are announced. Most of the announcements were AMC instead of BMO.

Earnings dates tend to occur in a very predictable pattern. For example, Intel announces earnings on the second Tuesday of month following the end of the calendar quarter. Cisco's quarters end one month later than most firms, and they typically announce on Tuesday of 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 correspond to the exact dates that were ex-ante expected. 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

[14]We thank James Knight of Citadel Asset Management for pointing out that common databases have incorrectly dated earnings announcements.

was an increase in the number of firms announcing on time. Moreover, large firms with active analyst coverage tend to miss their expected announcement date less than smaller firms. Second, we searched Factiva for each earnings announcement for possible evidence of missed dates yet did not find any evidence of missed anticipated earnings dates. Given both the short sample and the large size of the firms in the sample, this is not surprising. Third, as discussed in Appendix C, the exact timing is immaterial if there is uncertainty regarding the date, provided the distribution of jump sizes does not change.

The options expire on the third Friday of every month. For all firms, the majority of options traded are in the shortest maturity expiration cycle, until a few days prior to expiration, when traders commonly "roll" to the next maturity cycle. Since firms' quarterly earnings announcements are dispersed over a three to four week interval, the time-to-maturity of the options on the EAD varies across firms. In principle, one could create a composite, constant-maturity observation by interpolating between different strikes and maturities. This cannot be done in our setting because interpolation is problematic in sharply-sloped term structure of IV environments as it requires an arbitrary weighing of each observation. This would severely blur the impact of earnings announcements, as it would average out the precise differences in IV across maturities we seek to explain.

Table 1 provides basic summary statistics for the firms in our sample. The first thing to notice is the high historical volatilities, which are not surprising because firms with high volatility (high earnings uncertainty) would also have high trading volume in options. The column labeled 'earnings' lists the proportion of total variance that occurs on the quarterly EADs. To frame these values, there are four EADs, which, if there was not increased volatility on EADs, would results in $4/252 \approx 1.6$ percent of total volatility. Thus, earnings announcements explain a large, disproportionate share of volatility.

As mentioned earlier, we only consider pure stochastic volatility models and do not consider models with randomly-timed jumps in returns. Prima facie evidence for jumps in returns is often a strong 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 1 indicates that there are not strong unconditional non-normalities in the stocks in our sample, 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. Normal time-variation in volatility could explain most of the large moves without requiring jumps. This is in strong contrast to equity indices, which have relatively low daily volatility (for the S&P 500, less than one percent) but have very large moves relative to this volatility (i.e., the crash of 1987). This is consistent with the observation in Bakshi, Kapadia, and Madan (2003), that IV curves for individual equities are quite flat across strikes compared to those for aggregate indices.

Finally, Appendix A provides an intuitive test analyzing the assumption that earnings announcements induce a jump or discontinuity in economic trading time. Intuitively, jumps are outliers, or rare movements. Utilizing close-to-open and open-to-close returns, we find that the standard deviation of close-to-open returns on earnings days is more than three times higher than on non-earnings days, indicative of outliers or "abnormally" large movements on earnings days. The standard deviation of open-to-close returns is only slightly higher for earnings days. This is consistent with the presence of jumps induced by earnings announcements and largely inconsistent with the continuous sample path model in Patell and Wolfson (1979, 1981).

3.1 Nonparametric tests

In this section, we provide nonparametric tests of three main implications of earnings jumps: IV should increase prior to an earnings announcement, the term structure of IV should be downward sloping prior to the announcement, and IV should decrease subsequent to the earnings announcement date. The statistical tests we use are the Fisher sign test and Wilcoxon signed rank test, which test whether or not a series of observations are positive or negative (see, e.g., Hollander and Wolfe 1999 for the details of the test). We apply the tests to the changes in IV leading up to an earnings announcement, to the difference in the IV of two options straddling the maturity date (the term structure implication) and to the change in IV subsequent to the announcement.

Under the null of no difference in IV (earnings announcements have no impact) the Wilcoxon signed-rank test assumes the distribution is symmetric around zero, while the Fisher test assumes the median is zero. The tests are nonparametric in that they place no other restrictions on the distribution other than independent observations and the symmetry/median restriction. For example the shape (normal versus t-distribution) and variance could change from observation to observation. We naturally use the one sided tests to examine whether volatility increases or decreases, depending on the implication. Following

	Min	Max	Std. Dev.	Earnings	Skew	Kurt	Volume	Rank
AAPL	-73.12	28.69	65.60	7.44	-2.83	60.77	10.5	12
ADBE	-35.32	21.49	66.40	5.17	-0.59	9.96	3.9	16
ALTR	-31.56	22.46	77.38	5.06	-0.09	5.07	3.5	17
AMAT	-15.10	22.82	66.86	3.78	0.27	4.12	17.2	10
AMGN	-14.40	12.95	46.82	6.32	0.06	4.84	11.1	11
CSCO	-14.54	21.82	57.32	5.59	0.13	5.91	69.1	3
DELL	-21.00	16.37	58.19	6.57	-0.22	4.82	51.7	4
EMC	-32.95	22.20	66.43	5.52	-0.35	7.59	19.1	9
INTC	-24.89	18.33	52.96	7.90	-0.38	7.41	85.5	1
KLAC	-18.62	22.39	76.87	3.22	0.25	4.05	3.1	18
MSFT	-16.96	17.87	41.07	11.17	-0.11	7.00	82.5	2
MU	-26.19	21.72	75.61	5.47	0.01	4.50	29.1	7
MXIM	-30.31	20.89	69.32	4.83	0.10	4.98	1.5	20
NVLS	-35.05	28.77	77.93	8.58	0.22	6.11	3.0	19
ORCL	-34.46	27.07	65.44	14.14	-0.18	9.12	31.6	5
PMCS	-25.90	29.61	93.89	7.04	0.23	4.97	4.8	15
PSFT	-39.56	22.92	77.96	9.17	-0.28	8.28	5.5	13
QCOM	-18.45	32.72	70.14	8.45	0.37	6.46	24.3	8
SUNW	-31.09	26.03	65.34	6.42	-0.13	6.51	31.3	6
XLNX	-23.69	16.61	74.37	3.80	-0.12	4.19	5.1	14
Pooled	-28.16	22.69	67.30	6.78	-0.18	8.83	24.7	

Table 1: Summary statistics for the underlying returns for the firms in our sample for the period 1996 to 2002. The minimum and maximum returns are in continuously-compounded percentages and the standard deviations are annualized and in percentages. The skewness and kurtosis statistics are raw statistics (not excess skewness or excess kurtosis). The volume column gives total option volume over the entire sample, in millions of contracts (each contract is on 100 shares of the underlying equity). The rank is the within sample rank based on option volume. The pooled numbers are the averages of the statistics across firms.

Patell and Wolfson (1979, 1981), who also use the Fisher and Wilcoxon tests, we implement the tests with differences in variance. Patell and Wolfson (1979, 1981) examine the time series implications (increase prior to and decrease subsequent to earnings), but not the term structure implication.

It is important to understand how the presence of stochastic volatility could affect these tests. Stochastic volatility models assume that V_t moves around independently of earnings announcements, mean-reverting with random shocks. Thus, even if earnings announcements are important, normal time-variation in volatility could result in a decrease in volatility prior to an EAD, a decreasing term structure of IV at an EAD, or an increase in IV subsequent to an EAD. Thus, stochastic volatility would introduce additional noise, biasing our tests toward not rejecting, increasing the chances of Type II errors (not rejecting a false null). This is especially true in our sample over which market volatility changed rapidly.

To implement the tests, we take the two closest-to-the-money call options and average their implied volatilities. If only one strike is available, we use that implied volatility. Calls on individual stocks generally have a higher trading volume and we average the IV to reduce any microstructure noise (e.g., stale quotes). This practice is common (e.g., the VIX index averages various strikes, see Whaley 2000). As noted in Bakshi, Kapadia, and Madan (2003), IV smiles for individual firms are very flat so the averaging of close-to-the-money strikes just reduces any noise in the option data. To test the increase prior to earnings we use a two week change in ATM IV and for the decrease after earnings we use the one day change. For the term structure tests, we use ATM options for the first two available maturities.

Table 2 reports the $p-$values of the Fisher and Wilcoxon tests for the three hypotheses. The tests reject all of the hypotheses at conventional levels of significance, with the only exceptions being for the first test, the increase in IV prior to earnings, for two firms, MXIM and QCOM. All other firms for all of the other tests reject the each of the null hypotheses. Such strong rejections are surprising given our relatively small sample size (28 earnings dates). The first test is the most likely to be noisy due to stochastic volatility as the standard deviation of two week changes is quite large.[15] We place little weight on the lack of rejection for MXIM and QCOM for the prior increase tests for a number of reasons:

[15] Even for these firms, volatility still tends to increase: it increases for 18 (16) of 28 announcements for QCOM (MXIM).

MXIM had the lowest volume in our sample; (although not reported) MXIM and QCOM had the highest bid-ask spread around earnings announcements over the sample, and the other two tests overwhelmingly reject the null hypothesis.

Overall, the results provide extremely strong statistical evidence that earnings announcements impact option prices. Option IV increases leading into earnings announcements, the term structure declines for the first two maturities, and IV decreases subsequent to the earnings announcement.

One potential concern is that, for the increase in IV and declining term structure of IV prior to earnings, as time-to-maturity decreases, option IV tends to increase. Patell and Wolfson (1981) find that this occurs in their sample, although the effect is largest in the final days of the option's life, but it is important to recall that their sample was from the 1970s. There are four reasons this is not a major concern. First, and most importantly, if the time-to-maturity effect is in the data, it would have a mixed impact on our tests. While it would bias the pre-earnings increase and term structure test towards rejection, it would have the *opposite* effect on the time series test subsequent to earnings, as the maturity bias would increase IV rather than decrease it. The fact that the time series test rejects for every single firm implies that this is not a particularly important feature.

Second, none of our conclusions change if you remove all options with a maturity of less than one week. For both individual firms and for the pooled data, the tests still overwhelmingly reject the null of no effect. Third, many of the firms with the lowest average time-to-maturity (INTC, MSFT, SUNW) are those with the highest volume implying that any liquidity effects (which could explain the Patell and Wolfson finding) in short-dated options will be minimal. Finally, the impact is the strongest in some firms like CSCO that have a relatively long time-to-maturity (nine days). Thus, time-to-maturity biases could not explain our results.

It is difficult to imagine an alternative to our explanation for the strong predictability in implied volatility. One potential explanation is Mahani and Poteshman (2005), who document that retail investors increase holdings of growth stocks prior to earnings dates. If supply is not perfectly elastic, increases in investor demand translate into increases in prices and IV (see also Garleanu, Pedersen, and Poteshman 2005). If, for some reason, retail investors were to sell their entire positions the following day (and there is no evidence for this), prices would similarly fall subsequent to the earnings announcement. Could the demand of retail investors generate the magnitudes observed in the data? For example, in

	Increase Prior to EAD		Term Structure at EAD		Decrease after EAD	
	Wilcoxon	Fisher	Wilcoxon	Fisher	Wilcoxon	Fisher
AAPL	4.5E-06	1.4E-05	2.1E-06	1.1E-07	1.9E-06	3.7E-09
ADBE	1.8E-06	5.6E-08	1.4E-06	5.6E-08	1.8E-06	8.1E-07
ALTR	2.1E-04	1.4E-05	3.6E-06	1.1E-07	2.9E-06	1.1E-07
AMAT	2.6E-06	1.1E-07	1.9E-06	3.7E-09	2.1E-06	1.1E-07
AMGN	0.0057	0.0436	1.9E-06	3.7E-09	4.1E-05	1.4E-05
CSCO	2.5E-05	2.8E-06	2.8E-06	7.5E-09	1.9E-06	3.7E-09
DELL	5.2E-04	9.0E-05	2.1E-06	1.1E-07	2.9E-06	1.1E-07
EMC	0.0034	0.0020	5.0E-05	7.6E-04	3.2E-04	4.6E-04
INTC	1.9E-06	3.7E-09	1.9E-06	3.7E-09	2.5E-05	1.1E-07
KLAC	0.0084	0.0436	4.5E-05	4.6E-04	0.0191	0.0063
MSFT	8.9E-05	2.5E-05	1.9E-06	3.7E-09	3.4E-05	1.4E-05
MU	0.0011	0.0019	1.5E-05	1.4E-05	8.4E-04	0.0019
MXIM	0.1997	0.2858	1.3E-05	9.0E-05	4.1E-04	9.0E-05
NVLS	3.8E-04	4.6E-04	3.3E-06	1.5E-06	3.8E-04	0.0019
ORCL	2.6E-05	4.0E-07	1.9E-06	3.7E-09	3.2E-04	4.6E-04
PMCS	0.0014	7.6E-04	2.8E-06	7.5E-09	4.4E-04	4.6E-04
PSFT	0.0017	4.6E-04	6.8E-06	1.5E-06	8.4E-06	1.4E-05
QCOM	0.0390	0.2122	6.6E-06	5.2E-06	5.0E-06	1.5E-06
SUNW	4.7E-06	4.0E-07	4.7E-06	4.0E-07	0.0012	7.6E-04
XLNX	2.5E-04	9.0E-05	2.6E-06	1.1E-07	9.4E-05	4.6E-04
Pooled	7.0E-56	2.4E-61	1.1E-87	3.5E-119	3.9E-67	3.3E-83

Table 2: Wilcoxon and Fisher nonparametric test p-values testing the increase in implied volatility in the two weeks prior to an earnings announcement, the decreasing term structure of implied volatility prior to the earnings announcements, and the decreases in implied volatility after the earnings announcement. The column labeled days gives the average number of days that our short dated option is from maturity.

the Intel example, could retail investor behavior generate the pattern in implied volatilities in the introduction, whereby the first two implied volatilities were 95 percent and 65 percent and the short-dated volatility falls to 55 percent?

We find it implausible that retail investors have this great of an impact for three reasons. First, returns on EADs are far more volatile than returns on other dates. This naturally leads to an increase in implied volatility. Second, retail investors make up a small portion of option market volume (about 10-15 percent according to Mahani and Poteshman 2005). Third, while net demand factors are statistically important, it is unlikely that they could explain the large movements in IV around earnings dates. The results in Bollen and Whaley (2004) indicate that net buying pressure of calls and puts significantly impacts changes in implied volatility, but Garleanu, Pedersen, and Poteshman (2005) find that the magnitude of the effect to be quite small. For the S&P 500 index, doubling open interest in a day increases IV by 1.8 percent, which is within bid-ask spreads and they find the impact is smaller for individual stocks.

3.2 Estimates from a Black-Scholes analysis

The previous section found that uncertainty surrounding earnings announcements had a statistically significant impact on IV and found support for the three main implications of jumps on EADs. In this section, we are interested in quantifying the uncertainty present in earnings by estimating $\sigma_j^{\mathbb{Q}}$ across time and across firms.

3.2.1 Jump volatility estimates

Tables 3 and Table 4 summarize the earnings jump volatility estimates for the term structure and time series estimators using the same data that was used in the previous section. For each firm, we report summary statistics of the estimates for each company over time (mean, median, quantiles, and fraction of total volatility explained). All numbers are in volatility units which is conservative due to Jensen's inequality.[16] We also report the

[16]In our setting, Jensen's inequality implies that the average of the standard deviations is less than the square root of the average variances since

$$\left(N^{-1}\sum_{j=1}^{N}\sigma_j\right)^2 < N^{-1}\sum_{j=1}^{N}\sigma_j^2.$$

number of dates on which the term structure or time series estimator was negative.

For the term structure estimator, Table 3 indicates that $\sigma_j^{\mathbb{Q}}$ is large, economically and statistically, consistent with the earlier nonparametric tests. The average jump volatility is 11.31 percent and the estimates indicate that the expected jump volatility can be very large: a jump volatility of 15 percent implies that an expected 3 standard deviation confidence band is ± 45 percent. One intuitive way to interpret the estimates is to compare them to the average daily volatility/variance (from Table 1) and compute the number of days of volatility/variance that the jump on an EADs generates. The jump generates, on average, about 3 days worth of volatility with a minimum of 2.2 for QCOM, KLAC and NVLS and a 3.6 for ADBE. The effect is drastically understated due to Jensen's inequality: in terms of variances, the results are more striking as earnings announcements generate 7.8 days worth of variance on average, with a low of 4.8 days for QCOM, NVLS and KLAC and a high of 13 days for ADBE. There are very few problematic dates on which we could not compute the term structure estimator: across firms and on average, about 1.5 out of 28 announcements did not have a declining term structure. Large, actively traded firms had fewer problem dates (DELL, INTC, CSCO, and ORCL had none). We will discuss the problem dates in greater detail below.

The large estimates of earnings jump volatility can easily explain the spikes in Figure 1. Consider the following example. Assume the annualized diffusive volatility is 60 percent, which implies the daily diffusive volatility is about 3.8 percent $(0.60/\sqrt{252})$. If the jump is 15 percent and there is an option expiring in one week, the annualized IV of the short-dated option is about 124 percent prior to the announcement and subsequently falls to 60 percent. In terms of option prices, consider an ATM call and straddle position with one-week to maturity ($\tau = 1/52$), an interest rate of five percent and $S_t = 25$. Prior to the announcement, the call and straddle were worth about \$1.72 and \$3.42, respectively, and, assuming the stock price did not change the following day, the prices after the announcement fell to \$0.84 and \$1.66, a 50 percent decrease due to the drop in implied volatility. If, however, the stock price fell 20 percent, then the ex-post prices would be \$0.0 and \$4.98, which shows the large and severe risks associated with writing options around EADs.

Table 4 provides the results for the time series estimator. Overall, the times series results are similar to the term structure results, although the time series estimator has a lower average and more problematic dates, which is consistent with the arguments in Appendix C.

Term	# Neg	Mean	Median	Std. Error	25%	75%	Av. Fraction
AAPL	1	12.44	11.66	0.72	9.80	14.11	79.86
ADBE	1	14.78	13.64	0.97	11.64	16.84	85.40
ALTR	1	12.41	10.81	0.97	10.26	12.85	72.12
AMAT	0	12.13	11.42	0.84	9.43	13.99	79.19
AMGN	0	7.15	6.80	0.45	5.55	8.37	57.23
CSCO	0	9.37	7.97	0.82	6.17	12.70	67.52
DELL	1	9.76	9.78	0.59	7.82	11.16	74.61
EMC	5	11.27	10.06	1.34	7.26	14.11	62.02
INTC	0	10.17	9.62	0.56	8.01	11.23	88.38
KLAC	5	10.53	10.09	0.88	7.03	12.99	63.05
MSFT	0	7.44	7.15	0.60	5.85	8.79	72.90
MU	3	13.88	11.77	1.32	8.24	18.13	65.98
MXIM	4	10.23	9.78	0.73	8.30	11.09	61.10
NVLS	2	10.41	8.99	1.06	7.57	14.00	59.31
ORCL	0	12.73	12.15	1.12	8.38	16.50	76.11
PMCS	0	14.57	14.46	1.12	11.23	16.64	66.85
PSFT	2	13.68	12.14	1.01	9.45	17.50	59.18
QCOM	2	9.30	9.92	0.81	6.61	12.20	51.65
SUNW	1	12.06	11.68	0.67	9.44	14.60	82.29
XLNX	1	11.85	11.74	0.92	8.31	15.01	70.56
Average	1.45	11.31	10.58	0.20	8.32	13.64	69.77

Table 3: 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.

Time	# Neg	Mean	Median	Std. Error	25%	75%	Av. Fraction
AAPL	0	9.25	8.91	0.74	6.40	11.31	50.61
ADBE	2	11.31	10.15	0.80	9.04	13.15	55.31
ALTR	1	8.90	9.48	0.89	5.64	11.05	50.28
AMAT	1	11.00	10.32	0.83	8.54	13.09	67.90
AMGN	3	6.41	5.58	0.66	4.62	7.76	48.37
CSCO	0	8.47	8.24	0.61	6.31	9.62	62.03
DELL	1	8.60	8.66	0.56	7.70	10.07	58.82
EMC	5	10.20	9.66	1.27	5.54	12.65	55.74
INTC	1	7.96	7.87	0.56	6.30	9.46	67.73
KLAC	7	7.10	6.12	0.86	3.91	9.83	37.49
MSFT	3	6.66	5.84	0.52	4.99	7.86	51.19
MU	6	10.75	9.34	1.36	8.16	12.78	47.29
MXIM	6	6.78	5.88	0.86	5.00	7.12	38.43
NVLS	6	8.46	7.53	0.98	5.80	11.47	44.24
ORCL	6	10.83	10.36	0.79	8.53	13.99	58.44
PMCS	5	10.09	10.28	0.99	5.84	14.32	39.05
PSFT	3	12.10	11.38	0.90	9.00	14.98	51.61
QCOM	2	9.47	8.64	0.83	6.59	12.66	48.44
SUNW	5	8.54	7.93	0.70	6.16	11.10	48.43
XLNX	5	9.07	9.61	0.81	6.12	11.11	44.62
Pooled	3.25	9.10	8.63	0.19	5.96	11.37	51.79

Table 4: 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.

Despite the additional noise in the time series estimator, the results are remarkably similar even though one uses ex-ante information and the other ex-post. The correlation between the mean estimates is 80.42 percent across firms and the correlation between the pooled observations is 71.69 percent. The high correlations indicate that both of the methods are capturing the same common effect.

For both metrics, we are occasionally unable to estimate the jump volatility as the term structure is not upward sloping or the IV increases after the announcement. Tables 3 and 4 indicate that, across firms, this occurs 1.45 and 3.25 times out of 28 announcements for the term structure and time series estimators, respectively. As mentioned above and discussed in Appendix C, we anticipate that the term structure estimator is more robust than the time series estimator and the relatively higher likelihood of problematic dates for the time series estimator is consistent with that argument.

We do not find these problem dates particularly surprising. To understand the source of this problem, we compiled some facts about the conditions when they occur. First, the problem occurred disproportionately when there was not an option available under one month and long-dated options were used. For example, for the term structure estimator, we were more than twice as likely to have a problematic date for maturities of more than one month as with options maturing in less than one month. Second, the vast majority of the problem dates occur for small, low volume, high volatility firms. For example, for the term structure estimator there was only one problem date for the five largest firms (CSCO, DELL, INTC, MSFT, and ORCL) while there were 17 (out of a total of 29) for just four firms (EMC, KLAC, MU, and MXIM) all of which are low volume, high volatility firms. The time series estimator has a similar pattern. To quantify this, the rank correlation (to take into account the discreteness of the problem dates) is about 0.5 (-0.5) between the rank of the number of problem dates and volatility (option volume).

Third, for the term structure estimator the volatility of close-to-close returns was 50 percent higher on days on which we could estimate $\sigma^{\mathbb{Q}}$ (8.83 versus 5.84 percent), implying that there was less earnings news on these days. This is particularly surprising given that the majority of the problem dates occurred for high volatility firms (e.g., KLAC, MU, NVLS). There was no overriding pattern for the time series estimator.

We have been able to identify a number of potential causes for the problem dates, some of which are not mutually exclusive. The most likely cause is that OptionMetrics uses close-price data, and close prices could suffer well-known problems such as stale quotes or nonsynchronous pricing. Battalio and Schultz (2004) document that virtually all of the put-call parity violations found in Ofek, Richardson, and Whitelaw (2004) using OptionMetrics data were apparently due to these factors. Using intradaily data, Battalio and Schultz (2004) find virtually no violations of put-call parity. Put-call parity implies that Black-Scholes implied volatilities should be equal and large differences in implied volatilities of same-strike options implies that there is an arbitrage. Anecdotally, we have some evidence that this is a significant source of the problematic dates.[17] Moreover, these data issues would likely be exacerbated for small, low volume, high volatility firms and for long-dated options.

Next, consistent with the arguments in the Appendix C, the time series estimator has more problems with highly volatile firms, as the shocks to V_t are larger. This is especially true for long-dated options. The time series estimator also relies on two dates worth of data, which could introduces additional sources of noise. For the term structure estimator, the problem dates tend to occur with longer maturity options and when subsequent returns were less volatile. If $\sigma^{\mathbb{Q}}$ was even slightly smaller on these days, the combination of close price issues, small firms (less liquid, larger spreads) and long-dated options could easily explain the problematic dates.

Finally, general model misspecification is another potential source. There are numerous other factors, outside of our model, that could have an important impact on implied volatility: stocks splits, mergers and acquisitions, mid-quarter updates, earnings warnings, or industry effects (correlation across firms). Many firms in the sample had multiple stock splits (DELL split six times) which results in spikes in IV (see Sheikh 1989). We do not have data on when the splits were announced so we are not able to account for this. Many

[17] The following example highlights the problem. On August 8, before market open, KLAC announced earnings and for this EAD, we were not able to compute either the term structure or time series estimator. KLAC closed at 22.875 the previous day and the closing implied volatilities (in percent) for the near-the-money strikes (in parentheses) were as follows: for the August expiration, the call implied volatilities were 48.21 (22.5) and 63.57 (25) and the put implied volatilities 83.54 (20) and 72.73 (22.5); for the September expiration, the call implied volatilities were 58.15 (22.5) and 54.99 (25) and the puts were 65.06 (20); 65.75 (22.5). The 22.5 call implied volatilities appear anomalous as they are much significantly lower than any of the other implied volatilities and generates a substantial violation of put-call parity. The term structure estimator, in this case, works fine with the 25 calls, the 22.5 puts, or the 25 puts. Moreover, the following day the implied volatility of the 22.5 August call increased, although the implied volatility of the 20 and 22.5 puts decreased, to 61.27 and 55.22, respectively, as expected (the 25 strikes didn't trade the following day). The bid-ask spread of the potentially problematic call option was also very large, more than 20 percent of the bid-price.

firms were also involved in major mergers and acquisitions which generate predictable behavior in IV (see Jayaraman, Mandelker, and Shastri 1991 and Subramanian 2004). If earnings are especially good or bad, firms will often pre-warn a couple of weeks prior to the earnings date. This eliminates much of the uncertainty and can easily result in either very small or negative jump variance estimates. Unfortunately, we have not been able to find a reliable source of data on pre-scheduled mid-quarter updates or earnings warnings. Similarly, since many of the firms are in similar industries (semi-conductors, computers, software, etc.), there is occasionally an industry effect. For example, an industry leader such as Intel announces poor earnings and the IV of other semi-conductor companies in our sample (ALTR, MXIM, NVLS, KLAC, AMAT, PMCS, and/or XLNX) moves. This, not surprisingly, indicates that there is a strong industry common component in earnings.

3.2.2 Case study: Cisco

In order to better understand the estimators, we provide a brief case study of CSCO, one of the largest firms which had no problem dates for either the term structure or time series estimator. This is due to the high liquidity of CSCO and the fact that CSCO always announced earnings two weeks prior to option exercise. A case study allows us to highlights the levels and movements in IV around earnings dates.

Tables 5 provides implied volatilities and jump estimates for CSCO: the first two columns contain IV for the first two available maturities; the third column contains the term structure estimator, the fourth contains IV of the short-dated option one day after earnings were announced, and final column contains the time series estimates. On August 4th, 1998, OptionMetrics did not report implied volatilities for options maturing in September or later, which explains why we were not able to provide a term structure estimator, thus the 'NaN'.[18]

The first notable result is that the estimators are highly correlated, over 80 percent. For more than half of the dates, the difference is less than 1.5 percent. For example, the largest estimated jump volatility was in August 2002 where the term structure estimate was 20.48 percent compared to the time series estimate of 19.53 percent. Many of the

[18]This situation, where there were no long-dated option implied volatilities, happened only seven times in our sample. In many cases, however, a single maturity had no reported option implied, which causes us to move to longer-dated contracts.

EAD	$IV_1(t)$	$IV_2(t)$	Term	$IV_1(t+1)$	Time Series
02/08/1996	59.74	50.74	6.04	41.39	7.18
05/09/1996	56.98	40.58	7.15	27.85	8.29
08/15/1996	47.46	44.84	10.22	45.25	4.69
11/05/1996	56.33	43.10	7.47	40.74	7.35
02/04/1997	61.27	48.32	10.23	57.44	5.03
05/06/1997	77.99	51.11	12.25	58.26	9.80
08/05/1997	55.06	44.74	6.07	38.07	7.52
11/04/1997	46.06	40.82	5.98	35.75	6.84
02/03/1998	46.98	38.96	6.97	38.32	6.41
05/05/1998	45.43	39.08	5.14	31.31	6.22
08/04/1998	50.83	NaN	NaN	41.99	6.75
11/04/1998	43.62	42.82	3.69	36.16	5.54
02/02/1999	63.41	59.86	4.88	49.95	9.21
05/11/1999	50.33	49.08	2.41	42.12	5.21
08/10/1999	59.96	49.46	6.71	39.38	8.54
11/09/1999	57.45	42.62	7.97	36.00	8.46
02/08/2000	54.04	44.95	6.46	47.30	4.94
05/09/2000	90.78	66.28	12.85	79.77	8.19
08/08/2000	66.34	54.02	8.24	46.85	8.88
11/06/2000	89.53	63.73	14.21	62.37	12.79
02/06/2001	89.42	64.40	13.78	77.00	8.59
05/08/2001	98.07	76.25	13.32	81.61	10.28
08/07/2001	80.37	61.75	11.07	62.06	9.65
11/05/2001	81.39	63.60	11.29	65.60	9.60
02/06/2002	67.34	53.23	7.73	60.53	5.26
05/07/2002	88.37	58.45	13.47	57.62	12.66
08/06/2002	120.08	72.85	20.48	61.12	19.53
11/06/2002	68.13	62.30	16.83	56.40	13.83

Table 5: Cisco earnings announcement jump estimates. The first two columns provide the implied volatility of the two shortest maturity option contracts, the third provides the term structure estimator of σ_j^Q, the fourth provides the implied volatility of the shortest dated option the day following earnings, and the final the time series estimator of σ_j^Q.

largest differentials occurred when the term structure estimate was rather small (February, May, and August 1999) which is consistent with the arguments in Appendix C.

These estimates are even more reasonable once bid-ask spreads and stochastic volatility are taken into account. In terms of bid-ask spreads, average bid-ask spreads for the short-dated CSCO option around earnings dates were about $0.10 for the short–dated option and $0.15 to $0.20 for the second and third maturity cycles. This translates into about five percent in terms of Black-Scholes IV and increasing or decreasing Black-Scholes IV in this amount alters the estimates of $\sigma_j^{\mathbb{Q}}$ by roughly 1.5 percent. Thus the estimates are in many cases within bid-ask spread differentials. If, in addition, we take into account the impact of stochastic volatility (Appendix C), it would not be unreasonable to see time series estimates of $\sigma_j^{\mathbb{Q}}$ be one or two percent below the term structure estimates. Overall, the results point to a very strong and consistent impact.

3.2.3 Risk premia, time variation, and specification

Given the estimates of $\sigma_j^{\mathbb{Q}}$, we can investigate a number of interesting implications regarding jumps on EADs. In this section, we examine the evidence regarding risk premia, time-variation in the jump volatilities, the informational content of the jump-volatility estimates, and model specification.

First, we use the ex-ante estimated jump volatilities, combined with the realized returns to examine risk premia attached to jump means and jump variances. Our model assumes that jumps to continuous-compounded returns under the $\mathbb{Q}$-measure are normally distributed with a volatility of $\sigma_j^{\mathbb{Q}}$, but does not place any restrictions on the behavior under the objective measure. If we assume that the functional form of the distribution remains normal under $\mathbb{P}$, then a mean jump risk premia would imply that the mean sizes of the jumps under $\mathbb{P}$ are positive. Similarly, if there is risk premium attached the volatility of jump sizes, we would expect that $\sigma_j^{\mathbb{Q}} > \sigma_j^{\mathbb{P}}$.

To analyze these issues, we use equity returns for the day after the earnings announcement. Table 4 show that the observed returns can be quite large, as measured by the minimum and maximum, and are very volatile (the column 'P-vol' gives the realized volatility). We first examine the issue of a mean-jump risk premia. Unlike a jump-mean risk premium for randomly-timed jumps, which appears in the form of a negative risk-neutral mean jump sizes, the risk-neutral mean jump sizes are constrained under $\mathbb{Q}$. Therefore, to analyze a

	Min	Max	Q-vol	P-vol	Ratio	Skew	Kurt.	t-stat	K-S	J-B
AAPL	-18.84	21.27	12.95	9.05	1.43	0.44	2.90	0.18	0.65	0.84
ADBE	-14.29	14.01	15.23	7.63	2.00	-0.88	3.31	1.63	0.03	0.35
ALTR	-22.47	16.79	13.11	8.47	1.55	-0.32	4.60	0.20	0.85	0.88
AMAT	-9.78	18.82	12.74	6.51	1.96	0.70	4.01	1.99	0.21	0.52
AMGN	-14.40	12.29	7.68	5.88	1.30	-0.66	2.57	1.15	0.24	0.41
CSCO	-14.05	21.82	9.91	6.90	1.44	0.23	2.75	1.20	0.25	0.16
DELL	-21.00	10.98	10.28	7.56	1.36	0.09	1.84	-0.51	0.23	0.63
EMC	-18.22	15.51	11.90	8.52	1.40	0.30	3.31	1.20	0.14	0.60
INTC	-19.89	18.33	10.49	7.43	1.41	0.32	2.99	-0.04	0.65	0.68
KLAC	-18.62	13.18	11.49	7.23	1.59	-0.23	2.24	0.25	0.69	0.65
MSFT	-16.96	17.87	7.86	6.86	1.15	-1.36	5.97	-0.38	0.92	0.87
MU	-26.19	13.15	14.55	9.05	1.61	-0.17	2.21	-2.74*	0.18	0.70
MXIM	-30.31	10.60	10.93	7.69	1.42	-1.36	7.04	-1.73	0.06	0.00
NVLS	-35.05	23.98	11.47	11.21	1.02	-1.41	6.22	-0.06	0.61	0.02
ORCL	-34.46	27.07	13.21	12.29	1.08	-2.37	10.44	-0.70	0.49	0.25
PMCS	-25.90	21.13	15.46	11.52	1.34	-0.72	3.29	2.10*	0.02	0.29
PSFT	-26.53	22.92	14.43	12.24	1.18	-1.62	6.77	-0.13	0.58	0.72
QCOM	-17.34	32.72	10.12	10.21	0.99	1.07	5.11	1.25	0.33	0.17
SUNW	-31.09	9.49	12.52	8.53	1.47	-0.87	3.16	-0.82	0.49	0.00
XLNX	-13.67	12.77	12.63	7.37	1.71	-0.01	2.01	-1.40	0.38	0.47
Pooled	-21.45	17.74	11.95	8.61	1.34	-0.44	4.14	0.13	0.40	0.46

Table 6: 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 the t-statistic for a zero mean and p-values for the Kolmogorov-Smirnov and Jarque-Bera tests for normality, respectively. A '*' indicates significance at the five percent. For the $t-$test, we use the exact t-distribution to obtain critical values.

mean-jump risk premium, we have to estimate the mean under the objective measure. The column labeled '$t-$stat' provide the t-statistics for the return means and there is little evidence for any premia in average returns, in the sense that one cannot reject the hypothesis that the mean return the day after the announcement is zero.[19] Ten firms have positive means, ten firms have negative means and there are two firms (MU and PMCS) for which there is some evidence of a non-zero mean. For these firms, the statistic is only marginally significant (just under the five percent level) and the mean estimates are of different signs. Since we are using small samples of noisy return data, it would be difficult to statistically identify a jump-mean risk premium even if it were present. Overall, we conclude there is no evidence for jump-mean risk premia.

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 $\mathbb{Q}$. To do this, we compute the expected volatility under $\mathbb{Q}$ (denoted as 'Q-vol') from the options data and the realized volatility under $\mathbb{P}$ ('P-vol') from returns. To formally analyze this, we perform a one-sided test of the hypothesis that $\sigma_j^{\mathbb{Q}} = \sigma_j^{\mathbb{P}}$ against the alternative that $\sigma_j^{\mathbb{Q}} > \sigma_j^{\mathbb{P}}$. We can reject the null of equality for the pooled data and all firms except for MSFT, NVLS, ORCL, PSFT, and QCOM. For these firms, the differences between $\mathbb{Q}$-volatility and $\mathbb{P}$-volatility are still positive (except for QCOM), but not statistically different. In no case can we reject the null that $\sigma_j^{\mathbb{Q}} > \sigma_j^{\mathbb{P}}$. The magnitudes can be quite large as $\mathbb{Q}$-volatility is much greater than the $\mathbb{P}$-volatility for many firms: for CSCO, DELL, and INTC, $\mathbb{Q}$-volatility is around 40 percent higher than $\mathbb{P}$-volatility. This implies that there is evidence for a jump-volatility risk premium. Broadie, Chernov, and Johannes (2005) find evidence for a jump-volatility risk premium in S&P 500 index options.

To place some economic significance on the jump-volatility risk premium, consider option prices on an underlying stock with $\sigma = 0.50$, $S_t = 25$, and $\sigma_j^{\mathbb{P}} = 0.10$. The dollar value of a one-week ATM call option and straddle position assuming $\sigma_j^{\mathbb{Q}} = 0.10$ is 1.22 and 2.42, respectively. If we assume that $\sigma_j^{\mathbb{Q}} = 1.25\sigma_j^{\mathbb{P}}$, then the value of the call and straddle increase to 1.44 and 2.85, respectively, increases of about 17 percent. Clearly, this is an economically significant risk premium.[20]

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

[20] This large premium is even more surprising given the fact that there does not appear to be a large jump or volatility risk premium embedded in individual equity options as measured by the difference between implied and realized volatility across longer periods of time, see, e.g., Carr and Wu (2005) or Driessen,

As a comparison, consider the risk premiums embedded in S&P 500 options. For example, typical estimates of the objective measure mean $\left(\mu^{\mathbb{P}}\right)$and volatility $\left(\sigma^{\mathbb{P}}\right)$ of jump sizes are around minus two to minus four percent and three to five percent (see, Andersen, Benzoni, and Lund 2001 or Eraker, Johannes, and Polson 2003), based on the time series of returns. Broadie, Chernov and Johannes (2005) 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.

It is important to note that while we can estimate $\sigma_j^{\mathbb{Q}}$ accurately from options, the average return volatility is based on a relatively small time series sample. Our results indicate that options market participants expected very large movements, which were not fully realized. This raises the potential for Peso-type problems, whereby the lack of large observed return moves is in part due to the small sample. Future earnings announcements may generate very large movements, and it is important to recognize that this could be partially responsible for the large risk premia that we find.

Given that caveat, there are a number of economic mechanisms that could generate a significant jump-volatility risk premium. First, if an individual firm's earnings contain a systematic component, then the risk embedded in this systematic component could command a premium. It is certainly true that the earnings of many of the larger firms in our sample (for example, INTC, MSFT, and DELL) are highly correlated with overall economic activity. Second, in our model, jumps cannot be perfectly hedged and the risk premium could compensate option writers for their inability to hedge the earnings announcement jump. The demand-based arguments in Bollen and Whaley (2004) or Garleanu, Pedersen, and Poteshman (2005) indicate that a combination of demand pressure and unhedgeable risks could create excess option-implied volatility. One factor mitigating both of these explanations is the potential for option writers to diversify this risk away, by writing options across many different firms.

The previous results indicate that $\mathbb{Q}$-volatility is greater than the $\mathbb{P}$-volatility. Another related issue 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

Maenhout, and Vilkov (2005).

estimate $\sigma_j^{\mathbb{P}}$ based on a single observation occurring after an earnings announcement.[21] We focus on 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 Q-vol and P-vol) is about 54 percent, 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.

Next, we investigate some general specification issues. If we let $r_{\tau_j+1} = \log\left(S_{\tau_j+1}/S_{\tau_j-}\right)$ be the return on the day after the announcement, then the standardized returns,

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

should be normally distributed. Both $\sigma_j^{\mathbb{Q}}$ and σ are estimated from options. Due to the jump-volatility risk premium, the $J_{\tau_{j+1}}$'s may not be unit variance. To investigate non-normalities, we report the skewness and kurtosis statistics, as well as the p-values for the Kolmogorov-Smirnov and Jarque-Bera tests. The first two columns indicate that while earnings announcements result in very large movements, there is little evidence of non-normalities. The skewness and excess kurtosis statistics indicate that any departures from normality are modest. As formal tests of non-normalities, we consider the Kolmogorov-Smirnov and Jarque-Bera tests. The Kolmogorov-Smirnov and Jarque-Bera tests find significant departures from normality for one and three firms, respectively, but interestingly, there is no overlap of the firms they identify. This is likely due to the relatively short time series sample for which option price data is available. This evidence is reassuring as there is no statistical evidence that the jumps come from a non-normal distribution.

Finally, we note that there is an interesting time-variation in the jump volatilities. 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 25 percent higher than the other years. 2000 and 2001 were clearly years of high earnings uncertainty.

[21]The pooled correlation between absolute returns and $\sigma_j^{\mathbb{Q}}$ is around 22%, indicating at least a positive relationship.

Year	1996	1997	1998	1999	2000	2001	2002
AAPL	11.07	11.82	12.57	10.73	16.21	13.67	11.35
ADBE	15.37	14.61	12.90	14.52	17.92	16.61	11.69
ALTR	11.21	10.34	11.05	13.40	15.32	14.11	11.26
AMAT	15.10	14.51	9.98	11.72	14.31	10.76	8.54
AMGN	8.54	5.91	5.66	7.44	9.87	6.58	6.07
CSCO	7.72	8.63	5.26	5.49	10.44	12.37	14.63
DELL	9.92	8.85	9.59	12.11	10.11	9.83	7.88
EMC	10.70	18.09	8.54	6.32	7.48	13.24	12.73
INTC	9.41	9.30	8.21	9.93	10.61	12.00	11.71
KLAC	8.39	8.28	14.16	9.74	11.14	10.29	11.56
MSFT	7.84	6.81	5.80	5.77	8.35	7.83	9.72
MU	13.98	10.75	11.16	11.74	24.99	10.68	15.41
MXIM	13.70	7.12	9.70	9.72	9.89	10.21	9.47
NVLS	10.91	7.75	7.14	6.08	13.45	14.34	11.27
ORCL	7.28	6.89	12.53	14.37	16.48	17.33	14.24
PMCS	15.78	13.35	12.57	13.23	14.11	20.67	11.52
PSFT	10.83	13.38	7.94	12.90	15.16	18.20	16.45
QCOM	6.15	8.66	6.85	8.77	15.94	9.49	10.99
SUNW	10.31	14.44	9.38	9.78	12.15	14.86	14.14
XLNX	8.79	13.41	8.63	11.53	9.81	15.56	14.44
Pooled Av	10.76	10.72	9.46	10.39	13.00	12.90	11.72
Pooled Std	0.50	0.53	0.46	0.44	0.74	0.57	0.53

Table 7: 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.

This time-variation is related to work of Pastor and Veronesi (2005). 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., their Figure 8). We also find that uncertainty over fundamentals, as measured by $\sigma_j^{\mathbb{Q}}$, was higher during these years, although the magnitude was smaller than the magnitude found in Pastor and Veronesi (2005).

3.3 Stochastic volatility models with deterministic jumps

The results in the previous section assume that diffusive volatility is 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. A stochastic volatility model (with constant parameters) allows us to impose a consistent model across dates, strikes, and time-to-maturity. Implicitly, in the analysis based on our extension of Black-Scholes, we placed no constraints on the speed of mean-reversion or the long-run level of V_t.

Our primary interest in estimating stochastic volatility models is quantifying the pricing improvements from incorporating jumps on earnings dates.[22] Intuitively, a pure SV model will have difficulty in fitting short and long-dated options around earnings. The data imply that short-dated options have a very high volatility, while the long-dated options have much lower implied volatility. This suggests that the SV model will have difficulty matching this with essentially one degree of freedom, V_t, and will instead underprice short-dated options and overprice long-dated options. Jumps on EADs will release this tension.

We use the entire time series of ATM call options from 1996 through 2002 to estimate the model. We use multiple maturities and the closest to-the-money call option for each maturity. In a stochastic volatility model, a short maturity ATM option provides information on V_t and the long-dated options provide information on the risk-neutral parameters.

[22] Although common in the literature, we do not perform an out-of-sample pricing exercise. As noted in Bates (2003), these tests, in general, are not particularly 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). In our setting, out-of-sample exercises are more difficult due to the time-heterogeneity: since $\sigma_j^{\mathbb{Q}}$ varies across earnings dates, an out-of-sample test would require estimating this parameter in addition to V_t.

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.[23] 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), MCMC (Eraker 2004), or the approximate MLE approach of Aït-Sahalia and Kimmel (2005). These approaches are 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 one per day).

To describe our approach, let $C\left(S_t, V_t, \Theta^{\mathbb{Q}}, \sigma^{\mathbb{Q}}_{\tau_n}, \tau_n, K_n\right)$ denote the model implied price of a call option struck at K_n and maturing in τ_n days, where $\Theta^{\mathbb{Q}} = \left(\kappa^{\mathbb{Q}}, \theta^{\mathbb{Q}}, \sigma_v, \rho\right)$ and $\sigma^{\mathbb{Q}}_{\tau_n} = \left\{\sigma^{\mathbb{Q}}_j : t < j < t+\tau_n\right\}$. We maximize the objective function

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

where $C^{Mar}\left(t,\tau_n,K_n\right)$ 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 weighs long-dated options more than short-dated options, as long-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 long-dated options. Alternatives would include minimizing IV deviations or percentage pricing errors. We experimented with percentage pricing errors and found the differences were generally small.

We initially tried to estimate ρ, however, it is not possible to identify this parameter

[23] We 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.

based on ATM options as it does not have a significant impact on option prices.[24] 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 EADs. This, along with the requirement that the parameters be constant through the sample, makes the optimization problem computationally burdensome. For robustness, we start the optimization from numerous different starting values on multiple machines and randomly perturb the variance and parameters in order to ensure that the algorithm efficiently searches. Due to these computational burdens, we only consider five companies, APPL, AMGN, CSCO, INTC, and MSFT. The three largest and most actively traded companies are CSCO, INTC and MSFT and then we chose one company with small average jump sizes (AMGN) and one with large average jump sizes (AAPL).

3.4 Estimation Results

Estimation results for the five companies are in Tables 8, 9, and 10. Table 8 provides parameter estimates, standard errors based on a normal likelihood function, and log-likelihood function values for the SV model and the extension with jumps on earnings dates (SVEJ). 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 all models and firms, the Feller condition holds under $\mathbb{Q}$, which implies that risk-neutral volatility is well behaved.[25] For both models, the estimates of $\kappa_v^{\mathbb{Q}}$ are similar, in the range of two to three. While these values are low relative to those obtained for index options, which implies that individual

[24] To 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 are estimated, it is not identified based on at-the-money options.

[25] For certain models, Pan (2002) and Jones (2003) find evidence for explosive risk-neutral volatility for equity indices.

		κ_v^Q	θ_v^Q	$\sqrt{\theta_v}$	σ_v	σ_e	σ^Q	$L(\Theta, V_t)/NT$
	SV	2.4633	0.2694	0.5190	0.1131	0.0047	—	3.9420
AAPL		0.0456	0.0168	0.0162	1.5002	0.0018	—	
	SVEJ	1.7422	0.2401	0.4900	0.0773	0.0037	0.0848	4.1919
		0.0477	0.0286	0.0292	2.7094	0.0023	0.0023	
	SV	2.0358	0.1302	0.3608	0.0314	0.0031	—	4.3645
AMGN		0.0310	0.0194	0.0268	5.0163	0.0018	—	
	SVEJ	2.0697	0.1304	0.3611	0.0623	0.0030	0.0423	4.4035
		0.0299	0.0037	0.0052	0.5592	0.0019	0.0112	
	SV	3.3760	0.2122	0.4606	0.1152	0.0034	—	4.2652
CSCO		0.0355	0.0110	0.0120	1.4775	0.0021	—	
	SVEJ	3.1316	0.2025	0.4500	0.1015	0.0028	0.0708	4.4575
		0.0322	0.0094	0.0104	1.3540	0.0020	0.0036	
	SV	2.7635	0.1240	0.3522	0.0953	0.0032	—	4.3266
INTC		0.0360	0.0164	0.0233	1.9713	0.0011		
	SVEJ	2.2625	0.1042	0.3228	0.1322	0.0026	0.0599	4.5356
		0.0335	0.0139	0.0216	1.0560	0.0014	0.0016	
	SV	3.2897	0.1268	0.3560	0.0260	0.0025		4.5787
MSFT		0.0421	0.0062	0.0087	3.5977	0.0008		
	SVEJ	2.9954	.1225	0.2500	0.0710	0.0022	0.0391	4.6949
		0.0389	0.0056	0.0081	1.0973	0.0013	0.0041	

Table 8: 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_ε are multiplied by 100.

stock volatility is more persistent, this could be strongly influenced by the sample period (our sample does not include the Crash of 1987). The estimates of $\theta_v^{\mathbb{Q}}$ imply plausible values for the long-run mean of volatility, $\sqrt{\theta_v^{\mathbb{Q}}}$ (we report standard errors via the delta method). The long-run volatility tends to falls in the SVEJ model. 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: the standard errors are an order of magnitude larger than the estimate. This is not surprising as we only use near-the-money options and do not incorporate the time series of volatilities. ATM option prices are driven primarily by expected future volatility and from (2) it is clear that this parameter does not affect expected future volatility. The parameter σ_v can most easily be identified by the time series of implied volatilities and to a some extent from out-of-the-money options. 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 8 provides the average estimate of $\sigma_j^{\mathbb{Q}}$, denoted $\sigma^{\mathbb{Q}}$, for each firm with the average standard error reported below. To frame the results, recall that the average jump volatility for AAPL, AMGN, CSCO, INTC and MSFT based on the term structure estimator was 8.48, 4.23, 7.08, 5.99 and 3.91, respectively, compared to 12.44, 7.15, 9.37, 10.17, and 7.44 percent for the same firms. The results are similar, although the jump sizes based on the full estimation are lower. For AMGN, a biotech company, it is not surprising they have low uncertainty in earnings as their earnings are driven by drugs whose sales and regulatory status are typically announced outside of earnings.

There are three reasons why the estimates of $\sigma_j^{\mathbb{Q}}$ differ. First, in the Black-Scholes model, a number of earnings dates result in zero jump volatility estimates. In the stochastic volatility model, this does not happen for any of the earnings dates, although some are quite 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 contained in all options that are affected by earnings announcement jumps. This means that on each day at least three options are affected 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.

Table 10 provides the dollar pricing errors for the days surrounding an earnings announcement. For each model, we report pricing errors for short maturity options (five 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, '+1' is the day after the announcement for AMC announcements (and the day of the announcement for BMO announcements). 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.

For all of the firms, there is a significant pricing difference between the SV and SVEJ 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 CSCO and INTC and smallest for AMGN and MSFT, which have relatively small jump sizes. As an example, the mean-absolute pricing errors for short-dated CSCO options fall in the three days leading up to the earnings announcement from 0.2759, 0.4301 and 0.3776 in the SV model to 0.0934, 0.1902, and 0.1642 in the SVEJ model. For most firms and days, there is also a noticeable improvement in the pricing of the long-dated options.

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 SVEJ 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 SVEJ models perform similarly for the day after the announcement, although again there is a modest improvement in the SVEJ model.

Table 10 provides mean and mean absolute pricing errors for the entire sample. There is clearly a substantial pricing improvement for all of the firms and for all of the maturities, with the exception of Amgen. Also note that the mean errors are generally positive for

			-5	-4	-3	-2	-1	0	+1
	Short	SV	0.3574	0.3986	0.3385	0.4729	0.6198	1.0768	—
		SVEJ	0.1225	0.1573	0.1713	0.1897	0.1588	0.4536	—
AAPL	Med	SV	0.3249	0.3140	0.3094	0.3264	0.3152	0.3375	0.1597
		SVEJ	0.1085	0.0855	0.1063	0.1113	0.0952	0.1094	0.1068
	Long	SV	0.2706	0.3014	0.2786	0.2734	0.2643	0.2872	0.2862
		SVEJ	0.0811	0.0893	0.0683	0.0967	0.0815	0.1144	0.0762
	Short	SV	0.2041	0.2244	0.2357	0.2442	0.5397	0.7788	—
		SVEJ	0.1978	0.1546	0.1474	0.1262	0.3297	0.5875	—
AMGN	Med	SV	0.1187	0.1051	0.1330	0.1427	0.1348	0.1525	0.1160
		SVEJ	0.1310	0.1219	0.1590	0.1617	0.1533	0.1655	0.1349
	Long	SV	0.1065	0.0948	0.1188	0.1004	0.1135	0.1128	0.0906
		SVEJ	0.0955	0.0856	0.1170	0.1043	0.1153	0.1209	0.1214
	Short	SV	0.2504	0.2826	0.3200	0.2759	0.4301	0.3776	0.1197
		SVEJ	0.1070	0.1061	0.1009	0.0934	0.1902	0.1642	0.1345
CSCO	Med	SV	0.0946	0.0988	0.0944	0.0955	0.0721	0.0612	0.0561
		SVEJ	0.0887	0.0784	0.0755	0.0728	0.0557	0.0546	0.1020
	Long	SV	0.1003	0.1107	0.1027	0.1125	0.1814	0.1737	0.0866
		SVEJ	0.0703	0.0700	0.0496	0.0576	0.0820	0.0787	0.1841
	Short	SV	0.3683	0.4001	0.4057	0.4343	0.8153	1.1573	0.3123
		SVEJ	0.1468	0.1905	0.1705	0.1973	0.4234	0.6847	0.3731
INTC	Med	SV	0.0715	0.0816	0.1031	0.0955	0.1152	0.1036	0.0992
		SVEJ	0.0699	0.0680	0.0991	0.0837	0.1041	0.0966	0.1867
	Long	SV	0.1602	0.1797	0.1926	0.1774	0.2655	0.3389	0.1017
		SVEJ	0.0775	0.1043	0.1039	0.0993	0.1495	0.1974	0.0929
	Short	SV	0.2223	0.2161	0.4711	0.6386	1.0440	—	—
		SVEJ	0.1997	0.2037	0.2706	0.3397	0.6696	—	—
MSFT	Med	SV	0.1031	0.1222	0.1150	0.1373	0.1758	0.2344	0.1597
		SVEJ	0.1103	0.1213	0.1217	0.1320	0.1558	0.1943	0.1858
	Long	SV	0.1415	0.1523	0.1836	0.1806	0.2444	0.1578	0.1099
		SVEJ	0.0958	0.1115	0.1258	0.1269	0.1900	0.1357	0.1415

Table 9: 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	$3 < \tau < 15$		$16 < \tau < 35$		$\tau > 35$	
		MAE	ME	MAE	ME	MAE	ME
AAPL	SV	0.1826	0.0217	0.1051	-0.0186	0.0952	0.0082
	SVEJ	0.1334	-0.0009	0.0922	0.0088	0.0769	-0.0026
AMGN	SV	0.1717	0.0138	0.1373	-0.0014	0.1202	-0.0001
	SVEJ	0.1680	0.0321	0.1333	0.0006	0.1175	0.0029
CSCO	SV	0.1751	0.0296	0.1293	0.0233	0.1118	-0.0179
	SVEJ	0.1375	0.0264	0.1093	0.0132	0.0968	-0.0050
INTC	SV	0.2380	0.1153	0.1218	-0.0304	0.1221	-0.0045
	SVEJ	0.1872	0.0837	0.1037	-0.0001	0.0948	-0.0126
MSFT	SV	0.2171	-0.0143	0.1401	-0.0143	0.1338	0.0030
	SVEJ	0.1938	-0.0033	0.1386	-0.0033	0.1251	0.0008

Table 10: Overall mean absolute pricing errors broken down by firm and maturity.

short-dated options and negative for long-dated options, which indicates the SV model underprices short-dated options and over-pricing of long-dated options. These large improvements are somewhat surprising given that earnings announcements occur only four times per year. 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 ATM options across the maturity spectrum.

4 Conclusions

In this paper, we develop models incorporating earnings announcements for pricing options and for learning about the uncertainty embedded in an individual firm's earnings announcement. We take seriously the timing of earnings announcements and develop a model and pricing approach incorporating jumps on EADs. Jumps on EADs 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 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 EADs is extremely important for pricing options. Models without jumps on EADs 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.

There are a number of interesting extensions First, we are interested in the empirical content of $\sigma_j^{\mathbb{Q}}$ in comparison to other measures of earnings uncertainty such as firm age, analyst dispersion, or analyst coverage. Our measure provides a market-based alternative to these existing measures. Second, we are interested in understanding the ex-ante information in macroeconomic announcements. Ederington and Lee (1996) and Beber and Brandt (2004) document a strong decrease in IV subsequent to major macroeconomic announcements, which is the same effect we document for earnings announcements. It would be interesting to estimate the bond-market jump uncertainty ex-ante, and understand how it varies over the business cycle. We leave these issues for future research.

A Close/open and open/close behavior

We assume that an earnings announcement results in a discontinuity in the sample path of stock prices when the earnings are released. An alternative assumption is that the diffusion coefficient increases on days following earnings announcements, as in Patell and Wolfson (1979, 1981). Thus, the main difference between our model and Patell and Wolfson's model is the discontinuity of the sample path. In theory, prices are observed continuously and jumps are observed at $\Delta S_t = S_t - S_{t-}$. With discretely sampled prices, it is impossible to identify when jumps occurred with certainty and it is common to use statistical methods (see, e.g., Johannes 2004, Barndorff-Nielson and Shephard 2006, or Huang and Tauchen 2005). Identifying jumps on EADs is even more difficult in our setting as earnings are announced outside of normal trading hours.[26]

Since it is impossible to ascertain with discretely sampled prices whether or not there is a jump, we consider the following intuitive metric. Strictly speaking, there will almost always be a "jump" from close-to-open, as the opening price is rarely equal to the close price. For example, there are many events that could cause relatively minor overnight movements in equity prices and result in a non-zero close-to-open movement: movements of related equity and bond markets (e.g., Europe and Japan), macroeconomic announcements such employment or inflation (typically announced at 8:30 a.m. EST, an hour before the formal market open), or earnings announcements of related firms to name a few. The main difference, however, is that if our assumption of a jump on earnings dates is true, the magnitude of the moves should be much bigger for earnings dates versus non-earnings dates. Statistically, the movements should appear as outliers.

To analyze this issue, we compare the standard deviation of close-to-open to returns on announcement and non-announcement days over our sample. Table (11) provides the standard deviation of close-to-open and open-to-close returns for earnings and non-earnings dates and the ratios comparing earnings and non-earnings dates. Note first that the results indicate that the close-to-open returns on earnings dates are, on average, about 3.3 times more volatile. An F-test for equal variances is rejected against the one-sided alternative in every case at the one-percent critical level. For example, average volatility of close-to-open

[26] There is relatively little known about the behavior of after-hour prices. Barclay and Hendershott (2003, 2004) argue that, relative to normal trading hours, prices are less efficient as bid-ask spreads are much larger, there are more frequent price reversals, and generally noisier in post close or pre-open trading.

returns on earnings days was 6.55 percent compared to 1.98 percent on non-earnings dates. Since we usually identify outliers as movements greater than three standard deviations, this is clear evidence of abnormal or jump behavior. The effect is strongest for the largest firms: if we consider the five largest firms in terms of option volume, the standard deviation of close-to-open returns is over 7.1 percent on earnings days compared to 1.7 percent for non-earnings days, for a ratio of greater than four.

Second, note that open-to-close returns are slightly more volatile on earnings dates than non-earnings dates, on average 4.8 percent compared to 3.7 percent which indicates that returns are slightly more volatile during the day following earnings. However, if you look at the five largest firms, the difference is much smaller: the volatility during the day is 3.22 (2.96) percent on earnings (non-earnings) dates, indicating the volatility is quite similar (ratio of about 1.1). In contrast, the smallest firms are relatively more volatile during the day, 6.0 percent compared to 4.32 percent for a ratio of 1.4. The obvious explanation for the difference between the higher and lower-volume companies is liquidity, which could be exacerbated by opening features on the NASDAQ market. Barclay, Hendershott, and Jones (2004) argue that the Nasdaq opening procedure introduces more noise than the opening procedure on the NYSE.

Overall, the results are consistent with our assumption that the response of the stock price to an earnings announcement is (a) an abnormally large movement and (b) largely captured by the close-to-open returns as close-to-open returns are more than three times more volatile on earnings compared to non-earnings days.

B Transform analysis

This appendix provides the details of computing the option transforms. First, to price options, we need to evaluate the conditional transform of $log\left(S_T\right)$. By the affine structure of the problem, we have that for a complex valued c,

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

	EAD Close/open	Non-EAD Close/open	Ratio	EAD Open/Close	Non-Ead Open/Close	Ratio
AAPL	7.68%	2.33%	3.29	3.58%	3.31%	1.08
ADBE	6.43%	2.12%	3.04	3.20%	3.58%	0.89
ALTR	6.76%	2.34%	2.89	5.89%	4.29%	1.37
AMAT	4.25%	1.98%	2.14	4.58%	3.78%	1.21
AMGN	4.75%	1.38%	3.43	2.98%	2.63%	1.13
CSCO	5.33%	1.78%	2.99	2.82%	3.18%	0.88
DELL	6.79%	1.82%	3.73	2.78%	3.21%	0.86
EMC	4.79%	2.20%	2.17	5.55%	3.56%	1.56
INTC	6.20%	1.82%	3.41	3.89%	2.73%	1.43
KLAC	3.71%	1.93%	1.92	6.63%	4.38%	1.51
MSFT	5.29%	1.17%	4.51	2.73%	2.20%	1.24
MU	5.28%	2.17%	2.43	6.08%	4.06%	1.50
MXIM	5.02%	1.51%	3.33	5.04%	4.04%	1.25
NVLS	6.86%	2.02%	3.40	7.55%	4.34%	1.74
ORCL	11.88%	1.99%	5.96	3.87%	3.49%	1.11
PMCS	11.17%	2.59%	4.31	7.71%	5.27%	1.46
PSFT	9.35%	2.22%	4.20	7.56%	4.11%	1.84
QCOM	8.12%	2.07%	3.92	5.16%	3.82%	1.35
SUNW	5.93%	1.99%	2.98	3.90%	3.53%	1.10
XLNX	5.49%	2.13%	2.58	5.59%	4.25%	1.31
Average	6.55%	1.98%	3.33	4.85%	3.68%	1.29

Table 11: Comparisons of close-to-open and open-to-close returns on earnings (EAD) and non-earnings (non-EAD) announcements dates.

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

$$\beta_v(c,t,T) = \frac{c(1-c)\left[1-e^{\gamma_v(T-t)}\right]}{2\gamma_v - \left(\alpha_v - \kappa_v^{\mathbb{Q}}\right)\left[1-e^{\gamma_v(T-t)}\right]}$$

$$\alpha(c,t,T) = \alpha^*(c,t,T) - \sum_{j=N_t^d+1}^{N_T^d} \frac{c}{2}\left(\sigma_j^{\mathbb{Q}}\right)^2 + \frac{c^2}{2}\left(\sigma_j^{\mathbb{Q}}\right)^2$$

where

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

$\tau = T-t$, $\gamma_v = \left[\left(\sigma_v\rho c - \kappa_v^{\mathbb{Q}}\right) + c(1-c)\sigma_v^2\right]^{1/2}$, 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

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

where $\log\left(\widetilde{S}_T\right)$ 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:

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

where $E_t^{\mathbb{Q}}\left[\exp\left(c\sum_{j=N_t^d+1}^{N_T^d} Z_j\right)\right] = \exp\left(\alpha^d(t)\right)$ 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 the firm announces on a given date and $(1-p)$ that they announce the following day, the transform is unchanged provided the jump distribution does not change.

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.

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

where c is complex-valued. Duffie, Pan, Singleton (2000) and Pan (2002) price call options by breaking up the claims into two components, the all-or-nothing option minus the binary option. Pan (2002) 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 (2004) and compute the Fourier transform of the call option. This reduces the problem to one numerical inversion and improves the characteristics of the integrand thus reducing sources for error and computational demands.

We now briefly describe Carr-Madan's results. If we 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 that $\alpha = 2$ 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

$$\psi_c(v) = \int_{-\infty}^{\infty} \exp\left(i\alpha v\right) c(k) dk. \tag{5}$$

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

$$\psi_c(v) = \frac{\psi(v - i(\alpha+1), S_t, V_t, t, T, r)}{\alpha^2 + \alpha - v^2 + i(2\alpha+1)v}, \tag{6}$$

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,

$$C(k) = \frac{\exp(-\alpha k)}{\pi} \int_0^\infty \mathbf{Re}[\exp(-i\alpha k)\psi_c(v)]dv. \tag{7}$$

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:

$$|\psi_c(v)|^2 \leq \frac{E[S^{\alpha+1}]}{(\alpha^2 + \alpha - v^2)^2 + (2\alpha+1)^2 v^2} \leq \frac{A}{v^4} \tag{8}$$

and $|\psi_c(v)| \leq \sqrt{A} v^{-2}$. The integral tail can be bounded by the right hand side which is

$$\int_a^\infty |\psi_c(v)| dv < \frac{\sqrt{A}}{a}. \tag{9}$$

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

$$a > \frac{\exp(-\alpha k)\sqrt{A}}{\pi\varepsilon}. \tag{10}$$

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. 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.

C Black-Scholes and stochastic volatility

This appendix analyzes the impact of stochastic volatility on the earning announcement jump estimators. Standard stochastic volatility models imply that volatility has predictable components with the potential for large and asymmetric shocks. The time series and term structure estimators formally assumed a constant expected diffusive volatility and this assumption could create problems.

Stochastic volatility raises two issues: 1) how to interpret Black-Scholes IV when volatility is time-varying and 2) how would time-varying volatility affect our estimators based on Black-Scholes IV? The first concern is largely addressed using Hull and White (1987) and

Bates (1995), who argue that Black-Scholes IV is approximately equal to the risk-neutral expected variance over the life of the contract. Secondly, time-varying volatility introduces predictable time series variation in IV and various term structure of IV shapes, in contrast to the constant volatility assumption in our extension of Black-Scholes. This could affect our time series and term structure based estimators.

To understand these issues, assume that there are two ATM options available at two maturities, T_1 and T_2, and there is one earnings announcement between time r and $T_2 > T_1$. The Hull and White (1987) approximation states that

$$\left(\sigma_{t,T_i}^{BS}\right)^2 = T_i^{-1} E_t^{\mathbb{Q}} \left[\int_t^{t+T_i} V_s ds\right] + T_i^{-1} \left(\sigma^{\mathbb{Q}}\right)^2 \qquad (11)$$

is an accurate approximation if the shocks to V_t are independent of those to prices (see, e.g., Hull and White 1987 and Bates 1995). Bates (1995) argues that the error in implied volatilities is typically less than 0.5% (p. 38), which is within the bid-ask spread.[27] The approximation is better for short-dated options and our sample is dominated by very short-dated options. Chernov (2005) and Jones (2003) (in a more general stochastic volatility model) show that the approximation error is negligible in the context of index options where $\rho \approx -0.50$. As mentioned earlier, individual equity options have a smaller leverage effect than indices (about 1/5 as large, see Dennis, Mayhew and Stivers 2004) which implies the impact is smaller. Second, since all of our estimators rely on the difference between Black-Scholes implied variances, factors that introduce a fixed level bias in ATM IV are differenced out. This implies that the impact of jumps in prices driven by a Poisson process on the Black-Scholes implied variance would be similar for two different maturities and would be differenced out.

To frame the issues, consider a square-root stochastic volatility model augmented with randomly-timed jumps in the variance:

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

where the shocks are all independent, $Z_j^v > 0$ with mean $\mu_v^{\mathbb{Q}}$, N_t is Poisson with intensity $\lambda_v^{\mathbb{Q}}$, and all random variables are defined under $\mathbb{Q}$. It is important to note we have little

[27] As noted by Merton (1976) and Bates (1995), randomly timed jumps in returns do not introduce any problems as $\left(\sigma_{t,T_i}^{BS}\right)^2 = \sigma^2 + \lambda\sigma_J^2$, provided the jumps in log-returns are mean zero. If asymmetric jumps are present, it would introduce a level bias (provided the intensity and jump distribution are not time-varying) which would be differenced out in our estimators.

evidence that the variance for individual equities jumps, however, we include it here for completeness to understand its potential impact.

Both the term structure and time series estimators rely on differences between the implied variances of two option maturities. To understand how stochastic volatility affects these estimators, we need to compute $E_t^{\mathbb{Q}}\left[\int_t^{t+T_i} V_s ds\right]$ and study its variation over time and maturity. Re-writing,

$$
\begin{aligned}
V_s &= V_t + \int_t^s \kappa_v^{\mathbb{Q}}\left(\theta_v^{\mathbb{Q}} - V_r\right) dr + \int_t^s \sigma_v \sqrt{V_r} dW_r^v + \textstyle\sum_{j=N_t+1}^{N_s} Z_j^v \\
&= \widetilde{V}_s + \sum_{j=N_t+1}^{N_s} Z_j^v,
\end{aligned}
$$

and by Fubini's theorem we have that $\left(\widetilde{\theta}_v^{\mathbb{Q}} = \lambda\mu_v^{\mathbb{Q}} + \theta_v^{\mathbb{Q}}\right)$

$$
EIV_{t,\tau_i} = T_i^{-1} E_t^{\mathbb{Q}}\left[\int_t^{t+T_i} V_s ds\right] = T_i^{-1}\int_t^{t+T_i} E_t^{\mathbb{Q}}\left[V_s\right] ds \tag{12}
$$

$$
= T_i^{-1}\int_t^{t+T_i} E_t^{\mathbb{Q}}\left[\widetilde{V}_s\right] ds + \lambda_v^{\mathbb{Q}}\mu_v^{\mathbb{Q}} \tag{13}
$$

$$
= \widetilde{\theta}_v^{\mathbb{Q}} + \frac{\left(1 - e^{-\kappa_v^{\mathbb{Q}} T_i}\right)}{\kappa_v^{\mathbb{Q}} T_i}\left(V_t - \widetilde{\theta}_v^{\mathbb{Q}}\right). \tag{14}
$$

Both the term structure and time series estimators are based on the difference in implied variance between options or expiration dates. The accuracy of these estimators depends on how variable EIV_{t,τ_i} is as a function of T_i (for the term structure estimator) and t (for the time series estimator).

The term structure estimator relies on the difference between Black-Scholes implied variances, $\left(\sigma_{t,T_1}^{BS}\right)^2 - \left(\sigma_{t,T_2}^{BS}\right)^2$. Since jumps in volatility merely only alter the long-run mean in $EIV\ _{t,\tau_i}$, they don't have any impact of the term structure estimator above and beyond the mean-reversion term, so from now on we assume they are not present. Time-varying volatility can have an impact because $EIV\ _{t,\tau_1} \neq EIV\ _{t,\tau_2}$.

In our setting, this implies that there is a predictable difference in expected volatility over, for example, two weeks and six weeks. Independent of any model, we have some evidence that this difference is minor. Since volatility is very persistent, there will be very little difference in forecasts of volatility over the relatively short horizons we deal with. Moreover, the term structure of IV is very flat for both index options (Broadie, Chernov, and Johannes 2005) and individual stocks, which implies that the variation in expected variance over short horizons is rather small.

In the context of the model above, $V_t - \theta_v^{\mathbb{Q}}$, $\kappa_v^{\mathbb{Q}}$, and T_i could each potentially impact the term structure estimator, while jumps in volatility, σ_v, and Brownian paths have no impact. In each of these cases, intuition implies the impact will be minor. For example, unless there are large volatility risk premia (for which there is no evidence for individual stocks), $\theta_v^{\mathbb{Q}} \approx \theta_v^{\mathbb{P}}$ which implies that, *on average* $V_t \approx \theta^{\mathbb{Q}}$. This further implies that the errors will be small, at least on average. Since the IV term structure is very flat, even in periods of very high volatility and especially over the first two contracts, implying that V_t is close to $\theta_v^{\mathbb{Q}}$. Finally, volatility is highly persistent and we use short-dated options, implying that $\kappa_v^{\mathbb{Q}}$ and T_i are small and thus the predictable difference in implied variance over various maturities is rather small.

To get a sense of the size of the errors, consider the following reasonable stochastic volatility parameters: $\theta_v^{\mathbb{Q}} = (0.3)^2$, $\kappa_v^{\mathbb{Q}} = 2.5$, and $\sigma_{\tau_j}^{\mathbb{Q}} = 0.10$ (long-run, annualized diffusive volatility of 30 percent). Computing the term structure based estimator for $\sqrt{V_t} = (0.20, 0.40.0.50)$, assuming the short-dated option matures in one week (1/52), two weeks (2/52), or three weeks (3/52) and assuming the second option matures one-month later, we have that $\widehat{\sigma}^{\mathbb{Q}} = (0.0995, 0.1007, 0.1017)$, $(0.0988, 0.1017, 0.1038)$, or $(0.0979, 0.1029, 0.1064)$, respectively. The reason the effect is relatively small is that volatility is persistent and that option maturities are relatively small, implying that $\left(1 - e^{-\kappa_v^{\mathbb{Q}} T_i}\right) / \kappa_v^{\mathbb{Q}} T_i$ does not vary wildly across maturities. Most of our firms announce earnings in the two weeks prior to expiration, so it is clear that the term structure estimator is robust to stochastic volatility and to randomly-timed jumps in volatility.

Next, consider the time series estimator. The time series estimator in the presence of stochastic volatility is given by

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

where it is important to note that $EIV_{\ t,T_i}$ is a function of V_t while $EIV_{\ t+1,T_i-1}$ is a function of V_{t+1}. If $V_t \approx V_{t+1}$, then the estimator is quite accurate as the effect of mean-reversion over one-day is negligible. Using the parameters from above, the estimates for three weeks (relatively the worst of the three are) $\widehat{\sigma}^{\mathbb{Q}} = (0.10006, 0.09990, 0.09979)$.

If volatility increases or decreases substantially, the performance of the time series estimator deteriorates quickly, $EIV_{\ t,T_i}$ and $EIV_{\ t+1,T_i-1}$ are quite different. Changes in V_t are driven in the specification above by σ_v, the Brownian paths, and Z_j^v. For the firms in our sample, the volatility of daily changes in volatility is around three to five percent, which implies that normal variation could result in reasonably large movements in volatility. To gauge their potential impact, suppose that current spot volatility is 30 percent and we consider a range of changes in volatility on the following day, $V_{t+1} = (0.1, 0.2, 0.25, 0.35, 0.40, 0.50)$. While it is very unlikely that volatility would decrease this much in one day (as jumps in volatility are typically assumed to be positive), we include the lower volatilities to understand the potential impact. For options maturing in three weeks and the same parameters as above, $\widehat{\sigma}^{\mathbb{Q}} = (0.1197, 0.1127, 0.1072, 0.0908, 0.0789, 0.0369)$. The potential impact is much larger and, more importantly, is asymmetric: if volatility increases from 30% to 50%, the estimate is biased down by 6.31% while if volatility were to decrease from 30% to 10%, the estimate is biased upward only by 1.97%.

The effect increases with maturity, so that the bias is greater when long-dated options required. Intuitively, diffusive volatility is more important for long-dated options, magnifying the impact of the shocks. In the text, we noted that for more than 60 percent of the times when we could not calculate the time estimator (the difference was negative), there was no short-dated option available. For example, if $\sigma^{\mathbb{Q}} = 0.05$, the shortest-dated option has 6 weeks to maturity, and V_t increases from 30% to 35%, $\left(\sigma_{t,T_i}^{BS}\right)^2 - \left(\sigma_{t+1,T_i-1}^{BS}\right)^2$ is negative. Long-dated options, combined with close-price issues are, in our opinion, the major cause of the problematic dates for the time series estimator.

Our conclusions are as follows. First, the term structure and time series estimators will generally be reliable estimators of $\sigma^{\mathbb{Q}}$, even in the presence of stochastic volatility and/or jumps. Second, the ability of the term structure estimator to estimate $\sigma^{\mathbb{Q}}$ depends on V_t, $\theta_v^{\mathbb{Q}}$, and $\kappa_v^{\mathbb{Q}}$ and for reasonable parameters, the impact is quite small. The performance of the time series estimator depends additionally on σ_v and on the shocks driving the volatility process. Because of this, the time series estimator will be noisier and less reliable than the term structure estimator. Third, for the time series estimator, the magnitudes in the bias are large enough to generate problem dates. Finally, because increases in V_t result in a larger bias downward in estimates of $\sigma_{\tau_j}^{\mathbb{Q}}$ than decreases in V_t (holding the size of increase/decrease constant), we expect that the time series estimator will have a downward bias if the variance is time-varying or if there are positive jumps in the variance.

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