Fundamental uncertainty, earning announcements and equity options

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Abstract

This paper uses option prices to learn about the uncertainty surrounding the fundamental information that is revealed on earnings announcement dates. To do this, we introduce a reduced-form model and estimators to separate the uncertainty over the information revealed on earnings dates from normal day-to-day volatility. The fundamental uncertainty estimators are easy to compute and rely only on option price information available prior to the announcement. Empirically, we find strong support for our reduced form specification and investigate the fundamental uncertainty estimators. We find that they are quantitatively large, vary over time, and are informative about the future volatility of stock price movements. Finally, we quantify the impact of earnings annoucements on formal option pricing models.

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1 Introduction

This paper develops estimators of the anticipated uncertainty associated with the fundamental information that is revealed on earnings announcement dates (EADs). In general, fundamental uncertainty refers to the anticipated uncertainty over the fundamental drivers of firm value. This uncertainty plays a prominent role in many asset pricing models where it commonly appears as the uncertainty over parameters and state variables, see, e.g., Morris (1996), Pastor and Veronesi (2003, 2005), David and Veronesi (2002), or Brav and Heaton (2002). Despite its importance, little is known about fundamental uncertainty in a quantitative sense, for example, in terms of its magnitude or its time series behavior.[1]

This paper develops, justifies, and implements estimators of firm fundamental uncertainty using option prices. To do this, we combine three separate ingredients. First, while it is difficult to generically define fundamental uncertainty, we do know that much of this uncertainty is resolved on EADs. On these days, firms release the income statement, the balance sheet, the cash flow statement and additional "forward-looking" statements.[2] This valuation relevant information was, to varying extents, unknown to investors prior to the announcement, which is why stock prices often react violently after earnings are announced.[3]

The second ingredient is merely the observation that option prices are the natural source of information to learn about uncertainty. Since Patell and Wolfson (PW) (1979, 1981), it is well know that option prices contain information about earnings announcements, but it is not known how to estimate the uncertainty in the announcement. The predictable timing of the EAD generates a distinctive time series pattern in implied volatilities. Figure 1 displays this time series behavior for Intel Corporation, using data from 1996 to 2005.[4] Of

[1]Existing work uses indirect proxies for fundamental uncertainty in pricing or return regressions: Pastor and Veronesi (2003, 2005), Jiang, Lee and Zhang (2006) or Zhang (2006) use proxies such as firm age, return volatility, firm size, analyst coverage, or the dispersion in analyst earnings forecasts.

[2]As defined by the Securities Exchange Act, Section 27A, a forward-looking statement refers to, among other things, management projections of revenues, income, earnings, capital expenditures, dividends, capital structure, or other financial items; statements regarding the plans and objectives of management for future operations; and a statement of future economic performance of the firm or industry.

[3]To get a sense of the magnitudes, for typical firms in our sample, the variance of EAD returns is more than five times greater than on non-EADs. For one firm, IBM, the variance of EAD returns is almost 14 times greater than non-EADs.

[4]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

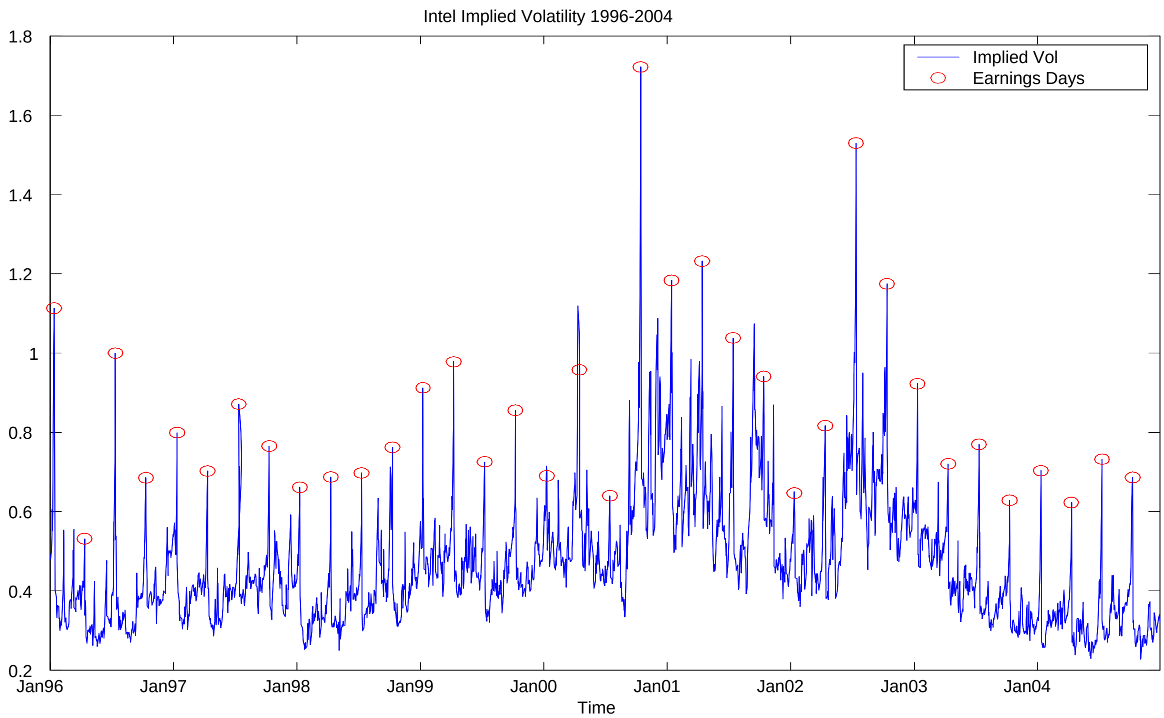

Figure 1: Black-Scholes implied volatility for the nearest maturity at-the-money call option for Intel Corporation from January 1996 to December 2004. The circles represent days on which earnings announcements were released.

particular interest are the strong predictable movements: implied volatility (IV) increases before a known earnings announcement date and decreases afterward.[5] The third ingredient is a simple reduced form model which provides a framework for separating total expected volatility into its constituent components, the fundamental uncertainty resolved on earnings dates and the normal day-to-day diffusive volatility.

The starting point for our analysis is a reduced form model with both jump and diffusive components. The jump component captures the response of equity prices to the information

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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).

[5] We will refer to both Black-Scholes implied volatility and implied variance as IV, only distinguishing the two where there is a substantive difference.

released on the EAD. Unlike traditional jump models that assume jumps arrive randomly, we assume that the timing of the jump is known, which coincides with the fact that earnings announcements are scheduled well in advance.[6] This predictable timing, combined with uncertainty of the stock price's response, generates the distinctive pattern in Figure 1.

The jump sizes translate shocks to firm fundamentals into shocks to equity prices. This is the key reduced form component, as we need only make assumptions about the distribution of shocks in prices and not the particular underlying fundamentals (earnings, earnings growth, etc.) that generate these shocks. The central parameter in the jump size distribution is the volatility of price jumps, which captures the anticipated uncertainty in firm fundamentals. The absence of arbitrage precludes a non-zero mean in the jump distribution.

The primary contribution of this paper is to develop and implement estimators of the fundamental uncertainty using option prices. We develop two estimators. One estimator uses only ex-ante information and is based on the term structure of IV prior to an EAD. The other is based on changes in IV around the EAD, and thus uses ex-post information. Both estimators are easy to compute, as they only require IVs on different dates or maturities. In theory, the two estimators perform very differently in the presence of stochastic volatility or microstructure noise. The time series estimator is noisier than the term structure estimator, as it depends on IVs on multiple dates. Because of this, we primarily focus rely on the term structure estimator, but are careful to compare the two estimators where appropriate.

Given the theoretical estimators, we examine the empirical evidence using a sample of 20 firms with the most actively traded options from 1996 to 2005.[7] We focus on the most actively traded firms to avoid microstructure or liquidity issues, which are likely smaller for actively traded firms. We choose low dividend firms, as we expect them to have relatively high fundamental uncertainty. Based on this sample, we have a number of empirical results.

First, we provide broad evidence to support our reduced form specification. Analyzing

[6] The model is closely related to Piazzesi (2000, 2005), who models bond market announcements as deterministically-timed jumps.

[7] Jiang and Johannes (2006) analyze a number of other issues using a broader cross-section of data. They focus on the cross-sectional evidence for predicting future returns and volatility, for the relationship between fundamental uncertainty and post-earnings announcement drift, and the informational content of option implied estimates of fundamental uncertainty vis-a-vis alternative measures which include analysts dispersion, frequency of analyst forecasts, age of the firm, time series volatility of returns, and the standard deviation of past earnings surprises.

the specification is important because our estimators rely on our reduced form model being a reasonable description of the data. Using non-parametric tests, we find extremely strong support for the three generic features of our model: that option IV increases prior to an earnings announcement, that IV falls after an earnings announcement, and that the term structure of IV is upwardly sloping prior to an announcement.[8] We also assume that the jump size distribution is conditionally normal, and we do not find any evidence inconsistent with this assumption.

Second, we are interested in understanding the quantitative implications of fundamental uncertainty. We find that fundamental uncertainty is statistically and economically large: the average ex-ante estimate of fundamental uncertainty is about 8%. Fundamental uncertainty also varies substantially across time: fundamental uncertainty for a given firm can varies by factors of three or more. In levels, the uncertainty can be extremely large, exceeding 15%, for even the largest firms.[9] Fundamental uncertainty increases in 2000, 2001, and 2002 during the recession and bursting of the dot-com bubble. This is not a surprise if there is any systematic component to fundamental uncertainty. This time-variation in fundamental uncertainty is in contrast to some proxies such as firm age which monotonically decline. The term structure and time series estimators are highly correlated: the correlation of the mean estimate for time and structure method is over 94% and the pooled correlation is about 70%. This implies that both estimators work well and the common effect is significant.

We next 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, that is, the extent to which a option implied fundamental uncertainty forecasts a subsequent stock price volatility. We find that the correlation across firm averages is positive and above 50% and the correlation pooling the observations is about 28%. This implies that our estimator is informative about future movements.[10]

Regarding risk premia, we find no evidence for a mean stock return premia on the day

[8] Two of these tests are closely related to those implemented in Patell and Wolfson (1979, 1981), although as we note below, there are important differences. We find much stronger evidence that Patell and Wolfson.

[9] For example, Cisco Systems, one of the largest firms in our sample, had a number of quarters where fundamental uncertainty was greater than 15 percent.

[10] Refining this, Jiang and Johannes (2006) find that the option based fundamental uncertainty is the strongest predictor of subsequent absolute returns when compared to analyst forecast dispersion, analyst forecast frequency, analyst forecast errors, past earnings volatility, book-to-market ratios, age of the firm, option implied diffusive volatility, past return volatility, or turnover.

of the earnings announcements. We also find mixed, at best, evidence for a fundamental uncertainty premium in option prices. For some firms, we find that the anticipated volatility under $\mathbb{Q}$ is greater than the subsequently observed volatility under $\mathbb{P}$, but the effect is not uniform. This is not surprising given our relatively small sample, and the mixed evidence on volatility risk premia for both index options and individual equity options. For example, there limited evidence for risk premia for individual firms based on the differences between realized and IVs (see, e.g., Carr and Wu (2005); Driessen, Maenhout, and Vilkov (2005); and Battalio and Schultz (2006)). Broadie, Chernov, and Johannes (2006) discuss the mixed evidence on volatility risk premia for index options.

Finally, we discuss the implications of our results for empirical option pricing research. To quantify the importance of accounting 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%. 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.

The rest of the paper is outlined as follows. Section 2 introduces the model, discusses our estimators, and provides a literature review. Section 3 discusses the empirical results, and Section 4 concludes.

2 The model

This section introduces our model for individual equity prices. Compared to indices, the extant literature on pricing individual options is limited. For index options, there is a reasonable agreement on a general class of models providing an accurate fit to both the time series of index returns and the cross-section of option prices.[11] The results indicate that factors such as stochastic volatility, jumps in prices, and jumps in volatility are present.

[11] 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 (2006).

The main debate focuses over the magnitude and causes of risk premia.[12]

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)). Together these results indicate that any jump or volatility risk premia are smaller for individual firms than for indices, and that jumps in prices are less important for individual equities than for indices. To our knowledge, the only paper analyzing formal pricing models for individual equities is Bakshi and Cao (2004). Of note, they find little pricing improvement by adding stochastic volatility, jumps in prices, or jumps in volatility. This is in contrast to the large pricing improvements that these factors provide for pricing index options.

This section discusses our model in terms of the objective measure specification (Section 2.1), the risk-neutral specification (Section 2.2), develops estimators of fundamental uncertainty (Section 2.3), and provides a comparison of our model and approach to the existing literature (Section 2.4).

2.1 Objective measure specification

The first step in our specification is modeling earnings announcements. We model the response of equity prices to an earnings release as a jump in prices. Huang (1985a) provides an intuitive motivation for including jumps by arguing that "continuous" information structures, such as those without jumps, are ones in which "no events can take us by surprise" (p. 61). Macroeconomic or earnings announcements are canonical examples of events that take market participants by surprise, and thus information structures contain jumps. These informational discontinuities immediately translate into discontinuities in the sample path of prices; thus, prices are *necessarily* discontinuous with announcements.[13]

[12] Pan (2002), Eraker (2004), and Broadie, Chernov, and Johannes (2006) provide estimates of the risk premia embedded in options. Bollen and Whaley (2004) and Garleanu, Pedersen, and Poteshman (2005) provide evidence that demand based pressures contribute to the risk premium embedded in options.

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

Formally, N_t^d counts 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 representing announcements.[14] 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, p. 128).

The jump assumption is consistent with existing work analyzing announcement effects (Beber and Brandt (2006) and Piazzesi (2005)), consistent with statistical evidence that identifies announcements as the cause of jumps in 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), they often generate a visible discontinuity in economic or trading time: the market open the following morning is often drastically different than the previous close.[15] Further evidence consistent with a jump is in PW (1984), who find that for earnings announcements during trading hours, the bulk of the response occurs within the first few minutes. We later provide a test of this implication.

In addition to jumps on EADs, we follow the option pricing literature and assume there is square-root stochastic volatility (see Heston 1993). Prices and volatility jointly solve the following stochastic differential equations

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

where all random variables are defined on the probability measure $\mathbb{P}$, $Z_j | \mathcal{F}_{\tau_j -} \sim \pi\left(Z_{\tau_j}, \tau_j -\right)$, $cov\left(W_t^s, W_t^v\right) = \rho t$, and N_t^d counts the number of earnings announcements.[16] Throughout, we assume the interest rate is constant, the Feller condition holds ($\theta_v \kappa_v > \sigma_v^2/2$), and we ignore dividends for notational simplicity.

The jump size $Z_j = \log\left(S_{\tau_j}/S_{\tau_{j-}}\right)$ captures the response of the stock price to the

[14] Piazzesi (2000, 2005) introduced deterministic jumps on macroeconomic announcement dates in the context of bond pricing. We apply her pricing methodology to new models for equity prices.

[15] 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 with the formal close of the equity market.

[16] 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.

fundamental information released on EADs. As mentioned earlier, firms are required to report the current quarter's cash flow, balance sheet and income statement, and many firms also provide forward-looking information. The jump sizes translate the shocks in fundamental variables that are relevant for valuation into shocks in stock prices. The jump distribution π characterizes the random nature of the jump sizes, and therefore serves as a reduced form of how fundamental information affects stock prices.

The anticipated volatility of Z_j, $\sigma_j^2 = var^{\mathbb{P}}\left(Z_j|\mathcal{F}_{\tau_j-}\right)$, captures the fundamental uncertainty and characterizing σ_j is our primary goal. Note that since the fundamental uncertainty is based on the response of the stock prices to fundamental information, it only captures valuation relevant information. For example, we do not assume that stock price uncertainty is generated by earnings forecast errors, although these are clearly one potentially important source of uncertainty.

Before proceeding, we briefly discuss our specification and its relation to common empirical work on earnings announcements. Consider the common approach in accounting and finance of computing the "earnings response coefficient" (Ball and Brown 1968). Here, earnings are unknown prior to the announcement, but there is a forecast available, $E^f_{\tau_{j-}}$. Stock price changes are regressed on current quarter earnings' surprises and an error term:

$$Z_j = \log\left(\frac{S_{\tau_j}}{S_{\tau_j-}}\right) = \alpha + \beta_j\left(E_{\tau_j} - E^f_{\tau_{j-}}\right) + \varepsilon_j, \tag{2}$$

where σ_j^{ε} is the anticipated volatility of ε_j and β_j is the "earnings response" coefficient. The residual captures additional information that is relevant for valuation. The earnings shocks could contain multiple components relating to, for example, economy wide conditions, industry factors, and firm specific factors.

In these models, it is important to note that common regressors such as earnings surprises explain a very small portion of the total variability of stock price changes around earnings announcements. For example, adjusted R^2's in earnings surprise regressions tend to be very small, less than 10%. For example, Imhoff and Lobo (1992) and Ang and Zhang (2005) find R^2's of around 3% and 6%, respectively, for the simple univariate regressions. Adding additional explanatory variables only increases this modestly. This implies that the vast majority of the variability in a stock price's response to earnings announcement information is unexplained by standard regressors.

In this model, if we denote σ_j^E as the conditional volatility of $E_{\tau_j} - E^f_{\tau_{j-}}$, then the total conditional volatility can be decomposed as

$$\sigma_{j}^{2}=\beta_{\tau_{j-}}^{2}\left(\sigma_{j}^{E}\right)^{2}+\left(\sigma_{j}^{\varepsilon}\right)^{2}.$$

It is important to note that σ_j varies across time and firms for a variety of reasons. For example, firm specific volatilities (σ_j^{ε}) could be driven by life-cycle issues, macroeconomic uncertainty could vary over time, or the response of investors to a given shock could change due to time-varying risk aversion.[17] In fact, there is no reason to believe that it is constant across time. It is important to note that it is *not* possible to directly estimate a time-varying σ_j directly from stock prices, as there is only one observation. Due to this most authors assume that the earnings response coefficient and the volatility of unexpected earnings are constant. This motivates our focus on option-based estimators of fundamental uncertainty.

Next, consider the distributional features of returns under $\mathbb{P}$. Deterministic jumps have a different impact on the return distribution than randomly-timed jumps. To see this, assume stochastic volatility is constant. In a randomly-timed jump model such as Merton (1976), returns are a random sum of normal distributions, generating skewness and kurtosis. For deterministically-timed jumps, the timing is known and so returns are a non-random sum of normals. 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 (2006) 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. Also note that deterministic jumps generate predictable heteroscedasticity.

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 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 at-the-money (ATM) IV. ATM options are not particularly sensitive to randomly-timed jumps in prices or in volatility as these primarily impact deep out-of-the money (OTM) options (see Broadie, Chernov, and Johannes (2005) or Bakshi and Cao (2004)). Second, unlike indices, there is little *prima facie* evidence for the importance of randomly-timed jumps in prices or volatility. The existing option pricing

[17] Jiang and Johannes (2006) find evidence that the earnings response coefficient does not change over time.

literature (cited above) documents that IV curves are flatter for individual equities than for indices, indicating that jumps in prices are less important for individual equities than for indices. The time series of returns provides similar intuition: unlike indices, which have strong evidence for non-normalities (for the S&P 500 index, a kurtosis of about 50 and a skewness of minus three), individual equities generally have little skewness and only a modest amount of kurtosis. These modest levels of kurtosis are consistent with standard stochastic volatility models.

2.2 Risk-neutral measure

To price options, we construct an equivalent martingale measure (EMM), $\mathbb{Q}$, which implies the absence of arbitrage. The pricing approach relies on insights in Piazzesi (2000) for asset pricing with deterministically-timed jumps.

Under $\mathbb{Q}$, discounted prices must be a martingale. This requires that prices are a martingale between jump times, which is the usual restriction that the drift of S_t under $\mathbb{Q}$ is equal to $r_t S_t$. To be a martingale at the jump times, the pre-jump expected value of the post-jump stock price is equal to the pre-jump stock price, that is, that $E^{\mathbb{Q}}\left[S_{\tau_j}|\mathcal{F}_{\tau_j -}\right] = S_{\tau_j -}$ since interest rate accruals do not matter.[18] Given the jump specification above, this requires that $E^{\mathbb{Q}}\left[e^{Z_j}|\mathcal{F}_{\tau_j -}\right] = 1$.

To construct the measure, define $d\mathbb{Q}/d\mathbb{P} = \xi_T$ and

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

where $\varphi_t = (\varphi_t^s, \varphi_t^v)$ are the prices of W_t^s and W_t^v risk 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 posit flexible risk premia of the form $\varphi_t^s = \eta_s V_t$ and $\varphi_t^v = -\left(1-\rho^2\right)^{-1/2}\left(\rho\eta_s\sqrt{V_t} + \left(\mu_t^{\mathbb{Q}} - \mu_t^{\mathbb{P}}\right)/\sigma_v\sqrt{V_t}\right)$ where $\mu_t^{\mathbb{Q}} = \kappa_v^{\mathbb{Q}}(\theta_v^{\mathbb{Q}} - V_t)$ and $\mu_t^{\mathbb{P}} = \kappa_v\left(\theta_v - V_t\right)$. A sufficient condition for this to be valid is that the Feller condition holds under both measures (see, Collin-Dufresne, Goldstein, and Jones (2005) or Cheridito, Filipovic, and Kimmel (2006)). This implies that volatility evolves according to

$$dV_t = \kappa_v^{\mathbb{Q}}\left(\theta_v^{\mathbb{Q}} - V_t\right)dt + \sigma_v\sqrt{V_t}dW_t^v\left(\mathbb{Q}\right).$$

[18] 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 guarantee that ξ_t is positive and a $\mathbb{P}-$martingale at jump times, we assume

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

This mild condition only requires that the jump densities have common support, since π and $\pi^{\mathbb{Q}}$ are both positive.

Unlike diffusion models, where only the drift coefficient 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 that the functional form of the distribution could change. Throughout, we assume that the jump sizes are state independent and conditionally normally distributed under $\mathbb{Q}$: $\pi^{\mathbb{Q}}\left(Z_j|\mathcal{F}_{\tau_{j-}}\right) \sim N\left(-\frac{1}{2}\left(\sigma^{\mathbb{Q}}_j\right)^2, \left(\sigma^{\mathbb{Q}}_j\right)^2\right)$. This implies that there is a single parameter indexing the jump distribution on each EAD, and estimating $\sigma^{\mathbb{Q}}_j$ for each earnings date is the primary focus of the paper.

At this point, note that we need not make any assumptions about π, which, in particular, implies that the volatility of jump sizes under $\mathbb{P}$ could be different and that the Z_j could evolve according to a regression like equation (2). It is also important to note that there is no prima-facie evidence for a volatility of jump sizes risk premia (which would imply that $\sigma^{\mathbb{Q}}_j \neq \sigma_j$). This sort of risk premia (as opposed to a mean stock price premia) would manifest itself as high returns to option writers around earnings announcements. We discuss this issue below in the empirical section.

Under $\mathbb{Q}$, prices evolve according to

$$dS_t = r_t S_t dt + \sqrt{V_t} S_t dW^s_t\left(\mathbb{Q}\right) + d\left(\sum\nolimits_{j=1}^{N^d_t} S_{\tau_{j-}}\left[e^{Z_j} - 1\right]\right)$$

where the jump size distribution is given above. For pricing ATM options, the total, annualized, expected risk-neutral variance of continuously compounded returns is important and it is given by

$$\frac{1}{T}E^{\mathbb{Q}}_0\left[\int_0^T V_s ds\right] + \frac{var\left(\sum\nolimits_{j=1}^{N^d_T} Z_j\right)}{T} = \theta^{\mathbb{Q}}_v + \frac{V_0 - \theta^{\mathbb{Q}}_v}{\kappa^{\mathbb{Q}}_v T}\left(1 - e^{-\kappa^{\mathbb{Q}}_v T}\right) + \frac{\sum\nolimits_{j=1}^{N^d_T}\left(\sigma^{\mathbb{Q}}_j\right)^2}{T}. \quad (3)$$

Appendix B derives the characteristic function and discusses numerical option pricing in the stochastic volatility model with jumps on earnings dates.

2.3 Estimating fundamental uncertainty

2.3.1 Motivating the estimators

To motivate our estimators, consider the simplifying case where volatility is constant:

$$S_T = S_0 \exp\left[\left(r - \frac{1}{2}\sigma^2\right)T + \sigma W_T(\mathbb{Q}) + \sum\nolimits_{j=1}^{N_T^d} Z_j\right], \tag{4}$$

$Z_j = -\frac{1}{2}\left(\sigma_j^{\mathbb{Q}}\right)^2 + \sigma_j^{\mathbb{Q}}\varepsilon$ and $\varepsilon \sim N(0,1)$. 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), continuously-compounded returns are exactly normally distributed. This implies that the price of a European call option struck at K and expiring in T_i days is given by the usual Black-Scholes formula with a modified volatility input. If we let $BS\left(x, \sigma_T^2, r, T_i, K\right)$ denote the usual Black-Scholes pricing formula, the modified volatility input is

$$\sigma_{t,T_i}^2 = \sigma^2 + T_i^{-1} \sum\nolimits_{j=1}^{N_{T_i}^d} \left(\sigma_j^{\mathbb{Q}}\right)^2.$$

Before introducing the estimators, we can clearly see the main implications of earnings announcements from this formula. First, assuming a single announcement to maturity, 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 IV decreases as the maturity of the option increases. We test these implications later, as they are the central implications of our reduced form model.

This also suggests at least two ways to separately estimate σ and $\sigma_j^{\mathbb{Q}}$. First, given two options maturing in $T_1 < T_2$ days and a single EAD prior to maturity, then $\sigma_{t,T_1}^2 > \sigma_{t,T_2}^2$ and we can solve the two equations in two unknowns to estimate the earnings uncertainty,

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

where we have dropped the time subscript on $\sigma_j^{\mathbb{Q}}$ to simplify the notation. We label this the *term structure* estimator.

The time series of IVs provides another method to estimate $\sigma_j^{\mathbb{Q}}$. 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,

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

We use these estimators in our empirical work.

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 IVs were 95.80% and 65.89%, respectively. In this example, we use the April and May 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 typical 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.

2.3.2 The impact of stochastic volatility

In this section, we evaluate how stochastic volatility could impact our estimators. Although there is always sampling error when estimating any parameter, it is important to document that stochastic volatility does not cause substantial biases in our estimates. The term structure and time series estimators are technically correct only if volatility is constant. Using implied volatilities calculated from the Black-Scholes model is not correct if volatility is stochastic and stochastic and mean-reverting volatility could introduce movements in IV unrelated to earnings announcements, and therefore impact the estimates. Thus, our estimates rely on two assumptions: that Black-Scholes implied variance accurately captures future expected variance and that the time-variation is expected variance, across either the term structure or across time, is small.

The first issue can be addressed using the insights of Hull and White (1987) and Bates (1995). Under mild conditions on stochastic volatility, if shocks to volatility and returns are independent, then the stochastic volatility option price is the expectation of the Black-Scholes price where the Black-Scholes implied variance is expected risk-neutral variance. Using our model, we have that expected future total variance is

$$\sigma^2_{t,T} = T_i^{-1} E_t^{\mathbb{Q}} \left[\int_t^{T_i} V_s ds\right] + T_i^{-1} \left(\sigma_j^{\mathbb{Q}}\right)^2.$$

Based on this, it is common to assume that Black-Scholes implied variance is an accurate proxy for expected risk neutral variance, that is, $\left(\sigma_{t,T}^{BS}\right)^2 \approx \sigma_{t,T}^2$.

The approximation errors in assuming this for ATM options are generally small for index options, and will be even smaller for individual equity options. Of course, the approximation errors can be quite large for out-of-the-money options. For ATM options, Hull and White (1987) find the errors are less than 1% with no leverage and only 1.6% when the $\rho = -0.6$. The errors are even smaller for shorter maturities, which we use. For index options, the leverage effect is estimated to be around -0.4, and the papers cited earlier argue that the leverage effect is much smaller for individual equities.

Jumps in prices also do not substantively bias the results. Merton (1976b) found that the errors of using the Black-Scholes model with a properly adjusted variance were extremely small, again, for ATM options.[19] Chernov (2006) quantifies the approximation in models for index option pricing with non mean-zero jumps in prices, non-zero correlation, and jumps in volatility and concludes the bias, for at-the-money options, is negligible. Any errors are even smaller for individual equity options, as the references cited above indicate that the leverage effect is smaller and the importance is less for individual equity than for indices. Since all of estimators rely on the difference between Black-Scholes implied variances, any level biases are differenced out. Thus we conclude that assuming $\left(\sigma_{t,T}^{BS}\right)^2 = \sigma_{t,T}^2$ does not introduce any substantive biases.

Next, to understand the specific impact of stochastic and mean-reverting volatility, we can compute, using the stochastic volatility model specified above, expected integrated variance:

$$EIV_{t,T_i} = T_i^{-1} E_t^{\mathbb{Q}} \left[\int_t^{t+T_i} V_s ds \right] = \theta_v^{\mathbb{Q}} + \frac{V_t - \theta_v^{\mathbb{Q}}}{\kappa_v^{\mathbb{Q}} T_i} \left(1 - e^{-\kappa_v^{\mathbb{Q}} T_i} \right). \qquad \text{(EIV)}$$

Since, EIV_{t,T_1} does not necessarily equal EIV_{t,T_2}, the term structure estimator could be polluted by expected mean-reversion in spot volatility and similarly for the time series estimator as EIV_{t,T_i} and EIV_{t+1,T_i-1} could be different.

From this, it is clear that the main factors driving maturity and time variation in ex-

[19] Merton was surprised how small the errors were: "What I did find rather surprising is the general level of the magnitudes of the errors. For the smallest frequency value examined, the percentage of variation caused by the jump component had to exceed forty percent before an error of more than five percent could be generated...In summary, the effect of specification error in the underlying stock returns on option prices will generally be rather small...However, there are some important exceptions...deep out-of-the-money options can have very large percentage errors." (p. 345). Tables 3a and 3b show the errors are typically less than one percent for short dated options.

pected integrated variance are mean-reversion ($\kappa_v^{\mathbb{Q}}$), option maturity (T_i), and spot variance (V_t). For example, if there is no mean-reversion, then $EIV_{t,T_i} = V_t$ for all t and T_i. The main issue for the term structure (time series) estimator models is how much EIV_{t,T_1} varies across maturity (time).

Appendix C provides 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 quite robust for a number of reasons: the term structure estimator does not depend on σ_v or realized shocks; diffusive volatility is very persistent which implies that $\kappa_v^{\mathbb{Q}}$ is very small; the term structure of implied volatility is flat, which implies that that $\theta_v^{\mathbb{Q}} \approx \theta_v^{\mathbb{P}}$ and/or that $\kappa_v^{\mathbb{Q}}$ is very small; and we use short-dated options which implies that T_1 and T_1 are small, typically less than 2 months.

Putting the pieces together, this implies that $EIV_{t,T_1} \approx EIV_{t,T_2}$. To get a sense of the nature of the biases, consider the somewhat extreme case where spot variance is either twice or half its long-run average. In the first case, $V_t = 2\theta_v^{\mathbb{Q}}$, $\theta_v^{\mathbb{Q}} = 0.3^2$, $V_t/2$, $T_1 = 2/52$, $T_2 = 6/52$, $\kappa_v^{\mathbb{Q}} = 3$, $\sigma_j^{\mathbb{Q}} = 0.08$, and our procedure delivers an estimate of $\sigma_{term}^{\mathbb{Q}} = 0.0832$. If spot variance is 50% of its long run value, $V_t = \theta_v^{\mathbb{Q}}/2$, $\theta_v^{\mathbb{Q}} = 0.3^2$, $\sigma_{term}^{\mathbb{Q}} = 0.0784$. These biases are small in absolute terms, but also relative to the normal noise involved with option prices. For example, typical bid-ask spreads on individual equity options are at least \$0.05 to \$0.10 on options that are often worth less than \$1. This could generate larger errors in the term structure estimator than time-varying and predictable volatility.

Finally, the time series estimator is far less robust as it relies additionally on the shock realizations over the next day. Large shocks could introduce a significant amount of noise into the time series estimator, which are directional: large positive shocks downward-bias estimates more than large negative shocks IV upward-bias estimates. Although we report both, we expect the time series estimator to be noisier.

2.4 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), PW (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.

PW (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 published 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. Cheung and Johannes (2006) analyzes stochastic volatility models with jumps on earnings dates and randomly timed Poisson jumps. The main findings are threefold: (1) that individual firm volatility is more persistent than index volatility; (2) that randomly timed jumps in prices for individual firms have mean-zero jumps; and that (3) randomly-timed jumps in prices are less important for individual firms than for indices.

Our paper is most closely related to PW (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 to and decreases subsequent to earnings announcements. PW (1979) find mixed evidence using a sample of annual earnings announcements from 1974 to 1978, while PW (1981) find relatively stronger evidence using a sample of quarterly earnings announcements from 1976 to 1977. The main difference between this paper and PW (1979, 1981) is that we focus on estimating $\sigma_j^{\mathbb{Q}}$, taking as granted the primary conclusion from PW that option prices contain information about earnings announcements.

It is important to contrast our model to the model in PW (1979, 1981). Their model relies on an observation in Merton (1973) that the Black-Scholes model can handle deterministically changing diffusive volatility. They 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 $\left(\sigma_{T_i}^{BS}\right)^2 = T_i^{-1}\int_0^T \sigma^2(s)\,ds = \sigma^2 + T_i^{-1}\sigma_E^2$, where σ_E is the volatility on the earnings date. Clearly, this delivers the result that annualized volatility increases prior to, and decreases after, an earnings release.

Despite the fact that PW's model generates similar implications in a simple extension of the Black-Scholes model, there are crucial theoretical differences. PW specify continuous sample path stock prices subject to increased diffusive volatility around earnings announcements, whereas in our model, there is a sample path 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 PW's model is complete, in the sense that options can be perfectly hedged by trading in only the underlying equity and a money market account. PW's (1979, 1981) model is also in contrast to the findings in PW (1984), who document the rapid reaction of the stock prices to earning announcements. We provide empirical evidence, based on close-to-open returns, consistent with a jump in economic time.

Unlike PW's model, it is straightforward to incorporate stochastic volatility into our model. An extension of PW 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, PW'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.

There are also crucial differences between our empirical work and PW's. First, PW focus solely on the time series behavior of IV, and do not analyze the term structure implications. As we note above, our primary estimator and empirical work is based on the term structure of IV. Second, PW do not estimate $\sigma_j^{\mathbb{Q}}$, and that is the main focus of our work. Third, PW implement all of their tests on volatilities, even though the relationships are additive in variance, not volatilities (see PW (1981, p. 442)).

Donders and Vorst (1996), Donders, Kouwenberg, and Vorst (2000), and Isakov and Pérignon (2001) apply PW'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 model is also closely related to Hanweck (1994).[20] Hanweck finds that unemployment announcement days are more volatile for Treasury bond and Eurodollar futures than

[20] I would like to thank Bob McDonald for pointing out Hanweck (1994), which is an unpublished Ph.D. dissertation.

other days, and builds an announcement based jump-diffusion model to capture this effect. Hanweck (1994) analyzes trading strategies around the announcements, and does not find any systematic mispricing. Ederington and Lee (1996), Beber and Brandt (2006) 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. Beber and Brandt (2005) relate these changes to news about the economy and argue that this effect is consistent by time-varying risk aversion. Beber and Brandt (2006) analyze options on macroeconomic announcements and find that the macroeconomic uncertainty is closely linked to changes in bond option implied volatility.

Our paper is closely related, at least on an intuitive level, to a number of formal asset pricing models. Accounting based models such as 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. In these models, the uncertainty over firm fundamentals (earnings, profitability, etc.) impacts prices and is important for valuation (see Pastor and Veronesi 2005). Fundamental uncertainty in the form of parameter or state variable uncertainty plays an important role in the learning models of Morris (1995), David and Veronesi (2002), Veronesi (2003), and Brav and Heaton (2002).

Pastor and Veronesi (2003, 2005) use firm age as a proxy for the uncertainty in profitability while Jiang, Lee and Zhang (2006) and Zhang (2006) 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.

3 Empirical Evidence

We obtain closing option prices from OptionMetrics for the period from 1/2/1996 to 12/30/2004. OptionMetrics is now the common data source for individual equity option prices 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)). 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 uses close prices, as opposed to transaction prices. Unfortunately, this is the only widely-available source of option price data since the close of the Berkeley Options Database in 1996. Intraday data is not publicly available.

Out of all possible firms, we use the following criterion to select 20 firms for analysis. For the period from 1996 to 2004, we found the 50 firms with the highest dollar volume that traded in every year. Next, we eliminate firms with a median dividend rate of more than 0.75%, firms whose stock price traded below $5, firms involved in major mergers and acquisitions, and ADRs.[21] The focus on low dividend stocks provides two 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." For these remaining firms, we computed the average dollar trading volume and took the twenty highest firms.

The selection criteria result in the following firms, with their ticker symbols in parentheses: Apple Computer (AAPL), Altera (ALTR), Applied Materials (AMAT), Applied Micro Devices (AMD), Amgen (AMGN), Cisco Systems (CSCO), Dell Computer (DELL), Home Depot (HD), International Business Machines (IBM), Intel (INTC), KLA Tencor (KLAC), Microsoft (MSFT), Micron Technology (MU), Maxim Integrated Products (MXIM), Motorola (MOT), Novellus Systems (NVLS), Oracle (ORCL), Qualcomm (QCOM), Texas Instruments (TXN), and Wal-Mart (WMT). With the exception of AMGN which is a pharmaceutical company and HD and WMT, all of the firms are in technology related industries. AAPL, DELL, and IBM are computer makers; MSFT and ORCL are software companies; and ALTR, AMAT, AMD, INTC, KLAC, MU, MXIM, MOT, NVLS, and TXN are semiconductor companies. The fact that the high volume, low-dividend stocks are all

[21] There are issues computing implied volatilities for stocks that trade below $5 because strikes are usually in either $1 or $2.5 increments. This implies that options are often either extremely deep in or out-of-the-money and these options are not particularly sensitive to changes in implied volatility. We eliminate firms with major merger activity (e.g., AOL, Exxon-Mobil and Hewlet-Packard) as Subramanian (2004) documents that there are severe movements in implied volatilities related to the timing and uncertainty surrounding the merger that are unrelated to the next earnings announcement.

technology stocks is not surprising.[22]

For these firms, we download option price information (strike, maturity, implied volatility, etc.) for all available option contracts. The implied volatilities are based on the midpoint of the best bid and offer prices, and are adjusted for dividends and the American feature. We eliminate any strike/maturity combinations with zero volume, zero IV, or maturities of greater than one year. We next eliminate options with less than three days to maturity to avert potential issues arising in the final days of the options contract. Eliminating options with very short maturities potentially has two negative effects on our results. First, short-dated options are the most informative about earnings announcements, and replacing them with less-informative longer dated options would have a negative effect on our results. Second, longer-dated options have lower trading volume and higher bid-ask spreads, which also should, if anything, adversely impact our results. The impact of removing these options is minor, as none of our results change either quantitatively or qualitatively if we include these short-dated options.

For every day in our sample and every expiration date, the options were sorted by moneyness. Based on this sort, we record the IVs for the three strikes that are closest to the money. We focus on ATM money options because they are the most actively traded and provide the cleanest information on expected volatility. For each strike and maturity, the IVs of the call and put need not be identical, due to the American feature or microstructure noise such bid-ask spreads or stale quotes. Since OptionMetrics reports close prices, stale option quotes are a particular concern. For example, Battalio and Schultz (2006) argue that the presence of stale option quotes biases tests of put-call parity. To minimize this effect, we average the IV of the call and put options for the strike that is closest to-the-money for a given maturity, which mitigates a large portion of any stale quote problem.[23]

[22] We know little about exactly why investors trade options. Plausible explanations include leverage for speculation, downside protection, disagreement over stock price characteristics (expected returns, volatility, etc), or hedging. In all of these cases, it is not surprising to see that technology companies have high option volume.

[23] Too see how this removes a large portion of the issues with respect to stale quotes, consider the following example. Suppose that you have at-the-money call and put option with $T-t=1/12$, $S_t=\$20$,$\sigma=20\%$ and the interest rate is 5%. The call and put prices are \$0.5024 and \$0.4193. If we assume that option quotes do not change (they are priced assuming the stock price is \$20) and that the closing stock price is actually \$20.10, the IVs are not 20 percent, but rather 22.28 for the call and 17.918 for the put. This generates a serious problem for tests of put-call parity, such as those in Battalio and Shultz (2006). Our procedure of averaging the call and put IVs, generates an implied volatility of 20.09 percent, which is very

If the differences in call and put IV are extremely large, we eliminate this maturity from our dataset.

Our estimators require both the date and exact time of the earnings announcement. Nearly all earnings announcements are either after market close (AMC) or before market open (BMO). We obtain earnings announcement dates and/or times from multiple sources: Thomson-First Call, IBES, Compustat, and Fulldisclosure.com. We found that there was substantial disagreement over the dates and/or exact release times.[24] If any of sources disagreed over the date or time of an announcement, we used Factiva to find the new release to obtain the correct data and time. The earnings date is defined as the last closing date before earnings are announced. The vast majority of the announcements were AMC instead of BMO.

Earnings dates 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. There are three factors that lead us to believe this is not a serious concern. First, Bagnoli, Kross, and Watts (2002) find that from 1995 to 1998 there was an increase in the number of firms announcing on time and large firms with active analyst coverage tend to miss their expected announcement date less often 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 relatively large sized firms in our sample, this is not surprising. Third, as discussed in Appendix A, the exact timing is immaterial if there is uncertainty regarding the date, provided the distribution of jump sizes does not change.

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.

close to the true IV. In practice, averaging also reduces problems with bid-ask spreads. Pan and Poteshman (2006) use a similar procedure.

[24]We thank James Knight of Citadel Asset Management for pointing these database errors out to us.

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 note is how high earnings day volatility (column 3) is relative non earnings day volatility (column 4). In terms of variance ratios (column 5), they average over five and one firm, IBM, is as high 13.88. This implies that one earnings date delivers more than 5 days worth of variance. To put this into context for IBM, this implies that 18.3% of the total annualized variance of returns is due to four days per year. For other firms, roughly 8% of total variance arrives on the four earnings dates. Thus, earnings announcements explain a large, disproportionate share of volatility.

Our model for earnings announcements returns assumes that, conditional on volatility, returns are normally-distributed. However, since volatility changes across EADs, returns will be non-normal. Columns 6 and 7 document that there are some mild non-normalities on earnings date, as expected. Finally, the last two columns display non-normalities for the non earnings dates. 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 our sample, with the exception of APPL and to some extent HD. The levels of non-normalities are consistent with standard stochastic volatility models which generate kurtosis in the range of five to 10. Even if there were random jumps, the lack of strong skewness indicates that they are close to mean-zero, and the results of Merton (1976b) indicate that this will not impact our options based estimators, as we use ATM options.

The lack of non-normality for individual firms should not be surprising. The average daily volatility across firms is about 4%, which implies that a three standard deviation confidence band is $\pm 12\%$. 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, 1%) 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 C provides an intuitive test of our central modeling 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 PW (1979, 1981).

3.1 Nonparametric tests

The fundamental uncertainty estimators assume the reduced form model incorporating deterministic jumps is a reasonable description of reality. In this section, we provide formal tests of three main implications of the model: (1) IV increases prior to an earnings announcement; (2) the term structure of IV is downward sloping just prior to the announcement; and (3) IV decreases subsequent to the announcement.

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. Hollander and Wolfe (1999) provide a textbook discussion of the tests. The tests are nonparametric in the following sense. 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. We follow PW (1979, 1981) who also used the Fisher and Wilcoxon tests, in their case, to analyze implications (1) and (3). Our implementation is different from PW because we use differences in variance (as opposed to volatilities), as this is the implication of the model. The Fisher test gives the same result using either volatilities or variances, as it only

EAD	Rank	EAD Vol	NonEAD Vol	Var Ratio	EAD Skew	EAD Kurt	NonEAD Skew	NonEAD Kurt
AAPL	16	8.62	3.69	5.46	0.05	5.59	-3.19	74.64
ALTR	20	7.97	4.46	3.19	-0.15	6.31	-0.05	8.57
AMAT	10	5.94	3.86	2.37	0.79	6.52	0.21	7.35
AMD	12	9.99	4.39	5.19	0.28	6.17	-0.31	12.15
AMGN	13	5.45	2.63	4.31	-0.50	6.18	0.09	8.27
CSCO	1	6.74	3.25	4.32	0.53	7.34	0.06	9.06
DELL	6	7.09	3.21	4.87	-0.51	6.02	-0.10	8.25
HD	15	4.71	2.41	3.80	-0.74	6.41	-1.28	25.85
IBM	4	7.64	2.05	13.90	-0.37	5.47	0.12	8.37
INTC	3	6.98	3.01	5.38	-0.12	7.02	-0.40	10.33
KLAC	18	6.39	4.37	2.13	-0.26	6.55	0.28	7.59
MOT	14	9.35	3.09	9.15	-0.56	6.27	-0.37	11.25
MSFT	2	6.45	2.26	8.11	0.13	6.64	-0.16	8.85
MU	11	8.18	4.30	3.62	-0.52	6.63	0.06	7.89
MXIM	19	7.14	3.95	3.27	-1.69	9.10	0.29	7.35
NVLS	17	10.65	4.37	5.94	-0.68	7.69	0.41	8.28
ORCL	5	11.24	3.52	10.19	-0.63	7.72	0.06	8.85
QCOM	7	9.18	3.89	5.58	0.74	8.23	0.19	8.68
TXN	8	7.59	3.47	4.69	-0.11	6.91	0.20	6.98
WMT	9	3.01	2.10	2.05	-0.41	3.65	0.07	8.09

Table 1: Summary statistics for the underlying returns for the firms in our sample for the period January 1996 to December 2004. The columns are as follows: option volume rank, earnings announcement day volatility, non earnings announcement day volatility, the variance ratio between returns on earnings and non-earnings announcement days, the EAD return skewness, the EAD return kurtosis, the non-EAD return skewness, and non-EAD return kurtosis. The kurtosis statistics is the raw statistics, not excess kurtosis.

depends on signs and is invariant to monotonic transformations.

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 either an increase or decrease in volatility prior to an EAD, an increasing or decreasing term structure of IV at an EAD, or an increase or decrease 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). If, however, fundamental uncertainty plays a dominant role (as Figure 1 would suggest), the stochastic volatility should have little effect as the time or maturity variation in EIV_{t,T_i} is swamped by the impact of fundamental uncertainty.

To implement the tests, we use average call and put IV for the closest to-the-money strikes. For the time series tests, we are always careful to insure that we are comparing changes in IV for the same expiration cycle, so that we do not switch from one maturity to another. We always use the changes in IV for the shortest maturity option such that on the EAD there is more than three days to maturity. The results are even stronger if we use options maturing in less than three days. To test the increase prior to earnings we use a two week change in ATM IV, although the tests are the same if we use the change over one week. For the decrease in IV, we use the one day change from before to after the earnings announcement. If data is missing for the shortest-dated maturity, we move one day in either direction. For the term structure tests, we use ATM options for the first two available maturities.

Table 2 reports the test $p-$values for the three hypotheses. The tests reject all of the hypotheses at conventional levels of significance, with the only exceptions the Fisher term structure test for WMT. As we will see in the next section, WMT has the lowest fundamental uncertainty of all firms, and therefore, stochastic volatility will introduce relatively more noise for WMT than other firms. Such strong rejections are surprising given our relatively small sample size (36 earnings dates) and provide support for our reduced-form model and the importance of jumps on EADs. The results are strongest for the highest volume firms in our sample. For CSCO, DELL, IBM, INTC, MSFT, and ORCL, the highest p-value is 4.36×10^{-5}. 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.

	Increase Prior to EAD		Term Structure at EAD		Decrease after EAD	
	Wilcoxon	Fisher	Wilcoxon	Fisher	Wilcoxon	Fisher
AAPL	6.03E-7	6.46E-6	3.73E-7	1.14E-7	1.08E-7	9.71E-9
ALTR	4.89E-5	1.56E-4	2.42E-6	9.71E-6	1.32E-6	1.14E-7
AMAT	5.57E-7	9.71E-9	1.25E-7	1.05E-9	8.4E-8	1.46E-11
AMD	1.54E-6	9.71E-9	6.77E-5	1.16E-3	8.4E-8	1.46E-11
AMGN	1.51E-2	1.44E-2	2.08E-6	9.71E-9	1.18E-7	5.38E-10
CSCO	3.44E-7	1.14E-7	8.4E-8	1.46E-11	8.4E-8	1.46E-11
DELL	1.37E-5	6.46E-6	2.69E-8	1.05E-9	1.08E-7	5.38E-10
HD	1.49E-3	5.97E-4	7.32E-6	3.83E-7	1.66E-6	9.71E-9
IBM	6.03E-7	5.38E-10	5.75E-7	2.04E-9	8.4E-8	1.46E-11
INTC	8.4E-8	1.46E-11	1.46E-11	5.38E-10	8.4E-8	1.46E-11
KLAC	7.95E-4	1.97E-3	5.42E-4	5.97E-4	2.49E-7	6.46E-6
MOT	1.66E-6	1.14E-7	3.8E-6	5.46E-6	1.27E-5	1.46E-11
MSFT	5.44E-6	6.46E-6	3.02E-6	3.48E-5	7.07E-7	1.46E-11
MU	1.37E-5	9.71E-9	1.06E-6	2.31E-7	8.4E-8	5.38E-10
MXIM	3.92E-2	1.44E-2	1.68E-5	9.71E-7	1.27E-5	6.46E-6
NVLS	2.24E-6	9.71E-9	3.0E-5	5.84E-5	7.07E-7	1.14E-7
ORCL	1.54E-6	1.14E-7	4.36E-5	3.83E-7	8.4E-8	1.46E-11
QCOM	3.54E-6	0.0144	1.24E-7	2.91E-11	2.7E-7	1.14E-7
TXN	4.15E-3	1.97E-3	9.38E-7	2.09E-7	3.18E-7	9.71E-9
WMT	3.78E-6	1.14E-7	0.0195	0.148	6.53E-7	1.14E-7

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 decrease in implied volatility after the earnings announcement.

One potential concern is that the increase in IV and declining term structure of IV prior to earnings could be driven by issues related to expiration cycles: as the time-to-maturity decreases, option IV tends may increase. There are three reasons this is not a major concern. First, and most importantly, if this is the case, 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 of no decrease in IV subsequent to an EAD is rejected for every single firm, and that the $p-$values for the decrease tend to be the lowest of the three tests, implies that this is not a particularly important issue.

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 or CSCO) are those with the highest volume implying that any liquidity effects (which could explain the PW finding) in short-dated options will be minimal. For firms with a long average time-to-maturity such as IBM, MSFT and ORCL (20, 20, and 13 days, respectively), the tests strongly reject. Thus, time-to-maturity biases could not explain our results.

It is difficult to imagine an alternative to our explanation for the strong predictable behavior in IV. One potential explanation is Mahani and Poteshman (2005), who document that retail investors increase holdings of options on growth stocks prior to EADs. 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 this occurs), prices and IV would similarly fall subsequent to the earnings announcement. Could the demand of retail investors generate the magnitudes observed in the data? For example, in the Intel example, could retail investor behavior generate the pattern in IVs in the introduction, whereby the first two IVs were 95% and 65% and the short-dated volatility falls to 55%?

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 IV prior to and decrease in IV subsequent to an EAD as shown by our model. Second, retail investors make up a small portion of option market volume (about

10-15% 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 IV, 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%, which is within the bid-ask spread, and they find the impact is smaller for individual stocks.

Overall, the results provide extremely strong statistical evidence in support of our reduced-form model and its main implications. Option IV increases leading into earnings announcements, the term structure declines for the first two maturities, and IV decreases subsequent to the earnings announcement. Given this support, we next turn to the analysis of the fundamental uncertainty estimators.

3.2 Characterizing fundamental uncertainty

3.2.1 Fundamental uncertainty estimates

Tables 3 and 4 summarize the term structure and time series estimates 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, standard error, and quantiles). All numbers are in volatility units which is conservative due to Jensen's inequality.[25]

Table 3 indicates that fundamental uncertainty estimates using the term structure approach are large, both economically and statistically, which is consistent with the earlier nonparametric tests. Across firms, the average fundamental uncertainty is 7.93% and for nearly all firms, the mean is greater than the median, indicating that fundamental uncertainty has positive skewness. The upper quantile indicates that the anticipated fundamental uncertainty can be quite large: an anticipated fundamental uncertainty of 12% implies that an expected 3 standard deviation confidence band is ±36%. This implies that the large moves observed around EADs may be largely anticipated. The estimates also vary across

[25] Jensen's inequality implies that the average of the standard deviations is less than the square root of the average variances since

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

Term	Mean	Median	Std. Error	25%	75%	Err_1	Err_2
AAPL	8.83	8.33	0.52	6.73	10.21	2	0
ALTR	9.60	9.42	0.88	6.91	11.44	3	0
AMAT	8.85	9.22	0.44	7.05	10.32	0	0
AMD	10.65	10.41	0.67	8.32	12.92	0	0
AMGN	5.75	5.44	0.41	4.74	6.86	1	0
CSCO	8.50	7.50	0.60	6.14	10.90	0	0
DELL	7.57	7.61	0.53	5.44	9.20	1	0
HD	5.05	4.85	0.32	4.18	5.47	2	0
IBM	6.31	5.44	0.40	4.83	7.76	0	0
INTC	8.29	7.53	0.45	6.61	9.34	0	0
KLAC	7.32	6.07	0.77	4.05	9.79	4	0
MOT	9.27	9.27	0.68	6.65	11.28	0	0
MSFT	5.17	5.29	0.36	3.87	6.49	0	0
MU	10.71	9.85	0.83	6.47	13.65	1	0
MXIM	8.11	7.59	0.67	5.66	9.55	5	1
NVLS	8.54	7.56	0.66	5.92	10.48	3	0
ORCL	10.09	9.55	0.69	7.49	11.31	0	0
QCOM	8.58	7.71	0.74	5.56	11.17	3	1
TXN	7.70	7.21	0.56	5.16	9.49	2	0
WMT	3.40	2.99	0.41	2.18	3.75	3	0
Pooled	7.93	7.30	0.15	5.12	10.17	1.5	0.05

Table 3: Fundamental uncertainty estimates 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, and the 75 percentile. Err_1 counts the number of days in which $\sigma_{t,T_1} < \sigma_{t,T_2}$ and Err_2 counts the number of days where $\sigma_{t,T_1} - \sigma_{t,T_2} < -5\%$.

firms.[26] AMD, MU, and ORCL averaging over 10%, while WMT average on 3.4%. One obvious explanation for the differences is that retailers release monthly sales data, so there is substantially less uncertainty for these firms.

The large fundamental uncertainty estimates can easily explain the spikes in Figure 1. Consider the following example. Assume the annualized diffusive volatility is constant at 40%, which implies the daily diffusive volatility is about 2.5% ($0.40/\sqrt{252}$). If the fundamental uncertainty is 10%, then the annualized IV of an ATM option expiring in one-week is about 92% prior to the announcement and then subsequently falls to 40%.

To quantify the economic impact, consider an ATM call and straddle position with one-week to maturity ($\tau = 1/52$), an interest rate of 5% and $S_t = 25$. Prior to the announcement, the call and straddle values were about \$1.53 and \$3.03, respectively. Assuming the stock price did not change the following day, the prices after the announcement fall to \$0.68 and \$1.65, an almost 50% decrease due to the drop in volatility. If, however, the stock price fell 20% (a two standard deviation move), then the positions are worth \$0.0 and \$5.03. For the straddle, the loss is almost 40%, showing the severe risks associated with writing options around EADs. We will discuss the evidence on option returns around earnings dates below.

The last two columns in Table 3 decompose any problem dates. The column labeled Err_1 counts the number of EADs for which $\sigma_{t,T_1} < \sigma_{t,T_2}$, in contrast to our maintained assumption. The results indicate that on average there are 1.5 problematic announcements per firm out of 36. A small number of errors are not at all surprising for a number of reasons. First, they are not evenly distributed, as the five largest firms, CSCO, IBM, INTC, MSFT, and ORCL had no problem dates and 19 of the 30 problem dates occurred for the five firms with the lowest trading volume (AAPL, ALTR, KLAC, MXIM, and NVLS). This suggests that microstructure or liquidity issues are likely responsible. Second, though rare, the magnitudes of these errors were also extremely small. Err_2 counts the number of these errors for which $\sigma_{t,T_2} - \sigma_{t,T_1} > 5\%$. Out of the 30 errors, only two were greater than 5%. As a comparison, option bid-ask spreads for the maturities we use are around 5%, in terms of implied volatilities. This is especially be relevant for firms with low fundamental uncertainty (HD and WMT), as the differences in IVs for options on these firms are smaller. Finally, the time series estimator was positive for two-thirds of the error dates. Together, this

[26] Jiang and Johannes (2006) provide a detailed analysis of the cross-sectional information contained in fundamental uncertainty estimates using a large cross-sectional sample.

indicates that the errors in the term structure estimator are likely driven by microstructure or data recording errors.

Table 4 provides the time series estimator results. The times series estimates are quantitatively and qualitatively similar to the term structure estimates. The average term structure estimate across firms is 7.93%, compared to 7.76% for the time series estimate, which is not statistically different. Again, the means are larger than the medians, indicating positive skewness. The fact that averages are not statistically or economically different indicates that were are capturing a strong common effect. Also, if either the term structure or time series estimators had biases, the estimators would generate different results, which they do not. This is reassuring.

The correlation between the time series and term structure estimates are also high. The correlation across firms of the mean fundamental uncertainty estimates using the two methods is 92%. To decompose the correlations a bit further, column 6 in Table 4 provides the within firm, across time correlation between the term structure and time series estimates, conditional on both estimates being positive. In general, the correlations are quite high and the pooled correlation is 69.4%.

An analysis of problematic dates for the time series estimator reveals that the time series estimator is less reliable than the term structure estimator for two reasons. First, looking at the error columns in Table 4, we see that the overall error rate for the time series estimator is more than twice the rate for the term structure estimator. More importantly, the there are now more dates on which σ_{t,T_1} is substantially lower than σ_{t,T_2}. As in the case of the term structure estimator, both the total errors and the large errors are concentrated in the lower volume firms (KLAC, MXIM, and NVLS). Second, there are now a number of dates on which we not able to find implied volatilities before and after the announcement for the same maturity. These were heavily concentrated in the beginning of the sample. For example, seven of the first ten EADs for AMD resulted in no available pairs for estimation and 23 out of the 29 problem dates were in the first three years of the sample.[27] The increased error rate for the time series estimator is also consistent with the arguments in Appendix C, which document that firms with very high volatility (e.g., KLAC, MXIM, AMD, NVLS) or very low fundamental uncertainty (e.g., WMT) will have noisier time

[27] One explanation for this is that prior to August 1999, options were not cross-listed on different exchanges. The practice was changed after a Department of Justice lawsuit in summer of 1999 accused the major exchanges of collusion in restricting listings to only one exchange. After 1999 OptionMetrics can use the best bid and offer from all four major exchanges, reducing and data errors.

Time	Mean	Median	Std. Err	25	75	$Corr_1$	Err_1	Err_2	No Data
AAPL	9.23	8.35	0.75	6.16	11.15	48.5	3	0	0
ALTR	9.49	9.00	0.76	6.24	12.14	77.2	4	1	0
AMAT	9.76	10.22	0.51	6.98	11.70	57.6	1	0	1
AMD	12.60	12.16	1.56	8.40	13.95	33.4	6	1	7
AMGN	5.40	5.14	0.41	4.03	7.00	32.2	2	1	0
CSCO	8.05	7.35	0.50	5.58	9.46	88.2	0	0	0
DELL	7.83	8.05	0.50	6.04	9.49	68.3	1	0	1
HD	4.30	3.74	0.35	3.11	4.85	85.7	3	1	2
IBM	6.41	6.02	0.47	4.86	8.54	73.9	1	0	2
INTC	7.83	7.04	0.52	5.87	9.17	73.2	1	1	0
KLAC	7.22	6.37	0.69	4.85	9.49	71.5	8	3	0
MOT	8.72	8.84	0.61	6.49	11.07	88.9	4	1	3
MSFT	6.25	5.68	0.40	4.97	7.32	53.7	6	1	0
MU	9.44	9.06	0.59	8.10	11.26	49.6	2	0	5
MXIM	6.47	6.05	0.57	4.99	7.55	73.5	4	2	0
NVLS	7.94	7.49	0.62	5.54	10.02	55.1	6	3	1
ORCL	8.90	8.75	0.68	6.41	10.96	73.0	3	2	2
QCOM	8.66	7.73	0.61	6.19	10.48	85.6	0	0	1
TXN	6.94	6.04	0.52	4.77	9.32	73.0	3	0	1
WMT	3.25	2.46	0.59	1.65	3.84	82.3	13	0	3
Pooled	7.76	7.07	0.16	5.09	9.89	69.4	3.55	0.85	1.45

Table 4: Fundamental uncertainty estimates using the time series 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, and the 75 percentile. $Corr_1$ gives the within firm correlation between the time series and term structure estimator, conditional on both existing. Err_1 counts the number of days in which $\sigma_{t,T_1} < \sigma_{t,T_2}$ and Err_2 counts the number of days where $\sigma_{t,T_1} - \sigma_{t,T_2} < -5\%$. The column labeled "No Data" indicates that there were not options available that satisfied the requirement for computing the time series estimator.

series estimates.

In what remains, we use only the term structure estimates of fundamental uncertainty because they are far more accurate and the are based solely on ex-ante data.

3.2.2 Information content of fundamental uncertainty

Given the estimates of $\sigma_j^{\mathbb{Q}}$, we can investigate a number of interesting implications including time-variation of fundamental uncertainty and risk premia, the informational content of the jump-volatility estimates, and model specification.

We note that there is an interesting time-variation in the jump volatilities. Table 5 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 2000-2002 and was significantly lower in 1996-1999 and 2003-2004. The magnitude of the effect is substantial: the average in 2000-2002 was 39% higher than in the other years.

This time-variation in fundamental uncertainty is closely related to Pastor and Veronesi (2005) in two ways. First, in their simple model, investors learn about a fixed parameter, and because of this uncertainty declines monotonically for a given firm across time. Our results indicate that fundamental varies substantially within a firm across time. This could be easily accommodated in a straightforward extension of Pastor and Veronesi (2005) that allows for the mean-level of profitability to be a mean-reverting state variable, as in Veronesi (2003). Second, Pastor and Veronesi (2005) argue that aggregate uncertainty regarding firm profitability was much higher around 2000 than in other periods and this uncertainty can, to a large extent, explain 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 1999-2001 (see, e.g., their Figure 8). We also find that uncertainty over fundamentals, as measured by $\sigma_j^{\mathbb{Q}}$, was higher in 2000-2002, but the magnitude is somewhat smaller than Pastor and Veronesi (2005).

There are also issues related to risk premia, associated with the jumps on EADs. These risk premia could appear in different forms. 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 places few 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

Year/Firm	1996	1997	1998	1999	2000	2001	2002	2003	2004
AAPL	9.65	7.57	9.52	7.12	10.33	13.34	7.24	6.75	8.58
ALTR	9.58	7.39	11.09	11.36	13.38	12.37	11.15	6.45	3.66
AMAT	10.24	10.15	8.59	8.78	11.59	9.43	8.04	5.79	7.05
AMD	8.36	8.06	13.54	7.36	15.88	12.82	10.75	11.01	8.03
AMGN	5.36	4.50	5.10	7.93	9.63	6.21	4.30	3.97	4.47
CSCO	6.50	7.89	5.65	6.01	10.69	11.61	13.87	8.12	6.11
DELL	8.84	9.02	8.37	10.97	9.21	6.50	6.10	3.32	4.75
HD	3.53	5.02	4.57	3.96	7.45	5.01	5.71	5.16	4.79
IBM	7.05	7.40	4.87	5.94	8.84	8.56	5.72	4.84	3.58
INTC	8.74	7.80	6.67	8.34	9.57	10.34	10.05	6.96	6.16
KLAC	5.98	7.73	10.24	5.17	10.05	6.54	11.50	3.37	6.27
MOT	9.24	6.63	8.69	6.43	9.61	12.75	12.02	8.27	9.82
MSFT	5.40	3.96	5.73	4.79	7.07	5.38	5.66	5.21	3.33
MU	8.75	11.01	9.56	10.07	18.43	11.05	11.84	10.88	6.75
MXIM	11.57	6.81	7.18	8.55	11.31	9.44	8.47	6.20	3.90
NVLS	9.59	7.30	6.66	5.34	9.10	12.04	11.08	6.90	6.79
ORCL	8.74	6.82	10.01	12.54	12.36	14.76	12.74	7.61	5.21
QCOM	6.71	9.16	5.74	8.05	15.07	9.50	10.29	5.30	5.75
TXN	7.79	4.56	5.96	4.53	9.84	11.02	9.92	6.94	7.53
WMT	3.00	3.20	3.14	2.77	6.22	3.61	3.59	2.15	2.67
Pooled	7.84	7.20	7.56	7.42	10.67	9.57	8.94	6.29	5.78

Table 5: 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. The pooled row gives pooled averages.

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, and provide a number of different metrics. 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 mean-jump risk premium, we have to estimate the mean under the objective measure. Simple announcement day returns are problematic as volatility, σ_j, can be time-varying and we therefore compute standardized returns. If $\log\left(S_{\tau_j+1}/S_{\tau_j-}\right)$ is the return on the day after the announcement, then

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

is the standardized return, where $\sigma_j^{\mathbb{Q}}$ is the estimate of fundamental uncertainty and σ^2 is the diffusive volatility, both estimated from option prices.

The column labeled '$t-$stat' in Table 6 provides the $t-$statistics for the standardized means. There is little evidence for any premia in average returns, in the sense that one cannot reject the hypothesis that the average standardized return. 11 firms have negative returns and 9 have positive returns. Using the exact critical values for the t-statistic, none of the statistics are significant using a one-sided tests, although MU and MAD are marginally significant in a two-sided t-test. The lowest t-values occur for the largest firms, CSCO, DELL, IBM, INTC, MSFT, and ORCL. This insignificance is not a surprise, given the high volatility of returns on EADs. Overall, we conclude there is no evidence for jump-mean risk premia.

Consider next the evidence for a risk premium attached to volatilities, which would manifest itself via $\sigma_j < \sigma_j^{\mathbb{Q}}$.[28] We will analyze this issue from three different perspectives. First we compare the observed volatility of returns under $\mathbb{P}$ with the average ex-ante expected daily volatility of returns under $\mathbb{Q}$, by computing the expected volatility under $\mathbb{Q}$ (denoted in Table 6 as 'Q-vol') from the options data and the realized volatility under $\mathbb{P}$ from returns (denoted in Table 6 as 'P-vol'). It is difficult to form a formal test for equality across these two estimates, as both are estimated, and the variances are changing over time. Standard

[28] There is some evidence for a risk premium attached to the volatility of jump sizes using index options, see Broadie, Chernov, and Johannes (2006).

	Qvol	Pvol	$Corr_2$	t-stat	Std	Skew	Kurt	KS	JB
AAPL	10.02	8.84	40.3	0.44	0.92	0.15	2.35	0.85	0.57
ALTR	11.52	8.09	5.6	0.71	0.94	-0.03	4.06	0.26	0.63
AMAT	9.92	5.94	18.4	1.66	0.63	0.96	4.34	0.03	0.03
AMD	12.16	9.99	23.4	-1.80	1.06	-1.90	10.05	0.05	0.00
AMGN	6.74	5.51	47.3	1.17	0.86	0.05	2.35	0.57	0.63
CSCO	9.66	6.74	37.5	-0.05	0.74	-0.15	2.55	0.40	0.72
DELL	8.71	7.17	44.4	0.05	0.90	0.43	2.58	0.64	0.48
HD	5.79	4.83	8.8	-0.58	0.95	-0.91	3.27	0.31	0.12
IBM	7.08	7.64	33.4	0.54	1.18	-0.22	2.12	0.37	0.42
INTC	9.11	6.98	37.4	-0.02	0.74	0.07	2.88	0.58	0.93
KLAC	9.39	6.42	48.5	-0.51	0.81	-1.30	6.02	0.48	0.00
MOT	10.65	9.35	41.6	-1.14	1.04	–1.16	4.82	0.55	0.00
MSFT	6.08	6.45	33.5	-0.62	1.14	-0.25	2.26	0.34	0.48
MU	12.42	8.22	15.6	-2.40	1.00	-2.80	14.10	0.01	0.00
MXIM	9.60	7.05	24.3	-0.49	0.73	-0.11	5.71	0.07	0.03
NVLS	10.35	10.70	-11.4	-0.19	1.32	-1.22	5.64	0.84	0.00
ORCL	11.39	11.24	3.4	-0.18	1.35	-2.14	10.46	0.65	0.00
QCOM	10.23	8.94	10.0	1.62	1.10	1.43	5.93	0.25	0.00
TXN	8.96	7.57	30.2	0.90	0.92	0.15	2.71	0.49	0.82
WMT	4.59	2.74	12.3	0.93	0.78	-0.69	3.61	0.24	0.27
Pooled	9.21	7.52	28.6	-0.00	0.95	-0.48	4.89	0.39	0.31

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.

tests are for equality of variances from two populations with an assumed constant variance. Overall, $\mathbb{Q}$-volatility is about 1.7% higher than $\mathbb{P}$-volatility, but the effect is not uniform. For most of the firms, the average $\mathbb{Q}$-volatility is larger than the average $\mathbb{P}$-volatility, but for other firms, such as IBM, MSFT, NVLS, or ORCL, the difference is negative or close to zero. There does not appear to be a level effect, as $\mathbb{Q}$-volatility is greater than $\mathbb{P}$-volatility for both high and low volatility firms. Thus, there is some evidence for a fundamental uncertainty premia, but certainly not uniform evidence. These results could be sensitive to outliers, as the mean estimate of $\sigma_j^{\mathbb{Q}}$ is more than 0.6% higher than the median.

A potentially more powerful diagnostic is to compute the standard deviation of $J_{\tau_{j+1}}$, which accounts for time-variation in the volatilities and is less sensitive to outliers. This metric is important as the standard deviation of $J_{\tau_{j+1}}$ is one, under our model specification assuming no risk premium. This metric is given in column 6 of Table **??**. Overall, the pooled statistics indicate that there is slight evidence for a volatility risk premium, as the pooled standard deviation is 0.95. However, many of the results differ from the previous test. For example, AMD, MOT, MU, and QCOM had $\mathbb{Q}$-volatility greater than $\mathbb{P}-$volatility, but now have $std\left(J_{\tau_{j+1}}\right) > 1$. Other firms such as ORCL, which had roughly equivalent $\mathbb{Q}$-volatility and $\mathbb{P}$-volatility, now have a $std\left(J_{\tau_{j+1}}\right) > 1$. Again, this provides inconclusive evidence for a volatility risk premium.

We provide one final test for a fundamental uncertainty volatility premium. If $\sigma_j^{\mathbb{Q}} > \sigma_j$, then writing straddles should be a profitable. To analyze this, we compute the returns to an investor who purchases an ATM call and put at the midpoint of the close price prior to the earnings announcement and sells these options at the midpoint of the close price on the first day after the announcement. We enforce the same data restrictions used previously, and are careful to be sure that the prices we use are for the same strike and maturity. In the interest of space constraints, we do not report all of the results and rather give a brief summary. The results indicate that returns to straddles are -1.21%, and the median return is -8.05%. This would be consistent with $\sigma_j^{\mathbb{Q}} > \sigma_j^{\mathbb{P}}$. However the returns are extremely volatility and non-normal. The raw standard deviation of the option returns is 39.18%, which is not surprising given the embedded leverage in options. The Sharpe ratio is not statistically significant. The skewness is 10.2 and the kurtosis is 177.3, indicating that extremely large positive returns are likely. Taken together, the option returns do not provide any evidence that $\sigma_j^{\mathbb{Q}} > \sigma_j^{\mathbb{P}}$. It is also important to note that the slightly larger estimates of $\sigma_j^{\mathbb{Q}}$ could reflect a Peso-type problem. Options market participants may have expect a large movement, but these were not always realized. Moreover, since the observed returns are conditionally normally distributed, it would not be surprising even with a large $\sigma_j^{\mathbb{Q}}$ to have a relatively small observed return.

Overall, we conclude that there is no convincing evidence for mean or volatility premia attached to fundamental uncertainty. This could be due to the very low signal-to-noise ratio present in the data or, alternative, that firm-specific fundamental uncertainty can be diversified cross-sectionally. It is important to note that there are also arguments that would support a fundamental uncertainty premium. For example, jumps are difficult to hedge which could lead to a premium. Similarly, 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-IV. 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.

Another important issue to analyze is predictive content: does a high $\sigma_j^{\mathbb{Q}}$ predict that subsequent returns are volatile? It is difficult to analyze this in a time series context because one cannot estimate a time-varying $\sigma_j^{\mathbb{P}}$ based on a single observation. To analyze this issue, we report the cross-sectional correlation between Q-vol and P-vol and the firm specific and pooled correlations bectween $\left|r_{\tau_j,\tau_{j=1}}\right|$ and $\sigma_j^{\mathbb{Q}}$. The cross-sectional correlation between $\mathbb{Q}$-volatility and $\mathbb{P}$-volatility is 79%, indicating that high $\mathbb{Q}$-vol firms tend to be high $\mathbb{P}$-vol firms. A more interesting statistic is the correlation between $\left|r_{\tau_j,\tau_{j=1}}\right|$ and $\sigma_j^{\mathbb{Q}}$, reported as $Corr_2$ in Table **??**. The correlations are positive and strongly significant (at the 1% level) for the largest five firms (CSCO, DELL, IBM, INTC, and MSFT) and for AAPL, AMGN, KLAC and MOT, but are marginally significant or insiginificant for the other firms. The average pooled correlation is 28% and is highly significant.

To understand the significance of these results, we need to understand the properties of the statistic. As an example, suppose that $\log\left(\sigma_j^{\mathbb{Q}}\right) \sim \mathcal{N}\left(2,(0.25)^2\right)$, which generates an average fundamental uncertainty of about 7.75%, and that $r_{\tau_{j+1}} \sim \mathcal{N}\left(0,\left(\sigma_j^{\mathbb{Q}}\right)^2\right)$. Then, the population correlation between $\left|r_{\tau_j,\tau_{j=1}}\right|$ and $\sigma_j^{\mathbb{Q}}$ is about 30%, with substantial uncertainty as a $(5,95)\%$ quantile is $(-0.01,0.56)$ in samples of our size. Thus, the range of values are in fact completely consistent with the model. Jiang and Johannes (2006) provide an alternative test of informativeness based on a large cross-section and find that fundamental uncertainty is the strongest predictor of absolute returns when compared to a number of other predictors including historical volatility, option implied diffusion volatility, analyst dispersion, age of the firm, market-to-book ratios, etc. Together, these results indicate that our fundamental uncertainty estimates are informative about future realized returns.

Finally, we consider some general specification tests. Our model implies that the standardized returns, $J_{\tau_{j+1}}$, are normally distributed. 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, two common tests for non-normalities. The skewness and excess kurtosis statistics indicate that any departures from normality are modest, with a few exceptions of AMD, MU and ORCL. As formal tests of non-normalities, we consider the Kolmogorov-Smirnov and Jarque-Bera tests. The Kolmogorov-Smirnov and Jarque-Bera tests often disagree (one is significant the other is not) and there is only significant departures for both for AMAT and MU. For the other firms, the results are either mixed (one test does and the other does not) or both are insignificant. For the pooled sample overall, there is not evidence for non-normalities. This evidence is reassuring as there is not strong evidence that the jumps come from a non-normal distribution.

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.[29] 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

[29] 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.

much lower IV. 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. 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.[30] 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 (2006). 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

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

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.

[30]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.

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 based on ATM options as it does not have a significant impact on option prices.[31] 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 7, 8, and 9. Table 7 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

[31] 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.

		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 7: 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.

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.[32] 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 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 (3) 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 IVs 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 7 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% 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.

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

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 9 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%. 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

			-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 8: 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 9: Overall mean absolute pricing errors broken down by firm and maturity.

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

Table 9 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 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 (2006) 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 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,

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

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

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

where

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

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

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

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 $\log\left(S_T\right)$ is just the product of the traditional affine transform and the transform of the deterministic jumps:

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

where $E_t^{\mathbb{Q}}\left[\exp\left(c\sum_{j=N_t^d+1}^{N_T^d}Z_j\right)\right] = \exp\left(\alpha^d\left(t\right)\right)$ for some state-independent function α^d, $\alpha^*\left(t\right)=\alpha^*\left(c,t,T\right)$, and $\beta\left(t\right)=\beta\left(c,t,T\right)$. 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

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

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:

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

and $|\psi_c(v)| \le \sqrt{A} v^{-2}$. 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.

B 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.

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 $T_2 > T_1$. For generality, 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 no 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 $\left(\widetilde{\theta}_v^{\mathbb{Q}} = \lambda\mu_v^{\mathbb{Q}} + \theta_v^{\mathbb{Q}}\right)$

$$EIV_{t,\tau_i} = T_i^{-1}E_t^{\mathbb{Q}}\left[\int_t^{t+T_i} V_s ds\right] = T_i^{-1}\int_t^{t+T_i} E_t^{\mathbb{Q}}\left[V_s\right]ds \tag{11}$$

$$= T_i^{-1}\int_t^{t+T_i} E_t^{\mathbb{Q}}\left[\widetilde{V}_s\right]ds + \lambda_v^{\mathbb{Q}}\mu_v^{\mathbb{Q}} \tag{12}$$

$$= \widetilde{\theta}_v^{\mathbb{Q}} + \frac{\left(1 - e^{-\kappa_v^{\mathbb{Q}}T_i}\right)}{\kappa_v^{\mathbb{Q}}T_i}\left(V_t - \widetilde{\theta}_v^{\mathbb{Q}}\right). \tag{13}$$

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,T_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,T_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 $EIV_{t,T_1} \neq EIV_{\ t,T_2}$.

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. As mentioned in the text, 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 (2006)) 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 for the shortest maturities, this implies that V_t is close to $\theta_v^{\mathbb{Q}}$ and/or $\kappa_v^{\mathbb{Q}}$ is small. Volatility is also 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.

More formally, there is some evidence regarding these issues. For index options, Pan finds that $\kappa_v^{\mathbb{Q}} = -0.05$, which implies explosive volatility, but it is not statistically different from zero.[33] Using time series models, Cheung and Johannes (2006) finds that individual firms, once earnings announcements are accounted for, have more persistent volatility than indices. The results point to values of $\kappa_v^{\mathbb{P}}$ being around 1.25. In later sections, we estimate

[33] Typical risk premium estimates imply that $\kappa_v^{\mathbb{Q}} < \kappa_v^{\mathbb{P}}$, see, for example, Pan (2002) or Eraker (2004). Jones (2003), like Pan (2002), finds explosive risk-neutral volatility, although its magnitude is small.

these models using option price data and find estimates of $\kappa_v^{\mathbb{Q}}$ to be less than 2.

The term structure of IVs is also very flat over short maturities. This is also true for both indices and individual equity options. For example, Broadie, Chernov, and Johannes (2006) found the slope of the IV term structure was less than 1% for S&P 500 options. The same result holds for the firms in our dataset. As an example, for two of these firms, Microsoft and Cisco, the average slope of the term structure for the front three contracts is 0.59 and 0.08%, respectively, for months that are not affected by earnings announcements.[34] A flat average term structure indicates that $\theta_v^{\mathbb{Q}} \approx \theta_v^{\mathbb{P}}$ and/or that $\kappa_v^{\mathbb{Q}}$ is very small. Further evidence pointing toward mild risk-neutral mean-reversion comes from variation in the slope of the IV term structure for individual equity options. In addition to little average slope, there is also very little term structure slope even in very high or very low states. For example, for Microsoft and Cisco the $(10, 90)\%$ quantile of the term structure slope is $(-2.13, 1.99)\%$ and $(-1.78, 1.85)\%$, respectively. This again points to a very low value of $\kappa_v^{\mathbb{Q}}$. Last, most of the trading volume is concentrated in short-dated options, and we use the shortest maturities for estimation. In practice, we almost always have the two near maturity option contracts. Putting the pieces together, this implies that any the impact of mean-reversion is very 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%). 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

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

[34] Since earnings announcements, generate large, negatively sloped IV term structures, we compute these statistics for the months after an EAD. This insures that any impact of EADs will be minimal.

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%, 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% 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% 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.

C Close/open and open/close behavior

We assume that earnings announcements generate a discontinuity in the sample path of stock prices. An alternative assumption is that the diffusion coefficient increases on days following earnings announcements, as in PW (1979, 1981). Thus, the main difference between our model and PW's model is the discontinuity of the sample path. In theory, prices are observed continuously and jumps are observed at $\Delta S_t = S_t - S_{t-}$, but with discretely sampled prices, it is impossible to identify when jumps occurred with certainty. It is common to use statistical methods (see, e.g., Johannes (2004), Barndorff-Nielson and Shephard (2006), or Huang and Tauchen (2005)) to identify jumps. Identifying jumps on EADs is even more difficult in our setting as earnings are announced outside of normal trading hours.[35]

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 exactly 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 10 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 3.53 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 returns on earnings days was 5.81% compared to 1.68% on non-earnings dates. Since we

[35] 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.

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 6.66% on earnings days compared to 1.44% for non-earnings days, for a ratio of 4.63.

Second, note that open-to-close returns are slightly more volatile on earnings dates than non-earnings dates, on average 4.09% compared to 3.03% which indicates that returns are slightly more volatile during the day following earnings. This could be due to a number of factors, such as price discovery through trading, liquidity, or inefficient opening procedures. Regarding the last point, Barclay, Hendershott, and Jones (2004) argue that the Nasdaq opening procedure introduces more noise than the opening procedure on the NYSE and the effect is excaberated for smaller stocks.

If liquidity caused increased variation the day after EADs, then actively traded firms should have a ratio closer to unity.[36] Focusing on the five largest firms, the difference is much smaller: the volatility during the day is 2.95 (2.57)% on earnings (non-earnings) dates, indicating the volatility is quite similar (ratio of about 1.15). In contrast, the smallest firms are relatively more volatile during the day, 5.35% compared to 3.75% for a ratio of 1.4. The obvious explanation for the difference between the higher and lower-volume companies is liquidity, which leads to more price discovery during market hours. 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.

[36] We would like to thank Joel Hasbrouk for pointing this issue out to us.

	EAD Close/open	Non-EAD Close/open	Ratio	EAD Open/Close	Non-Ead Open/Close	Ratio
AAPL	7.25%	2.11%	3.43	3.45	3.08	1.12
ALTR	6.01%	2.20%	2.73	5.45	3.98	1.37
AMAT	4.02%	1.87%	2.14	4.47	3.48	1.28
AMD	8.16%	2.29%	3.56	6.73	3.78	1.78
AMGN	4.32%	1.25%	3.45	2.75	2.41	1.14
CSCO	5.29%	1.64%	3.22	2.62	2.93	0.90
DELL	6.19%	1.64%	3.77	2.79	2.9	0.96
HD	3.11%	1.36%	2.29	2.49	1.99	1.25
IBM	6.09%	0.99%	6.15	3.30	1.83	1.81
INTC	5.85%	1.70%	3.43	3.53	2.55	1.39
KLAC	4.08%	1.78%	2.30	6.01	3.98	1.51
MSFT	8.61%	1.67%	5.16	4.29	2.68	1.6
MOT	4.99%	1.09%	4.56	2.52	2.03	1.24
MU	4.36%	2.09%	2.09	5.38	3.78	1.42
MXIM	4.55%	1.42%	3.2	4.77	3.70	1.29
NVLS	6.43%	1.88%	3.42	6.83	3.99	1.71
ORCL	10.77%	1.84%	5.85	3.52	3.19	1.10
QCOM	7.20%	1.90%	3.78	4.80	3.49	1.38
TXN	6.83%	1.75%	3.89	3.96	3.01	1.32
WMT	2.19%	1.02%	2.15	2.16	1.89	1.14
Average	5.81%	1.68%	3.53	4.09	3.03	1.34

Table 10: Comparisons of close-to-open and open-to-close returns on earnings (EAD) and non-earnings (non-EAD) announcements dates.

References

Aït-Sahalia, Yacine and Robert Kimmel, 2006, Maximum Likelihood Estimation of Stochastic Volatility Models, forthcoming, *Journal of Financial Economics.*

Andersen, Torben, Luca Benzoni and Jesper Lund, 2002, Towards an empirical foundation for continuous-time equity return models, *Journal of Finance* 57, 1239-1284.

Ang, James, and Shaojun Zhang, 2005, Forward-looking information and stock prices around earnings announcements, working paper, Florida State University.

Ang, Andrew and Jun Liu, 2001, A general affine earnings valuation model, *Review of Accounting Studies* 6, 397-425.

Bagnoli, Mark, William Kross, and Susan Watts, 2002, The information in management's expected earnings report date: A day late, a penny short, *Journal of Accounting Research* 40, 1275-1296.

Bakshi, Gurdip, and Charles Cao, 2004, Risk neutral kurtosis, jumps, and option pricing: Evidence from 100 most active firms on the CBOE, Working paper, University of Maryland.

Bakshi, Gurdip, Charles Cao and Zhiwu Chen, 1997, Empirical performance of alternative option pricing models, *Journal of Finance* 52, 2003-2049.

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

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

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

Barclay, Michael and Terrance Hendershott, 2003, Price Discovery and Trading After Hours, *Review of Financial Studies* 16 1041-1073.

Barclay, Michael and Terrance Hendershott, 2004, Liquidity Externalities and Adverse Selection: Evidence from Trading After Hours, *Journal of Finance* 58 681-710.

Michael Barclay, Terrence Henderschott, and Charles Jones, 2004, Which Witches Better? A Cross-Market Comparison of Extreme Liquidity Shocks, working paper.

Barndorff-Nielson, Ole and Neil Shephard, 2006, Econometrics of testing for jumps in financial economics using bipower variation, forthcoming, *Journal of Financial Econometrics*, 4, 1-30.

Bates, David, 1995, Testing Option Pricing Models, in Maddala, G.S. and C.R. Rao (Eds.), *Handbook of Statistics*, Vol. 14, Statistical Methods in Finance. Elsevier, Amsterdam, 567-611.

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

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

Battalio, Robert and Paul Schultz, 2006, Options and the Bubble, forthcoming *Journal of Finance* .

Brav, Alon and J.B. Heaton, 2002, Competing theories of financial anomalies, *Review of Financial Studies* 15, 575-606.

Beber, Alessandro and Michael Brandt, 2006, The effect of macroeconomic news on beliefs and preferences: Evidence from the options market, forthcoming, *Journal of Monetary Economics.*

Bollen, Nick and Robert Whaley, 2004, Does Net Buying Pressure Affect the Shape of IV Functions? *Journal of Finance* 59, 711-753.

Broadie, Mark, Mikhail Chernov and Michael Johannes, 2005, Model specification and risk premiums: Evidence from futures options, forthcoming, *Journal of Finance.*

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

Carr, Peter and Liuren Wu, 2005, Variance Risk Premia, working paper, Baruch College.

Cheridito, Patrick, Damir Filipovic, and Robert Kimmel, 2006, Market price of risk specifications for affine models: Theory and evidence, forthcoming *Journal of Financial Economics.*

Chernov, Mikhail, 2005, On the Role of Volatility Risk Premia in Implied Volatilities Based Forecasting Regressions, forthcoming, *Journal of Business and Economic Statistics.*

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

Chernov, Mikhail, Eric Ghysels, A. Ronald Gallant and George Tauchen, 2003, Alternative Models for Stock Price Dynamics, *Journal of Econometrics* 116, 225-257.

Cheung, Sam and Michael Johannes, 2006, Variance decompositions for stock returns, working paper, Columbia University.

Collin-Dufresne, Pierre, Robert Goldstein, and Christopher Jones, 2005, Can Interest Rate Volatility be Extracted from the Cross Section of Bond Yields? An Investigation of Unspanned Stochastic Volatility, working paper, USC.

David, Alex and Pietro Veronesi, 2002, Option prices and uncertain fundamentals: theory and evidence, working paper.

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

Dennis, Patrick and Stewart Mayhew, 2002, Risk-Neutral Skewness: Evidence from Stock Options, *Journal of Financial and Quantitative Analysis* 37, 471-493.

Dennis, Patrick, Stewart Mayhew and Chris Stivers, 2006, Stock Returns, implied volatility innovations, and the asymmetric volatility phenomenon, forthcoming in the *Journal of Financial and Quantitative Analysis*.

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

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

Driessen, Joost, Pascal Maenhout, and Grigory Vilkov, 2005, Option-Implied Correlations and the Price of Correlation Risk, working paper, INSEAD.

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

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

Eraker, Bjørn, 2004, Do equity prices and volatility jump? Reconciling evidence from spot and option prices, *Journal of Finance* 59, 1367-1404.

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

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

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

Garleanu, Nicolae, Lasse Pedersen, and Allen Poteshman, 2005, Demand-based option pricing, working paper, Wharton.

Hanweck, Gerald, 1994, Essays on interest-rate volatility and the pricing of interest-rate derivative assets, unpublished Ph.D. dissertation, Northwestern University.

Heston, Steven, 1993, A Closed-Form Solution for Options with Stochastic Volatility with Applications to Bond and Currency Options, *Review of Financial Studies* 6, 327-343.

Hollander, Myles and Douglas Wolfe, 1999, *Nonparametric Statistical Methods*, New York, Wiley Interscience.

Huang, Chi-Fu, 1985a, Information Structure and Equilibrium Asset Prices, *Journal of Economic Theory* 35, 33-71.

Huang, Chi-Fu, 1985b, Information Structure and Viable Price Systems, *Journal of Mathematical Economics* 14, 215-40.

Huang, Xin and George Tauchen, 2005, The Relative Contribution of Jumps to Total Price Variance, *Journal of Financial Econometrics* 3, 456-499.

Hull, John and Alan White, 1987, The Pricing of Options on Assets with Stochastic Volatility, *Journal of Finance* 42, 281-300.

Imhof, E. and G. Lobo, 1992, The effect of ex-ante earnings uncertainty on earnings response coefficients, *The Accounting Reivew, 67, 427-439.*

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

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

Jiang, Guohua, Charles Lee, and Grace Zhang, 2006, Information uncertainty and expected returns, forthcoming, *Review of Accounting Studies.*

Jiang, Wie and Michael Johannes, 2006, The informational content of fundamental uncertainty estimates obtained from option prices, working paper.

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

Jones, Christopher, 2003, The Dynamics of Stochastic Volatility: Evidence from Underlying and Options Markets, *Journal of Econometrics* 116, 181-224.

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

Lee, Roger, 2004, Option pricing by transform methods: extensions, unification, and error control, *Journal of Computational Finance* 7, 51-86.

Mahani, Reza and Allen Poteshman, 2005, Overreaction to Stock Market News and Misevaluation of Stock Prices by Unsophisticated Investors: Evidence from the Option Market, working paper, University of Illinois.

Maheu, John and Thomas McCurdy, 2004, News arrival, jump dynamics and volatility components for individual stock returns. *Journal of Finance* 59, 755-793

Merton, Robert, 1973, Theory of rational option pricing, *Bell Journal of Economics and Management Science*, 4, 141-183.

Merton, Robert, 1976a, Option pricing when the underlying stock returns are discontinuous, *Journal of Financial Economics* 3, 1235-144.

Merton, Robert, 1976b, The Impact on Option Pricing of Specification Error in the Underlying Stock Price Returns, *Journal of Finance* 31, 333-250.

Morris, Stephen, 1996, Trade with Heterogeneous Prior Beliefs and Asymmetric Information, *Quarterly Journal of Economics* 111, 1111-1133.

Morse, D., 1981, Price and trading volume reaction surrounding earnings announcements: A closer examination. *Journal of Accounting Research* 19, 374-383.

Ni, Sophie Xiaoyan, Neil Pearson, and Allen Poteshman, 2004, Stock Price Clustering on Option Expiration Dates, *Journal of Financial Economics* 78, 49-87.

Ofek, Eli, Matthew Richardson, and Robert Whitelaw, 2004, Limited arbitrage and short sales restrictions, evidence form the options market, *Journal of Financial Economics* 74, 305-342.

Ohlson, James, 1995, Earnings, book values and dividends, *Contemporary Accounting Research* 11, 661-687.

Pan, Jun, 2002, The jump-risk premia implicit in options: evidence from an integrated time-series study, *Journal of Financial Economics* 63, 3-50.

Pástor, Luboš and Pietro Veronesi, 2003, Stock valuation and learning about profitability, *Journal of Finance* 58, 1749–1789.

Pástor, Luboš and Pietro Veronesi, 2005, Was there a Nasdaq bubble in the late 1990s?, forthcoming, *Journal of Financial Economics*.

Patell, James and Mark Wolfson, 1979, Anticipated information releases reflected in call option prices, *Journal of Accounting and Economics* 1, 117-140.

Patell, James and Mark Wolfson, 1981, The ex ante and ex post price effects of quarterly earnings announcements reflected in option and stock prices, *Journal of Accounting Research* 19, 434-458.

Patell, James and Mark Wolfson, 1984, The intraday speed of adjustment of stock prices to earnings and dividend announcements, *Journal of Financial Economics* 13, 223-252.

Penman, Stephen, 1984, Abnormal returns to investment strategies based on the timing of earnings reports, *Journal of Accounting and Economics* 1984, 165-84.

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

Piazzesi, Monika, 2005, Bond yields and the Federal Reserve, *Journal of Political Economy* 113, 311-344.

Schreiber, Cynthia, 2005, Nike's implied volatility jumps as investors brace for results, The Wall Street Journal, June 27, C4.

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

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

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

Whaley, Robert, 2000, The Investor Fear Gauge, *Journal of Portfolio Management* 6, 12-17.

Zhang, Frank, 2006, Information uncertainty and stock returns, *The Journal of Finance* 61, 105-137.