Option Pricing of Earnings Announcement Risks

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This paper uses option prices to learn about the equity price uncertainty surrounding information released on earnings announcement dates. To do this, we introduce reduced-form models and estimators to separate price uncertainty about earnings announcements from normal day-to-day volatility. Empirically, we find strong support for the importance of earnings announcements. We find that the anticipated price uncertainty is quantitatively large, varies across time, and is informative about the future return volatility. Finally, we quantify the impact of earnings announcements on formal option pricing models. (*JEL* G12, G13, C53)

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Every quarter, the SEC requires public corporations to disclose a range of fundamental information via "earnings announcements." These information releases are arguably the primary conduit for corporate communication to investors and often generate dramatic equity price movements as prices quickly impound new information. As an example, almost 20% of Google's total equity price volatility occurs on the day following its quarterly earnings releases.

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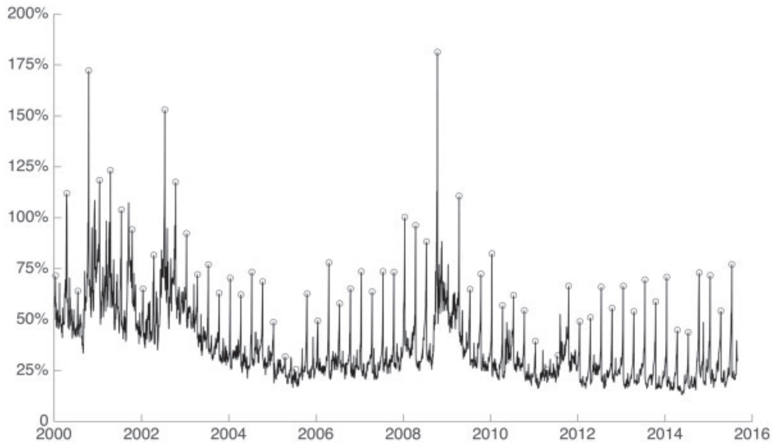

Figure 1
Short-term ATM implied volatility (Intel Corporation)
This figure shows the implied volatility of Intel (INTC) calculated as the average of the put and call implied volatility of the contracts closest to at-the-money (moneyness is defined as K/F, where F is the forward price of the underlying) for the shortest available option maturity. The sample period is from January 2000 to August 2015. Circles indicate EADs.

Large literatures model earnings, study the theoretical pricing of earnings risks and the ex post response of equity prices to the information releases, both contemporaneously (earnings response coefficients) and with lags (e.g., post-earnings-announcement drift). Overall, earnings announcements and risks are key events driving equity returns and prices.

This paper studies the pricing of earnings risk in option prices.[1] These announcements generate fundamentally different risks compared to Brownian or Poisson risks in asset pricing models due to their predictable timing. To see this, Figure 1 graphs short dated option implied volatilities (IVs) for Intel Corporation with earnings announcement dates (EADs) marked with a circle. IVs increase predictably prior to and sharply decrease after earnings are announced (previously noted by Patell and Wolfson 1979, 1981). The goal of this paper is to incorporate earnings announcements and risks into option pricing models, to use option prices to extract option-implied ex ante information about the impact of earnings risks on equity prices, and to study the information content of these announcements.

On the theoretical side, we specify new option pricing models building on Piazzesi (2000) with deterministically timed jumps on earnings dates with random sizes. This "earnings risk" model naturally generates the IV patterns seen in the data and motivates estimators of the ex ante equity price uncertainty associated with an earnings announcement, essentially the option implied price

[1] This paper subsumes and extends Dubinsky and Johannes (2006).

volatility associated with the news. A simplified version of our general model provides the intuition.

Consider an extension of the Black-Scholes model with a single, predictably timed price jump occurring at time τ_j (the EAD) whose size is normally distributed with a volatility of $\sigma_j^{\mathbb{Q}}$, where $\mathbb{Q}$ is the risk-neutral probability. Equity prices are log-normally distributed, and option prices are given by a modification of the Black-Scholes formula. For an option with time to maturity T and $t < \tau_j \leq t+T$, the IV at time t is

$$\sigma_{t,T} = \sqrt{\sigma^2 + \left(\sigma_j^{\mathbb{Q}}\right)^2 / T}, \tag{1}$$

where σ is the diffusive volatility. This simple model delivers three general implications of earnings announcements: (1) IVs increase continuously and nonlinearly prior to an EAD (as T decreases), (2) IV discontinuously falls after the announcement, and (3) the term structure of IV is downward-sloping prior to the announcement. The first two of these implications generate the distinctive pattern in Figure 1 and were previously noted in Patell and Wolfson (1981). We will mainly rely on the third implication for our empirical work.

The central quantity is the earnings price volatility $\sigma_j^{\mathbb{Q}}$, the risk-neutral anticipated announcement volatility. This parameter is a reduced form, capturing the impact of all information released, not just current quarter earnings or forward guidance. Earnings risks naturally vary over time and across firms, and an intermediate goal is to develop easy-to-compute and accurate option-based estimators of this parameter for each EAD.[2] Equation (1) can be used to develop ex ante estimators of $\sigma_j^{\mathbb{Q}}$ using options of different maturities (term structure estimators) and ex post estimators of $\sigma_j^{\mathbb{Q}}$ based on the post-announcement decrease in IV (time-series estimators).[3] We also consider more general models incorporating stochastic volatility and Poisson-driven jumps in prices and perform a structural estimation.

Given this theoretical framework, our main contributions are empirical. Using a broad data set of actively traded firms from 2000 to 2015, we characterize the information about earnings risks embedded in options. We first extend the initial work of Patell and Wolfson (1981) testing the impact of earnings announcements on option prices. Two of our tests are related to those in Patell and Wolfson (1979, 1981), but the third is new. These tests document strong evidence that earnings announcements affect option prices (consistent with Figure 1).

Our next goal is to quantify earnings uncertainty. Using estimators derived from Equation (1), estimates indicate that earnings uncertainty is large,

[2] Estimating realized earnings announcement volatility is difficult when using only a single observation.

[3] Although these estimators assume constant volatility, Section 1.2 shows the estimators are largely robust to stochastic volatility. We also calibrate formal stochastic volatility models in Section 3.7.

statistically significant, and varies across both firms and time. There is a strong business cycle pattern, with the level and cross-sectional variation in earnings risks increasing substantially in recessions. For our sample, the average earnings uncertainty ranges from roughly 4%–6% during pre- and post-crisis expansions to approximately 10%–11% at the height of the 2000–2002 or 2008–2009 recession, respectively. Cross-sectional earnings uncertainty dispersion increases in recessions, more than doubling from less than 3% to over 6%.

In terms of informational content, option-based estimates of earnings volatility are highly informative about future realized equity volatility: the ex ante estimates have a correlation of more than 50% with realized price volatility after the announcement. This is close to what could maximally be expected given normal sampling errors in realized volatility. The cross-sectional correlation between option implied average earnings volatility and subsequent post-earnings daily equity volatility is roughly 85%. Earnings volatility estimates also provide incremental information in forecasting the following month's equity volatility relative to diffusive IV (e.g., Christensen and Prabhala 1998; Lamoureux and Lastrapes 1993; Jiang et al. 2005).

Another commonly used measure of firm-level uncertainty is the dispersion in analysts earnings forecasts, based on the idea that firms with higher earnings uncertainty are more difficult to analyze, which in turn generates a broader range of analyst forecasts. We find no significant relationship between dispersion of analysts forecasts with our measure, consistent with Diether, Malloy, and Scherbina (2002). We also find that in our sample the dispersion of analysts forecasts has no statistical ability to forecast post-earnings daily equity volatility.

Next, we analyze the pricing of earnings announcement risks. For index options, there is strong evidence for volatility and/or Poisson drive jump risk premiums (see, e.g., Pan 2002; Broadie et al. 2007). Quantifying earnings volatility risk premiums is straightforward given precise estimates of $\sigma_j^{\mathbb{Q}}$ for each EAD, which can be compared to realized earnings volatility in a number of ways. One way compares averages of $\sigma_j^{\mathbb{Q}}$ to close-to-open equity return volatilities on EADs, which assumes all of the overnight price move is from earnings induced jumps. We also construct measures based on close-to-close returns, allowing for some "digestion" time for prices to adjust after the open, compute standardized returns (which are less sensitive to outliers), and analyze straddle returns.

Every measure points to significant earnings jump risk premiums. Average option implied earnings day volatility is 8.22% for the full-sample compared to a realized announcement day volatility of 7.42%, a premium of 80 bps. Focusing only on close-to-open returns (assuming all of the effect occurs at the open), the average premium is 56 bps. Averages are sensitive to outliers, and the results are stronger using medians, trimmed estimates, or standardized returns. The risk premium is consistent with a significant systematic component in earnings risks: ex ante earnings volatility estimates are strongly related to historical equity beta, with a correlation of roughly 60% across firms.

To connect earnings uncertainty risk premium estimates with economically interesting quantities, we compute at-the-money straddle returns on EADs. The straddle positions are opened prior to the EAD and closed the next day. The average (median) EAD straddle return is -8% (-10%). We compute bootstrap returns to account for the fact that straddle returns are generally negative, and results confirm statistically significant straddle returns consistent with an economically significant earnings jump risk premium. These risk premium results are related to robust patterns of equity returns around earnings dates. First noted by Beaver (1968), there are positive average equity returns for firms announcing earnings (see also Cohen et al. 2007; Frazzini and Lamont 2007). Savor and Wilson (2016) provide a model-based explanation for the firm-level earnings announcement premium. Our results contribute to this literature by documenting a robust earnings jump volatility risk premium.

Finally, we build continuous-time stochastic volatility (SV) models incorporating both randomly timed and earnings induced price jumps. These models allow us to quantify the impact of earnings via option pricing errors and the relative importance of EADs vis-a-vis SV and randomly timed jumps. Using IVs, we estimate the SV models for some of the largest firms in our sample: Amazon, General Electric, IBM, Intel, Microsoft, and Qualcomm. We again find strong earnings effects, which are strongest around EADs where pricing errors can be more than 50% lower when incorporating earnings jumps. Pure SV models cannot fit term structure IV patterns observed around EADs, resulting in large pricing errors. For example, average pricing errors for AMZN the day prior to earnings are 8.11%, 2.53%, and 3.82% for short, medium, and long term options, respectively, and fall to 3.69%, 1.49%, and 1.70%, respectively, when incorporating earnings announcements. Although there are only four EADs per year, overall option pricing errors fall on average by almost 20%. EADs are far more important than Poisson price jumps.

Our results have other research implications. There is a growing literature using firm IVs, either directly or via a variance risk premium calculation, as regressors or for portfolio sorts. These procedures may be sensitive to EADs and factors such as option maturity that are unrelated to the research questions. For example, consider a firm with $\sigma = 25\%$ and an average sized earnings jump volatility of 7.3%. From Equation (1), the IV of a 2-week option is almost 44% but only 32% for an option expiring in 6 weeks. Thus, for options spanning EADs, there is significant IV variation unrelated to fundamentals from maturity effects. An et al. (2014), for instance, sort stocks by changes in 30-day IVs, arguing that sharp increases in IV can be linked to informed trading. Our model suggests that firms with rapidly increasing IVs are also more likely to announce earnings. Similarly, Baltussen et al. (forthcoming) use short-term options and calculate the standard deviation of the IV over a calendar month. Our model suggests that firms with the highest volatility of IV are biased toward announcing firms, given the pattern of IVs around EADs, independent of fundamentals. We show empirically that earnings announcements increase the noise in the measurement of IV-based sort variables and provide guidance on how to minimize the impact of earnings announcement related time variation in IVs on cross-sectional studies.

All of our implications generally apply to other predictable events including macroeconomic announcements and elections, referendums, summits or other scheduled meetings (e.g., OPEC semiannual meetings). As an example, consider the Brexit vote on June 23, 2016. Just prior to the vote, 1-month and 2-month USD/GBP currency IV was 28.21% and 21.51%, respectively. The term structure estimate of the Brexit impact on the USD/GBP exchange rate was 7.45%. The pound fell 7.6% on the day following the vote. A similar pattern occurred prior to the 2016 U.S. election. Kelly et al. (2016) analyze the impact of predictable national elections and global summits on option prices.

1. Incorporating Earnings Announcements in Equity Price Models

1.1 Stochastic volatility models

This section incorporates earnings announcement risks into continuous-time SV models. The first step is a model of how earnings announcements impact equity prices. Earnings announcements normally occur outside of normal trading hours, either after the 4:00 p.m. market close or before the formal 9:30 a.m. open. We assume earnings induce a jump or discontinuity in the continuous-time price path. The jump assumption is intuitive, consistent with existing work analyzing macroeconomic announcement effects (e.g., Piazzesi 2005; Beber and Brandt 2006), consistent with statistical evidence identifying announcements as the cause of jumps in jump-diffusion models (Johannes 2004; Barndorff-Nielsen and Shephard 2006), and parsimonious.[4] For earnings announced during normal market hours, Patell and Wolfson (1984) find the bulk of the price response occurs within the first few minutes. For earnings announced outside of normal market hours, Martineau (2017) argues earnings news arrives as a "jump", with 80% of the price response occurring within the first few trades after news is released (see also Lee 2012).

Formally, N_t^d counts EADs prior to time t: $N_t^d = \sum_j \mathbb{1}_{[\tau_j \le t]}$ where $\mathbb{1}$ is the indicator function and τ_j is an increasing sequence of predictable stopping times representing earnings announcements. The jump size, $Z_j = \log\left(S_{\tau_j}/S_{\tau_{j-}}\right)$, is distributed according to a known distribution, $Z_j | \mathcal{F}_{\tau_j -} \sim \pi\left(Z_j, \tau_j -\right)$. In addition to earnings jumps, price jumps can arrive at random times $\bar{\tau}_j$ via a Poisson process $\bar{N}_t$ with intensity $\bar{\lambda}_y$ and jump size $\bar{Z}_j$. We do not consider

[4] Over finite sampling periods, it is always possible to construct a stochastic volatility model with similar distribution implications to a jump model. These models are generally more complicated than simple jump models, which is one reason the literature typically models these events as price "jumps," rather than a large spike in diffusive volatility.

other predictable events such as mid-quarter earnings updates, stock splits, or mergers and acquisitions although these do have interesting implications (see, e.g., Bester et al. 2013). We assume a square-root SV process, thus prices and variance processes solve:

$$
\begin{aligned}
dS_t &= \left(\mu - \bar{\lambda}_y \psi_t\right) S_t dt + \sqrt{V_t} S_t dW_t \\
&\quad + d\left(\sum_{j=1}^{N_t^d} S_{\tau_j -}\left[e^{Z_j} - 1\right]\right) + d\left(\sum_{j=1}^{\bar{N}_t} S_{\bar{\tau}_j -}\left[e^{\bar{Z}_j} - 1\right]\right), \\
dV_t &= \kappa_v(\theta_v - V_t)dt + \sigma_v \sqrt{V_t} dW_t^v,
\end{aligned}
$$

where ψ_t is the random jump compensator, W_t and W_t^v are two standard Brownian motions with correlation ρdt. This process is well defined in continuous time.[5]

The jump Z_j captures the equity price response to the information released in the earnings announcement. Firms report the current quarter's cash flow, balance sheet and income statement, and many firms also provide forward-looking information and answer questions via conference calls with analysts and investors. The jump sizes translate this valuation-relevant information into equity price shocks. Therefore, the jump distribution π serves as a reduced-form model of how fundamental information affects equity prices.

The volatility of Z_j, $\sigma_j^{\mathbb{P}} = std^{\mathbb{P}}\left(Z_j | \mathcal{F}_{\tau_j -}\right)$ is a central parameter of interest, capturing the ex ante anticipated uncertainty about the equity price response to the announcement information. To understand its sources, consider the earnings response model of Ball and Brown (1968): $Z_j = \alpha + \beta\left(E_{\tau_j} - \hat{E}_{\tau_{j-}}\right) + \varepsilon_{\tau_j}$, where $\hat{E}$ is an estimate of current earnings. In this model, the equity price response is driven by unexpected earnings and other announcement shocks. The variance due to the information released in the earnings announcement is $\left(\sigma_j^{\mathbb{P}}\right)^2 = \beta^2 var\left(E_{\tau_j} - \hat{E}_{\tau_{j-}} | \mathcal{F}_{\tau_j -}\right) + \sigma_\varepsilon^2$.

This useful decomposition implies that the earnings response coefficient β, the variance of unexpected earnings news, and other shocks drive the equity price response to earnings announcements. Empirically identifying the different sources of earnings induced equity volatility is difficult: earnings response models generate small R^2's, normally less than 10%, for various reasons (nonlinearities, time-varying regression coefficients, inaccurate estimates of expected earnings, the importance of forward guidance, small samples, etc.). Imhoff and Lobo (1992) and Ang and Zhang (2005) report R^2's between 3-6%, which implies that most of the price response to earnings announcements is

5 This process is a well-defined semimartingale that is continuous from the right with left limits (see, e.g., Protter 2005 for formal definitions). Prices are a product of an affine component and a discrete jump at earnings announcements, which implies numerical option pricing proceeds like in a standard affine specification.

unexplained by standard regressors. This motivates our focus on the EAD jump volatility as a reduced form of the valuation relevant uncertainty.

To price options, we construct a measure $\mathbb{Q}$ under which discounted prices are martingales. Risk corrections for randomly timed jumps and Brownian motions are standard. At predictable EADs, the martingale restriction implies that the pre-jump expected value of the post-jump equity price equals the pre-jump equity price, that is $E^{\mathbb{Q}}\left[S_{\tau_j}|\mathcal{F}_{\tau_j-}\right]=S_{\tau_j-}$ (see Piazzesi 2000). In terms of risk premiums, we assume that under $\mathbb{Q}$, prices and volatilities are affine, that the risk-neutral jump intensity is $\bar{\lambda}_y^{\mathbb{Q}}$ and $\bar{Z}_j(\mathbb{Q})\sim\mathcal{N}\left(\bar{\mu}_y^{\mathbb{Q}},\left(\bar{\sigma}_y^{\mathbb{Q}}\right)^2\right)$, and that

$$
\begin{aligned}
dS_t=&\left(r_t-\bar{\lambda}_y^{\mathbb{Q}}E_t^{\mathbb{Q}}\left[e^{\bar{Z}_j(\mathbb{Q})}-1\right]\right)S_t dt+\sqrt{V_t}S_t dW_t(\mathbb{Q})\\
&+d\left(\sum_{j=1}^{N_t^d}S_{\tau_j-}\left[e^{Z_j(\mathbb{Q})}-1\right]\right)+d\left(\sum_{j=1}^{\bar{N}_t(\mathbb{Q})}S_{\bar{\tau}_j-}\left[e^{\bar{Z}_j(\mathbb{Q})}-1\right]\right),\\
dV_t=&\kappa_v^{\mathbb{Q}}\left(\theta_v^{\mathbb{Q}}-V_t\right)dt+\sigma_v\sqrt{V_t}dW_t^v(\mathbb{Q}).
\end{aligned}
$$

Here, $W_t(\mathbb{Q})$ and $W_t^v(\mathbb{Q})$ are Brownian motions under $\mathbb{Q}$ with correlation ρdt and $E^{\mathbb{Q}}\left[e^{Z_j}\right]=1$, the martingale restriction.

The only additional no-arbitrage constraint for the jump distribution measure changes is common support, thus, for example, state variables could appear in one measure but not the other or that the distributional form could change. We assume EAD jump sizes are normal under $\mathbb{Q}$: $\pi^{\mathbb{Q}}\left(Z_j|\mathcal{F}_{\tau_{j-}}\right)\sim\mathcal{N}\left(-\frac{1}{2}\left(\sigma_j^{\mathbb{Q}}\right)^2,\left(\sigma_j^{\mathbb{Q}}\right)^2\right)$. This is parsimonious: there is a single earnings jump parameter on each EAD and estimating $\sigma_j^{\mathbb{Q}}$ is a primary focus of the paper. The model is affine, facilitating option pricing. Online Appendix A.1 discusses option pricing in the general SV model, which we later use for formal structural estimation. The next section develops a simplified version of the model to develop easy-to-implement and robust estimators of $\sigma_j^{\mathbb{Q}}$.

It is useful to note that deterministically and randomly timed price jumps have fundamentally different effects on the shape and dynamics of IV curves and are also identified by different data. The steepness of the short-term IV skew is particularly informative about the parameters of the random jump process (see, for instance, Broadie et al. 2007), whereas deterministic jumps in our model have virtually no effect on the slope of IV curves, see Equation (1). In contrast, deterministic jumps affect the term structure and the time-series behavior of IVs, two features that are largely unaffected by Poisson-driven price jumps. Our estimation procedure captures these model features and allows us to extract earnings announcement jump information from ATM options only. Out-of-the-money (OTM) and in-the-money (ITM) options are useful in our framework mainly to distinguish between random jumps, SV and earnings announcement jumps.

1.2 A simple model and earnings uncertainty estimators

To estimate $\sigma_j^{\mathbb{Q}}$, consider a model with constant volatility and price jumps on EADs:

$$S_t = S_0 \exp\left[\left(r - \frac{1}{2}\sigma^2\right)t + \sigma W_t(\mathbb{Q}) + \sum\nolimits_{j=1}^{N_t^d} Z_j(\mathbb{Q})\right], \tag{2}$$

where $Z_j(\mathbb{Q}) = -\frac{1}{2}\left(\sigma_j^{\mathbb{Q}}\right)^2 + \sigma_j^{\mathbb{Q}}\varepsilon_j(\mathbb{Q})$ and $\varepsilon_j(\mathbb{Q}) \overset{i.i.d}{\sim} N(0,1)$. Since $W_t(\mathbb{Q})$ and $\sum\nolimits_{j=1}^{N_t^d} Z_j(\mathbb{Q})$ are normally distributed, prices are log-normal. A European option with time to maturity T is given by the Black-Scholes formula with a modified volatility input:

$$\sigma_{t,T}^2 = \sigma^2 + T^{-1} \sum_{j: t < \tau_j \le t+T} \left(\sigma_j^{\mathbb{Q}}\right)^2. \tag{3}$$

This model provides the main implications of earnings announcements for option prices. First, assuming one announcement before maturity, annualized implied variance is $\sigma_{\tau_j -, T}^2 = \sigma^2 + T^{-1}\left(\sigma_j^{\mathbb{Q}}\right)^2$ just before the announcement and $\sigma_{\tau_j, T}^2 = \sigma^2$ after the announcement. Thus, IV discontinuously drops immediately after the announcement. Second, implied variance increases at the rate proportional to T^{-1} into the event. Third, holding the number of jumps constant, the term structure of IVs slopes downward.

This suggests two estimators of $\sigma_j^{\mathbb{Q}}$, one based on the IV term structure and the other based on IV dynamics. Given two options with time to maturity T_1 and T_2 ($T_1 < T_2$) and a single EAD prior to maturity, then $\sigma_{t,T_1}^2 > \sigma_{t,T_2}^2$ and $\sigma_j^{\mathbb{Q}}$ can be estimated via:

$$\left(\sigma_{j,term}^{\mathbb{Q}}\right)^2 = \frac{\sigma_{t,T_1}^2 - \sigma_{t,T_2}^2}{T_1^{-1} - T_2^{-1}}. \tag{4}$$

We label this ex ante estimator the *term structure* estimator as it uses IV term structure information prior to the EAD. The second estimator uses changes in IV. Assuming an earnings announcement after the close on date t (or before the open on the next trading date), then the post-announcement IV is σ (assuming no other EADs prior to maturity). Solving for earnings jump volatility gives the *time-series* estimator

$$\left(\sigma_{j,time}^{\mathbb{Q}}\right)^2 = T\left(\sigma_{\tau_j -, T}^2 - \sigma_{\tau_j + \Delta, T - \Delta}^2\right), \tag{5}$$

where $\Delta = 1/252$ (1 day).

To provide a concrete example, on October 23, 2014, Amazon.com released earnings after market close. The IV of at-the-money (ATM) options expiring in 8 and 15 days was 75.28% and 54.37%, respectively, which implies $\sigma_{j,term}^{\mathbb{Q}} =$ 10.26%. Short-dated option IV falls to 29.36% after the EAD, which implies $\sigma_{j,time}^{\mathbb{Q}} = 9.87\%$. This is a typical example with quantitatively similar estimates, even though the estimators use different information.

Although these estimators assume no SV or randomly timed price jumps, estimates are quite robust to both factors. To see this, consider parameter values in line with Bakshi, Cao, and Zhong (2012) and our estimates in Section 3.7: $\theta_v^{\mathbb{Q}}=0.4^2$, $\sigma_v=0.6$, $\rho=-0.4$, $\bar{\lambda}_y^{\mathbb{Q}}=5$, $\bar{\mu}_y^{\mathbb{Q}}=0$, $\bar{\sigma}_y^{\mathbb{Q}}=0.05$ and $\sigma_j^{\mathbb{Q}}=0.08$. For the term structure estimator, the main bias arises from mean reversion in V_t when spot volatility is significantly higher or lower than its long-run average. To understand the bias magnitude, we consider an extreme case in which $\kappa_v^{\mathbb{Q}}=2$ (about twice the value we estimate in Section 3.7) and that V_t is twice its long-run average. For typical maturities in our sample, $T_1=2/52$ and $T_2=6/52$, $\sigma_{term}^{\mathbb{Q}}=0.0848$. If spot variance is 50% of its long-run value, $\sigma_{term}^{\mathbb{Q}}=0.0785$. These biases of individual estimates of $\sigma_j^{\mathbb{Q}}$ are small in absolute terms, but also relative to microstructure noise. For example, typical bid-ask spreads on equity options are at least \$0.05 to \$0.10 for options that are often less than \$1 or \$2, which could induce significant noise in IVs. In addition, since the term structure in our sample is flat on average, any biases are likely to average out over the sample period.

Building on Merton (1976), Hull and White (1987), and Bates (1996), Online Appendix A.2 analyzes the estimators under model misspecification. The term structure estimator is robust for many reasons: (a) it does not depend on σ_v or realized shocks; (b) diffusive volatility is highly persistent, thus $\kappa_v^{\mathbb{Q}}$ is small; (c) the term structure of IV is flat, which implies that $\theta_v^{\mathbb{Q}} \approx \theta_v$ and/or that $\kappa_v^{\mathbb{Q}}$ is very small; and (d) we use short-dated options, typically less than 2 months. The time-series estimator is less robust as it relies on shock realizations over the next day and is sensitive to any lagged responses. These biases could directionally bias the results: large positive shocks downward biased estimates more than large negative shocks upward biased estimates (see Online Appendix A.2). Although we report both, the time-series estimator is noisier, thus we primarily focus on the term structure estimates.

1.3 Literature review and discussion

Our work relates to a number of papers using time-series data to analyze earnings announcements. A large literature (e.g., Ball and Brown 1968; Kim and Verrecchia 1991; Penman 1984, among others) analyzes the equity price response to earnings announcements. There are also anomalous movements around EADs (e.g., Bernard and Thomas 1990; Frazzini and Pedersen 2014; Barber et al. 2013). Hanweck (1994) finds that Treasury bond and Eurodollar futures are more volatile on unemployment announcement days and builds a model to capture this effect.[6] Patell and Wolfson (1984) study the price response to intraday earnings announcements using transaction data and find most of the response occurs within minutes, which is important as we assume announcements induce a discontinuous jump. Maheu and McCurdy (2004)

[6] We would like to thank Bob McDonald for pointing out Hanweck (1994), an unpublished PhD dissertation.

analyze GARCH jump models, assume the jump intensity increases on EADs, and find that many of the jumps they identify occurred on EADs. Andersen et al. (2003), Bernanke and Kuttner (2005), Savor and Wilson (2013), and Lucca and Moench (2015) study the impact of predictable macroeconomic announcements on equity prices.

Our paper is closely related to Patell and Wolfson (1979, 1981) who provide early descriptive work on IV dynamics around EADs. Their model has deterministically changing diffusive volatility and test whether IV increases prior to and drops after an EAD. Patell and Wolfson (1979) find mixed evidence using annual EADs from 1974 to 1978, and Patell and Wolfson (1981) find stronger evidence using quarterly EADs from 1976 to 1977. There are a number of importance differences between our approach/results and Patell and Wolfson (1979, 1981). First, we can easily incorporate SV in our model, while extending Patell and Wolfson (1979, 1981) to handle SV requires deterministically timed jumps in SV. Second, the model used in Patell and Wolfson (1979, 1981) does not allow earnings uncertainty to change across measures, as it is a diffusive model. Third, we provide ex ante estimators of anticipated earnings risks. Fourth, we do not require any assumptions about π. Fifth, Patell and Wolfson (1979, 1981) do not directly estimate the earnings uncertainty, rather they test the increase and decrease in IV.

Ederington and Lee (1996) and Beber and Brandt (2006) analyze announcement effects in Treasury bond futures options. Ederington and Lee (1996) find that IV falls after announcements. Beber and Brandt (2006) analyze the implied pricing density and find that, in addition to IV falling, implied skewness and kurtosis also change. Related to this, Donders and Vorst (1996), Donders et al. (2000), and Isakov and Perignon (2001) apply the approach of Patell and Wolfson (1979, 1981) to European options markets. Whaley and Cheung (1982) argue that the informational content of earnings announcements is rapidly incorporated into option prices, whereas Diavatopoulos et al. (2012) test whether option-implied skewness and kurtosis provide information about subsequent equity and option returns around EADs.

Kelly et al. (2016) study the pricing of political risk around events such as elections, and document strong effects generated by their predictable timing, consistent with our results from earnings announcements. Their model differs from ours as elections may induce a policy shift, which in turn, could persistently shift volatilities. Pástor and Veronesi (2013) provide additional equilibrium results.

Subsequent to Dubinsky and Johannes (2006), Barth and So (2014) use our estimators to study the impact of earnings announcements on market-wide, nondiversifiable volatility risk. They find earnings announcements contribute to volatility changes and command a premium. Rogers et al. (2009) study how management earnings forecasts affect IV, arguing that bad news disclosure affects short- and long-term IV whereas long-term IV remains unaffected by other disclosures. Neururer et al. (2015) find that the uncertainty measured by IVs prior to EADs declines with the firms' reputation. Billings and Jennings (2011) normalize option prices prior to announcements by the standard deviation of analysts' earnings forecast to separate equity market reaction to earnings information from earnings uncertainty.

2. Data

We use option price data from OptionMetrics' IvyDB. Because of microstructure concerns, such as bid-ask spreads and nonsynchronous trading, we focus on actively traded firms. For each calendar year in our sample, we rank all firms by dollar trade volume. From each of these yearly rankings, we eliminate firms with an average quarterly dividend yield of more than 2% and firms whose equity price traded below $5. The focus on firms without excessive dividend yields minimizes any issues associated with pricing options on high-dividend firms. Unlike indices, whose dividend payments are usually modeled as continuous, dividends on individual equities are discrete. Options on low equity price firms generates numerical issues when computing IVs because strikes are usually quoted in either $1 or $2.5 increments, implying that options are often either extremely deep in-the-money or out-of-the-money. Finally, we limit our analysis to firms with CRSP share code 10 or 11 (common stock).

Next, we identify the exact date and time of the earnings announcements from Thomson Reuters, the Institutional Brokers Estimate System (IBES) and Compustat. Thomson Reuters and IBES provide dates and times (either a time stamp or an indicator to determine if the announcement was before market open or after market close), whereas Compustat only provides dates. We find substantial disagreement over the dates and/or exact times (see also DellaVigna and Pollet 2009) and use the following reconciliation approach. First, we require the EAD is recorded in at least two of the three sources. As we focus on actively traded firms, there are only occasional gaps in Thomson Reuters' coverage while Computstat and IBES provide nearly full coverage. If there is date or time disagreement, we search the *PR Newswire*, *Business Wire*, and *Wall Street Horizon* in LexisNexis to identify the correct date and/or time. If the LexisNexis search is unsuccessful, either because there are no news items or we cannot identify the timing, we record the announcement as missing.

Our sample is restricted by OptionMetrics data availability (January 1996 until August 2015) and Thomson Reuters (first full calendar year is 2000). IBES and Compustat provide longer data histories. Since the exact announcement time is crucial for our analysis (and because of issues with IBES), we restrict the sample from January 2000 to August 2015.[7] After applying the filters, we select the 50 most liquid firms each year. Our liquidity-driven sample selection is similar to Carr and Wu (2009) and Bakshi, Cao, and Zhong (2012), although

[7] Removing the first four years from our sample has no effect on our results. An earlier version of this paper included options from this subperiod, and we found qualitatively and quantitatively similar results.

we apply our criteria year by year rather than to the full sample, avoiding potential biases due to delistings (such as Dell), default (such as Lehman), merger activity (such as Chase Manhattan and J. P. Morgan) or IPOs (such as Google). A range of highly liquid firms remain in the sample throughout the entire 16-year period: Amazon (ticker: AMZN), General Electric (GE), Intel (INTC), International Business Machines (IBM), Microsoft (MSFT) and Qualcomm (QCOM). On the other hand, many of the overall 196 firms pass the selection criteria in few years.

We obtain option information for all available contracts. IVs are based on best bid and ask price midpoints, adjusted for dividends and early exercise. We eliminate strike/maturity combinations with zero volume, zero IV, or maturities more than 1 year. Next, we eliminate options with less than 3 days to maturity, as microstructure issues are magnified with extremely short-dated options. For every day and expiration date, options are sorted by moneyness, and we record IVs for the nearest to-the-money strike. We define moneyness as $M \equiv K/F_{t,T}$ where K is the strike and $F_{t,T}$ the time t forward price with maturity T.[8] ATM options are actively traded and provide the cleanest information on expected volatility. For each strike/maturity, call and put IVs need not be identical, due to the American feature, microstructure noise such as bid-ask spreads or stale quotes. Since OptionMetrics reports close prices, stale quotes are a concern. Battalio and Schultz (2006) argue that stale option quotes bias put-call parity tests. To minimize this, we average call and put IVs for the closest to-the-money strike for a given maturity.[9] If call and put IV differences are extreme, we eliminate the option pair from our data set.

Table 1 (panel A) shows that an increase in trading around EADs. The average daily dollar volume is about twice as high the day after an earnings announcement compared to ordinary trading days near the EAD. These patterns are robust across subsamples, although the overall equity option trading volumes have increased over time. Panel B shows a slightly higher bid-ask spread on the day after earnings announcements, but the economic differences are small. For instance, pooled average bid-ask spreads for ATM options are 6.17% on EADs versus 6.05% over the period from 11 to 20 trading days after the announcement. Quoted bid-ask spreads are an imprecise measure of trading

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8 We calculate forward prices, using the dividend information in OptionMetrics, and the zero curve file, which provides risk-free rates.

9 To see how this mitigates the stale quote problem, consider an example. Consider an ATM call and put option with $T-t=1/12$, $S_t=\$20$, $\sigma=20\%$ and $r_t=5\%$). 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 equity price is \$20) and that the closing equity price is actually \$20.10, the IVs are not 20%, but 22.28 for the call and 17.918 for the put, generating problems put-call parity tests, such as those in Battalio and Schultz (2006). Our averaging procedure generates an IV of 20.09%, close to the true IV. In practice, averaging also reduces problems with bid-ask spreads. Pan and Poteshman (2006) use a similar procedure. Another possibility would be to employ intradaily option data in our analysis as they are now available for part of our sample period from various data vendors. Because of the extreme computational burden of intradaily option data (see Muravyev et al. 2013) and the benchmark character of OptionMetrics in the related literature, we focus on daily closing prices.

Table 1
Average dollar volume and bid-ask spreads around earnings announcements

Days realtive to EAD	−20 to −10	−9 to −5	−4 to −1	0	1	2 to 5	6 to 10	11 to 20
A. Average dollar volume (in 100 million USD)								
2000–2005	10.26	9.66	10.74	12.99	17.84	9.92	8.42	9.76
2006–2010	19.84	23.82	20.36	36.41	42.92	22.42	21.82	20.34
2011–2015	22.56	29.96	27.70	46.66	65.79	26.84	36.05	32.38
Pooled	17.07	20.37	18.99	30.74	40.48	19.07	21.14	20.04
B. Average bid-ask spread for ATM options (in percentage of the mid-option price)								
2000–2005	5.27	5.50	5.50	4.86	5.64	5.36	5.32	5.79
2006–2010	4.82	4.99	4.92	5.04	5.26	4.83	4.84	5.11
2011–2015	7.11	6.65	6.02	6.28	7.71	7.00	7.16	7.30
Pooled	5.70	5.70	5.47	5.37	6.17	5.70	5.75	6.05

Panel A provides the average daily dollar trading volume (mid-dollar price of option contract times traded volume) averaged over all firms in our sample and over trading days prior and after earnings announcements. Column 2 (-20 to -10) provides the average trading volume 20 to 10 trading days before the announcements. Column 5 (0) is the volume on the day prior to the announcement, and Column 6 (1) is the volume on the first day after the announcement (i.e., the day after the announcement for an AMC announcement and the same day for a BMO announcement). Other columns follow identical patterns. Panel B provides average bid-ask spreads for option with strikes between 95% and 105% of the current stock price (we divide by the mid dollar price of the option).

cost, Muravyev and Pearson (2016) show that actual option trading costs may be substantially lower.

3. Empirical Evidence

3.1 Summary statistics

Table 2 provides equity return statistics for firms with at least 7 years of EADs pooled by year. EAD return volatility is substantially higher than non-EAD volatility as variance ratios are close to six on average. The effect varies across firms and the business cycle, indicating strong heterogeneity in the pricing of earnings news. For example, our results imply that in 2015 more than 19% of the total annualized variance of individual equity returns occurred on EADs.[10] EAD volatilities are significantly higher during the 2000–2001 recession and in 2008. In 2008, due to the higher level of diffusive volatility, a similar calculation shows that total EAD variance drops to 6.2% of total variance, consistent with a greater role for systematic macroeconomic volatility. If volatility was constant across days, EADs would generate $4/252 \approx 1.6\%$ of the total annualized variance. Earnings announcements generate a large, disproportionate share of overall volatility, with a time-varying impact.

Table 3 disaggregates the data at the firm level. Note first that the number of EADs varies as firms enter and exit the sample based on trading volumes. There is a wide range of firms in terms of the relative importance of EADs.

[10] For example, in 2015, dividing the variance on EADs, 4×7.41^2, by the total non-EAD variance, $4 \times 7.41^2 + 248 \times 1.93^2$ is 19.37%.

Table 2
Summary statistics for the underlying returns (pooled)

Ticker	EAD vol	NonEAD vol	Var ratio	EAD skew	Non-EAD skew	EAD kurt	Non-EAD kurt	Num EAD
2000	9.60	5.80	2.74	0.47	0.53	3.10	7.49	190
2001	9.63	5.37	3.22	0.01	0.50	4.34	7.66	193
2002	7.13	3.38	4.44	0.23	−0.25	5.90	11.58	192
2003	5.43	2.13	6.46	0.67	1.03	5.15	21.53	196
2004	7.24	2.49	8.45	−0.87	16.08	10.66	833.01	192
2005	5.18	1.91	7.34	0.37	−0.39	6.66	41.93	199
2006	6.21	1.80	11.89	−0.61	0.48	5.27	10.16	197
2007	7.13	2.19	10.57	1.24	0.48	12.42	12.44	192
2008	9.38	4.62	4.12	−0.14	0.85	6.91	19.47	197
2009	7.23	3.01	5.75	0.92	0.63	6.20	12.76	193
2010	5.41	1.88	8.33	0.90	0.44	7.15	10.63	200
2011	6.82	2.28	8.90	−1.45	0.25	10.95	18.55	200
2012	7.65	1.80	18.13	−0.75	0.41	12.53	13.15	200
2013	7.70	1.76	19.15	1.32	1.57	8.35	45.64	199
2014	5.98	1.75	11.70	0.36	−0.01	6.28	12.18	197
2015	7.41	1.93	14.76	−0.45	0.45	5.42	19.53	150
Pooled	7.32	3.06	5.71	0.15	1.18	7.83	44.03	3087

This table provides summary statistics for daily percentage equity returns for all firms in our sample from January 2000 to August 2015, pooled by calendar year. Summary statistics are provided for EADs and trading days without earnings announcements. We report volatility (Vol), skewness (Skew), and kurtosis (Kurt) for EADs and non-EADs and the ratio (Var ratio) between EAD and non-EAD variance. The last column provides the number of EADs in our sample.

For example, NFLX has a variance ratio of 47.32, indicative of a relatively large amount of information on EADs. Presumably for firms like NFLX, it is difficult to obtain valuation relevant information like subscribers or revenue from public sources. For other firms, such as COP, CVX, FCX, or XOM, earnings announcements have little information as their earnings are driven by publicly available information like commodity prices. Altria's (the former Phillip Morris) earnings announcements have little impact, a finding that is not surprising given that this firm was involved in decades long tobacco litigation and the firm provides frequent corporate updates on non-EADs. Overall, there is substantial cross-sectional and times-series variation in the impact of earnings announcements on equity prices.

The model in Equation (2) assumes *conditionally* normally distributed returns, but since volatility changes across EADs, returns are not *unconditionally* normal, consistent with the observed return data. Non-EADs generally have greater nonnormality than EADs, consistent with time-varying volatility and non-EAD price jumps. If random jumps are present, the modest skewness for most firms indicates near zero jump means, thus Merton (1976) implies that these types of jumps will not adversely impact our estimators using ATM options.

To economize on space, Online Appendix A.3 reports tests of the assumption that earnings announcements induce a jump or discontinuity in economic trading time. The volatility of close-to-open returns on EADs is more than three times higher than on non-EAD days, indicating that EADs are outliers or

Table 3
Summary statistics for the underlying returns (by firm)

Ticker	EAD vol	NonEAD vol	Var ratio	EAD skew	Non-EAD Skew	EAD kurt	Non-EAD kurt	Num EAD
AAPL	6.12	2.55	5.77	−0.27	−2.65	2.31	60.55	51
AIG	3.73	1.93	3.73	−0.86	0.61	3.26	12.22	36
AMGN	5.59	2.34	5.74	0.44	0.41	3.70	7.23	40
AMZN	12.41	3.28	14.34	0.26	1.18	2.37	16.24	63
BA	3.67	1.99	3.41	−0.19	0.30	2.34	8.05	27
BAC	4.93	2.30	4.58	−2.61	0.91	15.50	27.15	51
C	3.26	1.81	3.24	0.74	−0.08	6.32	8.07	47
CAT	4.96	1.96	6.40	−0.42	0.24	3.06	8.49	46
COP	2.69	2.17	1.53	−1.05	−0.13	5.34	9.30	28
CSCO	7.71	2.51	9.42	0.62	0.54	3.78	10.98	60
CVX	1.74	1.74	1.00	−0.47	0.57	2.90	19.39	36
DELL	6.87	2.68	6.58	−0.14	0.46	3.26	7.75	28
EBAY	7.96	3.53	5.09	−0.06	0.77	3.54	12.02	30
FCX	4.10	3.22	1.63	−0.31	0.13	3.42	10.51	43
FSLR	16.41	4.24	14.95	0.52	0.79	1.89	13.91	27
GE	4.06	1.94	4.39	−0.10	0.45	5.30	12.09	63
GOOGL	7.19	1.77	16.52	0.41	0.14	2.67	8.56	43
GS	4.02	2.19	3.37	2.11	0.81	8.51	21.13	55
IBM	5.22	1.58	10.90	0.19	0.19	3.76	8.11	63
INTC	5.97	2.38	6.29	0.13	−0.13	5.08	9.06	62
JNJ	1.74	1.18	2.18	0.15	−0.93	1.99	19.97	36
JPM	3.60	2.62	1.89	0.97	0.88	4.74	18.53	59
MA	7.13	2.29	9.72	0.59	0.27	2.81	10.47	27
MO	1.77	1.63	1.17	0.05	0.28	2.87	14.63	44
MRK	3.17	1.65	3.70	−0.12	−1.67	2.74	37.20	40
MS	5.97	3.74	2.54	−2.05	6.38	9.43	158.41	31
MSFT	5.99	1.88	10.15	0.23	0.28	4.21	10.29	62
NEM	3.69	2.11	3.07	0.26	0.08	2.87	4.59	28
NFLX	20.91	3.04	47.32	−0.15	0.37	2.17	6.54	27
PFE	3.38	1.49	5.11	−1.04	−0.01	4.73	7.33	47
PG	3.12	1.38	5.14	−0.60	−3.64	2.90	93.59	52
QCOM	6.19	2.72	5.17	−0.23	0.30	3.43	8.82	63
SHLD	8.96	3.03	8.72	0.36	1.12	2.62	11.13	27
T	2.42	1.43	2.86	−0.40	0.98	3.96	17.54	35
UPS	2.57	1.26	4.14	0.43	0.20	2.89	8.40	28
VZ	2.58	1.46	3.10	1.29	−0.09	5.30	8.08	36
WFC	8.63	3.21	7.22	2.85	1.06	10.69	19.65	31
WMT	2.65	1.35	3.84	0.29	0.34	2.39	8.36	51
X	5.14	3.82	1.81	0.25	−0.09	2.26	6.44	27
XOM	2.21	1.57	1.98	−1.10	0.42	4.76	16.79	51
YHOO	8.90	3.28	7.34	−0.11	1.13	2.86	23.20	47

This table provides summary statistics for daily percentage equity returns for all firms with at least 7 years of EAD data from January 2000 to August 2015. Summary statistics are provided for EADs and for trading days without earnings announcements. We report volatility (Vol), skewness (Skew), and kurtosis (Kurt) and the ratio (Var ratio) between EAD and non-EAD variance. The last column provides the number of EADs in our sample.

"abnormally" large movements. The volatility of open-to-close returns is only slightly higher for EADs, consistent with the presence of jumps induced by earnings announcements, full digestion by market open like in (see Martineau 2017), and inconsistent with a continuous sample path (like in Patell and Wolfson 1979, 1981).

3.2 Nonparametric tests

This section tests the three main implications of earnings announcements on option prices: (1) IV increases prior to an EAD; (2) the term structure of IV is downward sloping before the EAD; and (3) IV decreases after the announcement.

The first tests use the Fisher sign and the Wilcoxon signed rank nonparametric tests to evaluate if a data series is positive or negative. Under the null that EADs have no impact, the Wilcoxon signed-rank test assumes the distribution is symmetric around zero, while Fishers exact test assumes a zero median. For both, for example, the shape (normal vs. t-distribution) and variance could change over time. We use one-sided tests to examine IV increases or decreases. Patell and Wolfson (1979, 1981) use the same tests, although our implementation differs because we use changes in variance (as opposed to volatility), as this is the main model implication.[11] The time-series tests compare IV changes for the shortest maturity options with at least 3 days to maturity post-announcement. To test the IV increase pre-announcement, we subtract the ATM IV one trading day before the announcement from the ATM IV 2 weeks prior to the announcement.[12] Our results are insensitive to these choices and are similar if we use the IV change over 1 week or increase the minimum time-to-maturity constraint. For the decrease in IV, we use the 1-day change around the EAD. If data are missing for the shortest maturity, we move 1 day in either direction. For the term structure tests, we use ATM options for the first two available maturities.

To economize on space, we summarize the findings and report detailed results in Tables A.3 and A.4 in Online Appendix A.4. The term structure and post-EAD decrease implications holds for all years, while the increase in IV prior to EADs holds for every year, except for 2009, when Fishers exact test is insignificant. 2009 marked the end of the crisis, market and firm volatilities fell dramatically, and volatility of volatility was quite high.[13] At the firm level, the null of no post-EAD decrease is rejected for every firm. These rejections provide strong evidence given our modest sample sizes (between 27 and 63 earnings dates per firm), supporting our reduced-form model and the importance of EADs. The term-structure evidence is also strong at the firm level, with only one exception (Altria, ticker MO), which was discussed earlier. The fact that IVs sometimes fall in the 2 weeks prior to an EAD is not surprising, given that volatility of 2-week IV changes is large (further evidence is provided in Online Appendix A.5). For example, for many firms, a large decrease in market volatility leading into a firm's EAD would likely be sufficient to generate an overall decrease in IV. Despite the small sample size, even for this test we reject the null of no effect for the vast majority of firms. Not surprisingly, the firms with the weakest evidence also had the smallest increases in return

[11] Fishers exact test gives the same result using either volatilities or variances, as it only depends on signs and is invariant to monotonic transformations.

[12] We are careful to ensure that both IVs are calculated from options with the same maturity date.

[13] The VIX index fell from approximately 50% to 20% by the end of 2009.

Table 4
Anticipated uncertainty (term structure estimator, by firm)

Term	Mean	Median	SE	25%	75%	Err_1	Err_2	Obs
AAPL	8.83	8.49	0.40	7.08	9.76	0	0	51
AIG	5.21	5.07	0.52	3.03	5.98	4	0	36
AMGN	5.46	4.79	0.47	3.60	6.64	4	0	40
AMZN	12.06	11.06	0.49	9.49	13.94	0	0	63
BA	4.33	4.09	0.29	3.35	5.01	2	0	27
BAC	3.96	3.31	0.47	2.28	4.69	5	0	51
C	3.34	2.90	0.21	2.29	4.48	8	0	47
CAT	5.67	5.07	0.38	4.31	6.13	0	0	46
COP	3.33	2.89	0.49	1.72	4.11	4	0	28
CSCO	8.13	7.28	0.35	6.59	9.10	0	0	60
CVX	2.53	2.52	0.19	1.85	2.94	11	0	36
DELL	6.25	5.90	0.51	4.53	7.06	4	0	28
EBAY	8.36	8.48	0.57	6.74	10.20	0	0	30
FCX	5.26	4.95	0.40	3.36	6.38	4	0	43
FSLR	14.13	14.17	0.67	11.14	16.02	1	1	27
GE	4.17	3.48	0.37	2.75	4.10	4	0	63
GOOGL	7.94	7.60	0.45	6.22	9.33	0	0	43
GS	4.98	4.00	0.41	3.17	5.93	6	1	55
IBM	5.68	5.02	0.30	4.49	6.15	0	0	63
INTC	7.04	6.27	0.36	5.31	7.66	1	0	62
JNJ	2.56	2.25	0.21	1.72	3.05	5	0	36
JPM	4.62	3.80	0.37	2.95	5.25	4	0	59
MA	6.90	6.14	0.53	4.76	8.58	0	0	27
MO	2.71	2.60	0.26	1.85	3.22	22	0	44
MRK	2.90	2.80	0.25	1.77	3.98	10	0	40
MS	6.39	4.36	0.86	3.24	7.69	5	0	31
MSFT	5.35	5.03	0.29	3.96	6.04	2	0	62
NEM	3.39	3.67	0.39	2.11	4.62	7	0	28
NFLX	14.92	13.98	0.91	11.25	18.39	0	0	27
PFE	2.99	3.21	0.18	2.16	3.73	6	0	47
PG	3.45	2.91	0.27	2.34	4.08	2	0	52
QCOM	6.78	6.15	0.32	5.35	7.53	1	0	63
SHLD	7.76	7.86	0.55	5.20	8.84	0	0	27
T	3.40	2.79	0.42	2.27	3.80	6	0	35
UPS	3.53	3.38	0.45	2.14	4.25	4	0	28
VZ	2.95	2.84	0.28	1.95	3.74	7	0	36
WFC	5.90	3.86	1.06	3.10	5.34	0	0	31
WMT	3.26	3.30	0.15	2.60	3.57	3	0	51
X	6.75	6.44	0.61	5.64	7.68	2	0	27
XOM	2.50	2.28	0.21	1.80	3.20	11	0	51
YHOO	9.96	8.87	0.62	7.09	10.33	1	0	47

This table provides the average estimate of anticipated uncertainty $\sigma_j^{\mathbb{Q}}$ using the term-structure estimator $\sigma_{term}^{\mathbb{Q}}$. We report the summary statistics over the sample period from January 2000 to August 2015 for all firms with at least 7 years of EAD data. We report the mean, (Mean), median (Median), the standard error (SE), and the lower and upper quartile (25% and 75%) of all observations without errors. Err_1 counts the number of EAD on which the hypothesis of a decreasing term structure is violated, and Err_2 counts the number of EAD on which the violations were more than 5% (i.e., $\sigma_{t,T_2} - \sigma_{t,T_1} > 0.05$). The last column provides the number of observations (Obs).

volatility on EADs. Online Appendix A.6 discusses the impact of SV on these results.

3.3 Characterizing anticipated earnings volatility

Tables 4 and 6 provide firm-level summaries of the term structure and time-series estimates of $\sigma_j^{\mathbb{Q}}$ given in Equations (4) and (5). We average these estimators in volatility units which is conservative due to Jensen's inequality.[14] Earnings announcement volatilities are large and statistically significant. Across firms, the average term-structure estimate is 6.87% and for nearly all firms the mean is greater than the median, indicating positive skewness. These ex ante earnings risks can be extremely high: for Amazon.com (AMZN), for instance, a historical 3-standard deviation confidence band for the EAD return is $\pm$36%. Thus, very large moves around EADs are clearly priced in options. Our estimates can easily generate the spikes in Figure 1.[15] Earnings volatility estimates also vary substantially across firms. For example, earnings jump volatility for AMZN, FSLR, and NFLX average over 10%, while other firms average less than 3%.

Table 4 also reports error dates. The column labeled "Err_1" counts the number of EADs for which $\sigma_{t,T_1} < \sigma_{t,T_2}$. A small number of error dates are not surprising for the reasons already discussed. First, error dates are concentrated in firms with low earning announcement volatility. Many of the largest and most actively traded firms have no error dates at all, suggesting microstructure or liquidity issues as possible causes. Second, the magnitudes of errors are quite small. There are only two dates on which $\sigma_{t,T_2} - \sigma_{t,T_1} > 5\%$. As a comparison, option bid-ask spreads for the maturities we use are around 5%, in terms of IV. This is especially relevant for firms with low earnings volatility (such as BAC, C, CVX, JNJ, JPM, MO, MRK, or XOM), as the differences in IVs for options on these firms are smaller. Online Appendix A.5 provides further evidence on the errors and these results suggest that the majority of errors in the term structure estimator are driven by a combination of low earnings volatility, microstructure and/or data issues (e.g., stale quotes).

Interesting time-series variation in the earnings volatility estimates is summarized in Table 5. Earnings uncertainty was highest in recessions, 2000–2002 and 2008–2009, and was significantly lower in expansions. The magnitude of the effect is substantial: the average in 2000–2002 was more than double the average in tranquil years. This is consistent with higher earnings volatility, but also with an increase in the sensitivity of equity prices to earnings shocks (via a higher β coefficient in an earnings response model). These results complement those of Campbell et al. (2001), who show that both market and idiosyncratic volatility increase during periods of recession, and those of Herskovic et al. (2016), who document a high degree of commonality in idiosyncratic volatility. Bloom (2009) finds that stock market volatility is strongly correlated with the cross-sectional spread of firm-level profit growth, our results imply that

[14] Jensen's inequality implies that the average of the standard deviations is less than the square root of the average variances since $\left(N^{-1}\sum_{j=1}^{N}\sigma_j\right)^2 < N^{-1}\sum_{j=1}^{N}\sigma_j^2$.

[15] Consider the following example. Assume the annualized diffusive volatility is constant at 40%, which implies that daily diffusive volatility is about 2.5% ($0.40/\sqrt{252}$). If the anticipated earnings uncertainty is 10%, then the annualized IV of an ATM option expiring in 1 week is about 92% prior to the announcement and then subsequently falls to 40%.

Table 5
Anticipated uncertainty (term structure estimator, by calendar year)

Term	Mean	Median	SE	25%	75%	Err_1	Err_2	Obs
2000	10.51	9.55	0.41	6.66	14.53	9	2	185
2001	10.91	10.76	0.45	6.13	14.78	13	0	190
2002	7.19	5.61	0.38	3.53	9.96	20	2	187
2003	4.90	4.78	0.18	2.90	6.53	31	2	194
2004	5.37	4.63	0.27	2.74	7.15	38	3	192
2005	5.13	4.47	0.24	2.81	6.88	30	1	195
2006	5.70	5.00	0.23	3.43	6.99	11	0	194
2007	5.95	5.21	0.25	3.49	7.37	16	0	189
2008	10.05	9.02	0.38	6.21	13.46	4	1	189
2009	7.01	6.18	0.34	3.96	9.37	12	0	188
2010	5.05	4.53	0.24	2.88	6.21	25	0	200
2011	6.16	5.11	0.31	2.83	8.11	15	1	200
2012	6.26	4.41	0.38	2.89	7.07	13	0	197
2013	6.83	5.13	0.33	3.60	8.86	3	0	198
2014	6.46	4.97	0.31	3.75	7.93	2	0	197
2015	5.93	4.99	0.29	3.32	7.82	3	1	149
Pooled	6.87	5.55	0.09	3.48	9.06	245	13	3008

This table provides the average estimate of anticipated uncertainty $\sigma_j^{\mathbb{Q}}$ using the term-structure estimator $\sigma_{term}^{\mathbb{Q}}$. We report the summary statistics over the sample period from January 2000 to August 2015 for all firms in the sample and pool the results by calendar year. We report the mean, (Mean), median (Median), the standard error (SE), and the lower and upper quartile (25% and 75%) of all observations without errors. Err_1 counts the number of EAD on which the hypothesis of a decreasing term structure is violated, and Err_2 counts the number of EAD on which the violations were more than 5% (i.e., $\sigma_{t,T_2} - \sigma_{t,T_1} > 0.05$). The last column provides the number of observations (Obs).

cross-sectional earnings uncertainty dispersion also increases in recessions. It is hard to identify these patterns in earnings announcement volatility using only realized equity returns and earnings, given there is only one noisy quarterly observation. Higher earnings volatility during recessions also may be related to leverage (e.g., Christie 1982). In the compound pricing model of Geske (1979) equity volatility increases as the ratio of market value of debt to equity increases during recession. Similarly, if earnings announcements lead to jumps in the market value of the firm, earnings announcement volatility does increase with higher leverage. This is particularly true for firms with short-term maturity debt.[16]

Table 6 summarizes results for the time-series estimator. The results are quantitatively and qualitatively similar to the term structure estimates. The average estimate is 6.04%, compared to 6.87% for the term structure estimator. As discussed earlier and in the Online Appendix, the time-series estimator is likely to be downward biased relative to the term structure estimator. The two estimators do capture the quantitatively the same effect: the correlation between the time-series and term-structure estimates across firms is 93%.[17]

16 Geske et al. (2016) study the compound option model empirically and find support for the impact of leverage on option prices.

17 We use Spearman's rho to be robust with respect to outliers in the data. Results for Pearson's correlation are similar.

Table 6
Anticipated uncertainty (time-series estimator, by firm)

Time	Mean	Median	SE	25%	75%	Err_1	Err_2	Corr	No data	Obs
AAPL	8.16	7.54	0.39	6.07	9.46	1	0	82.67	0	51
AIG	4.31	3.44	0.41	2.68	5.44	4	0	83.05	0	36
AMGN	4.73	4.20	0.38	3.35	6.11	1	0	49.13	1	40
AMZN	10.97	10.31	0.45	8.59	12.86	2	1	77.87	0	63
BA	3.74	3.66	0.29	2.86	4.62	5	0	9.71	0	27
BAC	3.29	2.68	0.33	1.87	4.14	12	2	28.07	0	51
C	2.43	2.23	0.15	1.70	2.91	13	2	33.63	0	47
CAT	4.97	4.22	0.34	3.74	5.56	2	0	66.41	0	46
COP	2.97	3.03	0.25	2.21	3.67	5	0	32.02	0	28
CSCO	7.58	7.29	0.34	5.97	8.34	1	0	77.07	0	60
CVX	2.06	1.95	0.17	1.43	2.39	10	0	41.42	0	36
DELL	6.14	6.28	0.28	5.40	7.08	2	1	21.35	0	28
EBAY	7.52	7.34	0.53	5.53	9.17	0	0	70.19	0	30
FCX	4.35	4.28	0.34	2.88	4.95	2	1	44.81	0	43
FSLR	12.90	13.03	0.69	10.03	14.85	1	1	83.39	0	27
GE	3.89	3.19	0.40	2.56	3.97	10	0	56.37	0	63
GOOGL	7.05	6.75	0.45	5.42	7.88	1	1	81.77	0	43
GS	4.30	3.45	0.35	2.76	5.15	2	0	69.39	0	55
IBM	5.18	4.60	0.21	4.31	5.53	1	0	73.31	0	63
INTC	6.17	5.69	0.28	4.81	6.73	2	0	66.51	0	62
JNJ	2.20	1.99	0.16	1.62	2.68	5	0	14.70	0	36
JPM	3.52	3.27	0.23	2.47	4.06	5	0	34.59	0	59
MA	5.83	5.39	0.51	4.02	8.04	1	0	87.67	0	27
MO	2.54	2.04	0.28	1.72	2.97	7	1	16.69	0	44
MRK	2.66	2.49	0.20	2.00	3.12	6	0	31.16	0	40
MS	4.42	3.90	0.53	2.97	5.11	5	2	29.25	1	31
MSFT	5.01	4.61	0.24	3.97	5.76	3	2	75.25	0	62
NEM	2.91	2.82	0.31	1.86	3.75	5	0	57.68	0	28
NFLX	12.91	12.24	0.86	9.99	16.73	1	1	81.20	0	27
PFE	2.74	2.99	0.16	1.96	3.41	8	2	22.32	0	47
PG	2.71	2.50	0.19	2.01	3.25	5	0	24.38	0	52
QCOM	6.79	6.09	0.40	5.13	7.40	2	0	68.38	1	63
SHLD	6.46	6.05	0.50	5.26	8.39	0	0	59.12	10	27
T	2.99	2.57	0.29	1.99	3.34	3	0	38.96	0	35
UPS	3.33	2.82	0.37	2.21	4.18	4	0	79.00	1	28
VZ	2.83	2.39	0.22	2.06	3.19	1	0	42.99	0	36
WFC	4.27	3.52	0.67	2.88	4.50	2	1	48.23	0	31
WMT	2.82	2.72	0.18	2.31	3.31	7	0	54.13	0	51
X	5.84	5.67	0.68	4.16	7.07	5	1	34.22	0	27
XOM	2.09	2.06	0.14	1.52	2.56	8	0	29.08	0	51
YHOO	8.71	7.70	0.62	6.02	10.37	1	0	62.12	0	47

This table provides anticipated uncertainty, $\sigma_j^{\mathbb{Q}}$, estimates using the time-series estimator $\sigma_{term}^{\mathbb{Q}}$. We report summary statistics over the sample period from January 2000 to August 2015 for all firms with at least 7 years of EAD data. We report the mean (Mean), median (Median), the standard error (SE), and the lower and upper quartile (25% and 75%) of all observations without errors. Err_1 counts the number of EAD on which the hypothesis of a decreasing implied volatility after the announcement is violated, Err_2 counts the number of EAD on which the violations were more than 5% (i.e., $\sigma_{\tau_j+1/252,T-1/252}-\sigma_{\tau_j-,T}>0.05$). The column Corr provides rank correlations between the term-structure and time-series estimators of Table 4, the column No Data counts the number of EAD on which we cannot calculate the estimator due to missing option data. The last column provides the number of observations (Obs).

To decompose the correlations further, column *Corr* in Table 6 provides the within firm, across time correlation between the term structure and time-series estimates, conditional on both estimates being positive. These correlations are also high with a pooled Spearman coefficient of 82%. These findings provide strong evidence that the estimators are capturing a common effect, both across firms and over time.

In terms of reliability, there are more error dates for the time-series estimator, as expected from the discussion above. To see this, note first from the error columns in Table 6, there are more dates on which σ_{t,T_1} is substantially lower than $\sigma_{t+\Delta,T_1-\Delta}$. Second, there are more dates on which we are unable to find pre-/post-EAD IVs for the same maturity, though these were concentrated in the beginning of the sample. Online Appendix A.3 and A.5 documents that firms with very high volatility or very low earnings volatility have noisier time-series estimates. In what remains, we use only the more reliable and fully ex ante term structure estimates.

3.4 Predictive content of anticipated uncertainty

The next step is to understand the informational content of the ex ante earnings price volatility measures. A large literature, cited earlier, finds that for individual firms, indices, currencies and other macroeconomic markets, option IV predicts subsequent realized return volatility, typically tested over horizons such as monthly. Our earnings jump volatilities correspond to shorter time horizons—daily or even overnight—for which it is more difficult to identify realized volatility predictors and the sampling problems are more severe.

Empirically, high $\mathbb{Q}$-Vol firms (those with high ex ante earnings announcement jump volatilities) have high realized EAD volatility: the cross-sectional correlation between average EAD $\mathbb{Q}$ and $\mathbb{P}$-Vol is 85%. At the firm level, the time-series correlation between the absolute EAD return $|r_j|$ (where r_j is the return from the close prior to the announcement to the first close after the announcement), and $\sigma_j^{\mathbb{Q}}$ (calculated using all available EADs for a given firm) is positive for all but three firms (see Table 7) with a highly significant averaged correlation of 53%. To understand the statistical properties of these results, suppose that $\log\left(\sigma_j^{\mathbb{Q}}\right) \sim \mathcal{N}\left(2,(0.25)^2\right)$, which generates an average anticipated uncertainty of about 7.4%, and that $r_j \sim \mathcal{N}\left(0,\left(\sigma_j^{\mathbb{Q}}\right)^2\right)$. Then the population correlation between $|r_j|$ and $\sigma_j^{\mathbb{Q}}$ is about 30% and a 95% confidence interval is (0.01,0.57) for samples of our size. The range of values in Table 7 is entirely consistent with the model and normal sampling noise. Overall, our option-based EAD volatility estimators provide accurate and significant forecasts of the earnings announcement impact on equity prices.

Table 8 formalizes these results via cross-sectional regressions of absolute announcement day returns (close-to-close) on various variables. Panel A focuses on option-implied EAD jump volatility, diffusive volatility (also extracted from option prices) and the standard deviation of IBES EPS forecasts. Following DellaVigna and Pollet (2009) and others, the IBES analyst earnings uncertainty variable is constructed by standardizing EPS forecast volatility by the equity price 10 days prior to the EAD. Results are based on all

Table 7
Predictive content of anticipated uncertainty

	EAD return abs				EAD return squared			
Firm	Corr	p-val	RankCorr	p-val	Corr	p-val	RankCorr	p-val
AAPL	23.73	0.09	28.50	0.04	16.06	0.26	28.50	0.04
AIG	27.21	0.13	20.19	0.26	29.16	0.10	20.19	0.26
AMGN	56.14	0.00	44.50	0.01	54.81	0.00	44.50	0.01
AMZN	−2.09	0.87	3.61	0.78	−2.62	0.84	3.61	0.78
BA	25.48	0.22	13.92	0.51	35.83	0.08	13.92	0.51
BAC	89.40	0.00	59.82	0.00	98.52	0.00	59.82	0.00
C	34.15	0.03	33.51	0.03	39.66	0.01	33.51	0.03
CAT	13.46	0.37	13.60	0.37	6.45	0.67	13.60	0.37
COP	70.21	0.00	10.26	0.63	91.38	0.00	10.26	0.63
CSCO	23.64	0.07	10.92	0.41	26.29	0.04	10.92	0.41
CVX	0.05	1.00	−0.92	0.97	−3.88	0.85	−0.92	0.97
DELL	50.49	0.01	29.89	0.12	68.33	0.00	29.89	0.12
EBAY	−0.13	0.99	2.47	0.90	0.98	0.96	2.47	0.90
FCX	57.47	0.00	27.80	0.08	71.34	0.00	27.80	0.08
FSLR	−3.99	0.85	−0.03	1.00	−2.67	0.90	−0.03	1.00
GE	44.89	0.00	31.53	0.02	54.51	0.00	31.53	0.02
GOOGL	−2.40	0.88	−1.43	0.93	−3.73	0.81	−1.43	0.93
GS	54.79	0.00	23.58	0.09	69.45	0.00	23.58	0.09
IBM	31.46	0.01	17.88	0.16	36.23	0.00	17.88	0.16
INTC	32.03	0.01	28.20	0.03	23.71	0.06	28.20	0.03
JNJ	34.14	0.05	39.21	0.02	31.03	0.07	39.21	0.02
JPM	41.18	0.00	37.74	0.00	36.63	0.01	37.74	0.00
MA	64.01	0.00	50.67	0.01	70.71	0.00	50.67	0.01
MO	46.23	0.02	44.00	0.03	42.90	0.03	44.00	0.03
MRK	14.92	0.41	16.01	0.37	12.93	0.47	16.01	0.37
MS	28.57	0.14	11.99	0.54	27.72	0.15	11.99	0.54
MSFT	4.93	0.70	−10.40	0.42	25.52	0.05	−10.40	0.42
NEM	52.89	0.02	59.85	0.01	36.82	0.11	59.85	0.01
NFLX	13.01	0.52	2.38	0.91	16.26	0.42	2.38	0.91
PFE	4.15	0.79	−13.85	0.38	11.00	0.49	−13.85	0.38
PG	57.46	0.00	50.56	0.00	55.04	0.00	50.56	0.00
QCOM	17.53	0.18	5.69	0.66	25.96	0.04	5.69	0.66
SHLD	42.61	0.05	50.31	0.02	35.10	0.11	50.31	0.02
T	62.41	0.00	34.68	0.06	78.87	0.00	34.68	0.06
UPS	47.40	0.02	36.77	0.07	47.94	0.02	36.77	0.07
VZ	6.50	0.74	7.64	0.69	1.83	0.93	7.64	0.69
WFC	75.13	0.00	45.48	0.01	74.11	0.00	45.48	0.01
WMT	18.03	0.22	7.98	0.58	23.11	0.11	7.98	0.58
X	−0.38	0.99	10.35	0.63	−5.45	0.80	10.35	0.63
XOM	18.26	0.26	17.47	0.28	12.26	0.45	17.47	0.28
YHOO	39.28	0.01	23.80	0.11	38.73	0.01	23.80	0.11
Pooled	54.88	0.00	53.45	0.00	43.34	0.00	53.45	0.00

This table provides correlations between anticipated uncertainty and the subsequent equity market return volatility for all firms with at least 7 years of EAD data. *EAD Return abs* provides Pearson correlation coefficients and rank correlations and their corresponding p-values between $\sigma_j^{\mathbb{Q}}$ and the absolute return on the EAD. *EAD return squared* provides the same statistics for the correlation between $\left(\sigma_j^{\mathbb{Q}}\right)^2$ and the squared return on the EAD.

firm/quarter observations with a minimum analyst coverage of ten. Consistent with our firm-level results, $\sigma_j^{\mathbb{Q}}$ has considerable predictive power, with a highly significant β-coefficient (the t-statistic is 11.42) and an R^2 value of 28.47%. The IBES-based dispersion variable is insignificant and generates an $R^2 < 1\%$. The only other variable with predictive ability is the diffusive volatility prior to the EAD, though the R^2 increases by only 1% to 29.68%

Table 8
Predictive content of option implied diffusive and EAD jump volatility (pooled regression)

	Model (1)		Model (2)		Model (3)		Model (4)	
A. Dependent variable: Absolute EAD return (close-to-close)								
Constant	0.01	(3.69)	0.05	(13.66)	0.02	(4.09)	0.01	(1.85)
EAD jump volatility	0.58	(11.42)					0.50	(7.02)
IBES disagreement			0.82	(1.15)			−0.45	(−0.72)
Diffusive volatility					0.09	(11.73)	0.03	(4.31)
R^2 (%)	28.47		0.17		15.28		29.68	
B. Dependent variable: 1-month standard deviation after EAD								
Constant	0.01	(9.74)	0.02	(12.72)	0.00	(2.30)	0.00	(0.30)
EAD jump volatility	0.26	(16.57)					0.12	(11.44)
IBES disagreement			1.05	(3.42)			0.12	(0.96)
Diffusive volatility					0.06	(16.98)	0.05	(16.24)
R^2 (%)	45.99		2.31		65.80		73.46	

This table provides results for cross-sectional regressions of EAD volatility variables on $\sigma_j^{\mathbb{Q}}$, diffusive equity volatility calculated from option prices and the standard deviation of EPS analyst forecasts (as reported in IBES) normalized by the equity price. We report regression coefficients for a range of different regression specifications and provide corresponding t-statistics in parentheses (we cluster standard errors by quarter and firm). Panel A provides regression results using the absolute EAD return as dependent variable, and panel B uses the 1-month equity volatility calculated from daily returns. Each observation corresponds to a unique earnings announcement, that is, a unique firm-quarter observation.

when including all three predictors. These results are robust across multiple dimensions.[18]

We provide additional results focusing on realized volatility over the month after an EAD. Our EAD-jump model predicts an increase in the impact of diffusive volatility over longer periods. Consistent with this, we find both option-implied variables are highly significant, although diffusive volatility is now more important. Diffusive IV explains almost 66% of the variation in a univariate regression, whereas the jump component explains 46%. Multivariate regressions confirm that the EAD-jump volatility provides significant incremental information about future realized volatility and is an important predictor of longer-term equity market volatility. Our findings are

18 First, we use different analyst dispersion estimates. The main results use equity-split adjusted statistics. Diether, Malloy, and Scherbina (2002) argue this series can be inaccurate, especially when the reported volatility is low. Although not a major concern here, we also use unadjusted analyst-level data to construct forecast dispersion. Our methodology of aggregating the individual forecasts into summaries use several screens with respect to four criteria: (1) the forecasts are for the same firm and period, (3) forecasts are issued before the IBES statistical period, (3) they are not voided by the IBES data sets "Excluded" or "Stopped," and (4) they are the most recent estimates issued by a broker once (1) to (3) are satisfied. We apply the screens in three ways to aggregate the raw data into an analyst dispersion measure. For the first set of estimates, rules (1) and (2) have to be fulfilled; for the second set rules (1), (2), and (4) have to be fulfilled; and for the third set of estimates all four must hold. Second, we alter the minimum number of analyst forecasts (up to a minimum of three). Third, we perform various subsample analyses. All of our conclusions are robust in subsamples, and no findings change substantively across definitions. And fourth, we estimate the HAR model of Corsi (2009) to predict 1-day-ahead daily variances and 1-month-ahead monthly variances using high-frequency data from the TAQ database rather than using implied volatility. Using these predicted variances as regressors instead of the diffusive part of the IVs does not change the significance of our earnings announcement jump measure. Overall, we find that—in line with a large existing literature—that the diffusive part of the option IVs is a better predictor than time-series-based estimators from the HAR model.

Table 9
Earnings announcement jump risk premiums

Year	Std	$\mathbb{P}$-vol (CC)	$\mathbb{Q}$-vol mean	$\mathbb{P}$-vol (CO)	$\mathbb{Q}$-vol jump	$\mathbb{Q}$-vol median
2000–2005	0.94	7.63	9.92	6.65	7.46	7.08
2006–2010	0.92	7.22	7.74	5.60	6.77	6.15
2011–2015	0.91	7.35	6.78	6.60	6.34	5.19
Pooled	0.92	7.42	8.22	6.31	6.87	6.03

This table provides summary statistics on $\mathbb{P}$ and $\mathbb{Q}$-measure volatility on EADs. The second column (*Std*) provides the standard deviation of standardized equity returns the day after the earnings release, column $\mathbb{P}$-Vol (CC) provides the 1-day close-to-close standard deviation of returns on EADs, $\mathbb{Q}$-Vol mean provides the risk-neutral counterpart. $\mathbb{P}$-Vol (CO) and $\mathbb{Q}$-Vol jump are based on close-to-open returns and the risk-neutral jump volatility $\sigma_j^{\mathbb{Q}}$, respectively. The last column provides estimates of the median of option-implied EAD volatility under $\mathbb{Q}$.

consistent with those of Athanassakos and Kalimipalli (2003), who argue that analyst dispersion has predictive power for monthly equity market volatility. Despite a highly significant slope coefficient, the explained variation of the analyst dispersion is low ($R^2 < 3\%$) and the coefficients are insignificant in multivariate regression.

3.5 Earnings announcement jump risk premiums

The large earnings announcement jump risks may require compensation from investors in the form of a jump risk premium. Our model assumes continuously compounded earnings price jumps under the $\mathbb{Q}$-measure are normally distributed with a volatility of $\sigma_j^{\mathbb{Q}}$, but places few restrictions on the behavior under $\mathbb{P}$. If there is a risk premium attached to the volatility of jump sizes, then $\sigma_j^{\mathbb{Q}} > \sigma_j^{\mathbb{P}}$.[19] This section analyzes the EAD jump risk premium by comparing average volatility under $\mathbb{P}$ and $\mathbb{Q}$-measures.

We quantify earnings jump risk premiums in three different ways. First, we compare the realized volatility of returns under $\mathbb{P}$ with the average expected daily volatility of returns under $\mathbb{Q}$. To do this, we compute the expected 1-day volatility under $\mathbb{Q}$ from option prices by adding to the earnings jump volatility 1 day's diffusive volatility (denoted in Table 9 as $\mathbb{Q}$-Vol) and compare this to the realized return volatility under $\mathbb{P}$ (denoted in Table 9 as $\mathbb{P}$-Vol). Test for equality across measures is difficult as both are estimated and time-varying. We first note that overall $\mathbb{Q}$-volatility is 80 bps higher than $\mathbb{P}$-volatility on average (8.22% vs. 7.42%), and the average $\mathbb{Q}$-volatility is larger than the average $\mathbb{P}$-volatility for most firms (untabulated), consistent with an earnings jump premium. These results could be sensitive to outliers, as mean estimates of $\sigma_j^{\mathbb{Q}}$ are higher than the median. Winsorized statistics (also untabulated) also indicate that $\mathbb{Q}$-Vol is higher than $\mathbb{P}$-Vol. A comparison of close-to-open return volatility under $\mathbb{P}$ with

19 There is evidence for a diffusive volatility risk premium and for some evidence for a risk premium attached to the volatility of jump sizes using index options (see Broadie et al. 2007).

EAD jump volatility $\sigma_j^{\mathbb{Q}}$ also supports an economically sizable EAD volatility risk premium.[20]

A second, likely more powerful, statistic is the standard deviation of standardized EAD returns, $stdr_j = r_j / \sqrt{\left(\sigma_j^{\mathbb{Q}}\right)^2 + \sigma^2 \Delta}$, where Δ is one trading day. This accounts for time-varying volatility and is less sensitive to outliers. The standard deviation of $stdr_j$ is one if there is no EAD jump risk premium. Results for this statistic are in Column 2 of Table 9. The pooled standard deviation is 0.92 and results are stable over the three subsamples with values ranging from 0.91 to 0.94. A chi-square test confirms that the standard deviations over the full sample period as well as overall subsamples are significantly different from one at the 1% level. Overall, these tests point toward a positive and statistically significant earnings jump volatility risk premium.

The third test computes average straddle returns. If $\sigma_j^{\mathbb{Q}} > \sigma_j^{\mathbb{P}}$, then writing straddles across EADs should be profitable. We calculate straddle returns from purchasing an ATM call and put at the close price prior to the earnings announcement and selling the position at the close after the announcement. To provide some intuition on magnitudes and to quantify the economic impact, consider an ATM call and straddle with 1 week to maturity, an interest rate of 5% and $S_t = 25$. Prior to the announcement, call and put values were about \$1.53 and \$3.03, respectively. Assuming the equity price did not change the following day, the prices after the announcement fall to \$0.68 and \$1.65, respectively, an almost 50% decrease solely due to the drop in volatility from the resolution of uncertainty from the earnings announcement. If, however, the equity price fell 20% (a 2-standard deviation move), then the options are worth \$0.0 and \$5.03, respectively.

Table 10 reports an average 1-day straddle return of −7.96% (across firm-quarter observations and not annualized), and a median return of −10.24%. Unreported robustness checks confirm these findings are consistent across time: straddle returns were negative during all 16 years in our sample and have (with one exception) highly significant t-statistics (−13.25 over the full sample period). The evidence for individual firms (also unreported) confirms that average EAD straddle returns are significantly negative. There are only rare exceptions to this and the highest average firm-level return observed is merely 1%. Given the large realized volatilities of option strategy returns and the small sample size for individual firms, firm-level results can be quite sensitive to outliers and high idiosyncratic volatility.

To frame these results relative to our model, we also conduct a small scale Monte-Carlo experiment and simulate straddle returns using our reduced-form

[20] We have also verified that splitting the close-to-close return into an overnight and intradaily component and estimating the intradaily variance using a high-low variance estimator leads to identical conclusions.

Table 10
Straddle returns

Statistic	Data	Bootstrapped distribution Mean	SD	1%	5%	25%	50%	75%	95%	99%
Mean	−7.96	−1.51	0.29	−2.17	−1.94	−1.73	−1.52	−1.31	−1.01	−0.82
Median	−10.24	−3.17	0.21	−3.66	−3.50	−3.32	−3.17	−3.01	−2.86	−2.69
SD	27.47	15.01	0.70	13.68	13.97	14.54	14.95	15.28	16.39	17.32
Skewness	1.44	2.27	0.91	1.17	1.40	1.77	2.03	2.44	4.09	5.81
Kurtosis	8.93	21.77	19.64	8.65	9.84	12.92	15.75	20.90	61.27	113.18
t-stat	−13.25	−5.40	1.17	−7.92	−7.12	−6.19	−5.44	−4.60	−3.50	−2.63

This table provides summary statistics on the returns of at-the-money straddles that are held the day before an earnings announcement to the next trading day. We use options of the shortest available maturity (with at least 3 days to maturity on the first trading day after the earnings release). We report the mean (*Mean*), median (*Median*), standard deviation (*SD*), skewness (*Skewness*), kurtosis (*Kurtosis*), and the t-statistic (t-stat). The table also provides bootstrapped distributions for all statistics. For each bootstrap run, we select for each firm and announcement date in our sample a random date between 35 and 5 days prior to the announcement or 5 to 35 days after the announcement and calculate ATM straddle returns. The bootstrapped distributions are calculated from 250 samples.

model of Section 1 for different values of $\sigma_j^{\mathbb{P}}$.[21] The results indicate that for realistic parameter values a wedge of 1% between real-world and risk-neutral EAD jump volatilities generate average straddle returns of −8.5% for options maturing 1 week after the EAD. Thus, our observed straddle estimates are completely consistent with a reasonably parametrized jump-diffusion. We interpret this as strong evidence supporting $\sigma_j^{\mathbb{Q}} > \sigma_j^{\mathbb{P}}$ and an earnings jump volatility risk premium.

To further investigate statistical significance, we perform a bootstrap experiment to understand average straddle returns around EADs vis-a-vis normal trading days. Although unlikely given the mixed evidence of variance risk premiums in Carr and Wu (2009) and the large negative straddle returns, our results could be affected by the presence of a diffusive variance risk premium or randomly timed jump risk premium realized on non-EAD days. To this end, we simulate random samples as follows. For each firm and EAD, we randomly select a trading day within a symmetric 70-day window around the EAD (but excluding dates within 5 days of the EAD) matching each EAD with a random day with similar overall market conditions. For a large number of random draws of these days for all firms/EADs, we calculate straddle returns and record return statistics. There are two noteworthy results (also reported in Table 10). First, straddle returns are substantially and statistically more negative on EADs than during otherwise similar normal market periods. The average straddle return of −7.96% compares to a 1%-percentile of only −2.17% on non-EAD trading days. And second, average straddle returns on non-EADs are negative providing new evidence for a negative variance risk premium and/or a risk premium attached to jump times and/or sizes.

21 We use the same parameters used in Section 1.2 and assume that $\kappa_v = 3$ which implies an additional diffusive volatility risk premium. We randomize the variance before the announcement day by sampling its stationary distribution. We impose no risk premiums on Poisson jump risk. Our results are not sensitive to these choices.

Whether it is possible to devise trading strategies to profit from these earnings announcement volatility risk premiums depends crucially on trading costs. Table 1 suggests that naive trading strategies based on closing bid and ask quotes may consume a substantial portion of these short straddle returns. Muravyev and Pearson (2016) show that trading costs in option markets are, however, much lower than quoted bid-ask spreads. An empirical investigation of the impact of trade timing on the profitability of straddle returns around EADs is an interesting avenue for future research.

Theoretical arguments also support nonzero EAD jump risk premiums. Jumps are difficult to hedge, and this difficulty could lead to a premium when combined with the demand-based arguments in Bollen and Whaley (2004). Garleanu et al. (2009) find that a combination of demand pressures and unhedgeable risks can create excess option IV. These results are also related to Ni et al. (2008), who analyze the volatility demand and predictable movements in realized and IV. As noted earlier, firms with higher EAD volatility have higher market exposure, which would also suggest a jump volatility risk premium (see also the learning-based explanation in Savor and Wilson (2016) for an EAD mean risk premium).

3.6 Implications for cross-sectional studies

IVs on individual firms have recently been used in a number of empirical studies, as regressors or for portfolio sorts. Since equity options spanning EADs have significant IV variation unrelated to fundamentals, some of these results may have additional noise. In this section, we replicate the results of Baltussen et al. (forthcoming) (BBG hereafter) and test whether some of their conclusions may be strengthened by explicitly accounting for EADs. Finally, we provide guidance for empirical research using equity IV data.

BBG use short-term equity options to calculate the standard deviation of IVs over a calendar month. They show that high volatility of volatility (vol-of-vol) stocks underperform low vol-of-vol stocks by about 10% per year. Denoting the ATM IV at time t for stock i as $\sigma_{i,t}^{ATM}(T_e)$ (where $T_e > t$ is the fixed expiration date of the option), the authors define the vol-of-vol for stock i at time t as

$$VoV_{i,t} = \sqrt{\frac{1}{20}\sum_{j=t-19}^{t}\left(\sigma_{i,j}^{ATM}(T_e) - \bar{\sigma}_{i,t}^{ATM}(T_e)\right)^2} \times \left(\bar{\sigma}_{i,t}^{ATM}(T_e)\right)^{-1}, \tag{6}$$

where

$$\bar{\sigma}_{i,t}^{ATM}(T_e) = \frac{1}{20}\sum_{j=t-19}^{t}\sigma_{i,j}^{ATM}(T_e). \tag{7}$$

For short-dated options, this vol-of-vol measure is quite noisy and potentially biased during earnings announcement months. As the time to maturity decreases over time (i.e., $T_e - t$ decreases), option IVs exhibit a deterministic upward trend prior to EADs. Then, after the EAD, IVs drop immediately which will mechanically increases the vol-of-vol for announcing firms. The effects can be particularly large for firms with high earnings uncertainty and/or for short dated options. This suggests that if vol-of-vol is indeed a predictor of future stock returns, accounting for EADs should remove noise in the portfolio sorts and strengthen BBG's main findings.

We replicate BBG's main analysis and form portfolios based on the VoV level. We obtain share prices from CRSP and (for comparison) restrict our sample from January 1996 to December 2009. We only retain stocks with share code 10 or 11 traded on NYSE, NASDAQ or AMEX. We remove closed-end funds, real estate investment trusts (REITs), and stocks whose prices is \$5 or less. Furthermore, we discard small firms with market capitalization of \$225 million or less (in 2009 value). At the penultimate trading day in each month, we sort remaining stocks into quintile portfolios based on VoV. Following BBG we use options that expire during the next trading month, and thus, at the time of the sort, the options used in the calculation of VoV have relatively short maturities (on average approximately 1 month). We then hold equally weighted quintile portfolios during the next calendar month and rebalance monthly.

Panel A of Table 11 reports the results and confirms the high-minus-low portfolio earns a negative CAPM alpha of -0.73% a month (BBG find a CAPM alpha of -0.50% with a t-statistic of -2.99). Note that our overall results differ marginally from BBG as our high-minus-low portfolio has a slightly larger return spread and quintile alphas are not completely monotone. Overall, our findings are quantitatively and qualitatively similar to BGG.

In panel B, we restrict the portfolio sorts to firms which report earnings during the formation month. Since the exact timing of the EAD is not critical for this exercise, we rely on Compustat data for these announcements. As expected, results for this subset are quite different from the overall results in panel A. We find no significant relationship between VoV and subsequent stock returns. In fact, excess returns and alphas now have opposite (positive) signs and are insignificant. In panel C, results for the subset of stocks that do not announce earnings *strengthen* the overall conclusions in BBG as VoV is a stronger predictor when VoV is less noisy as return spreads and significance levels both increase. We repeat the analysis with value-weighted portfolio sorts and a range of different data filters and in all cases arrive at the same conclusions. We provide further evidence below which confirm that the insignificant return spreads in panel B are due to the impact of EADs on IVs.

The empirical asset pricing literature considers a wide range of measures constructed from option prices and hence the impact of earnings announcements on empirical results may vary widely. And while it is difficult to provide general advice on how to deal with earnings announcements in empirical work, we can provide a list of important issues that should be considered when determining the impact of earnings announcements on measures of equity IVs.

Table 11
Quintile portfolios of stocks sorted by vol-of-vol

	Return	Excess return	CAPM alpha	FFC-4F alpha
A. Univariate sort by VoV				
Low VoV	0.83	0.55	0.22	0.04
Q2	1.03	0.75	0.40	0.34
Q3	0.81	0.53	0.16	0.11
Q4	0.63	0.34	−0.05	−0.02
High VoV	0.21	−0.08	−0.51	−0.41
High minus low difference		−0.63	−0.73	−0.46
t-statistic		(−2.14)	(−2.76)	(−2.17)
B. Univariate sort by VoV (EAD in formation month)				
Low VoV (EAD in formation month)	0.31	0.02	−0.31	−0.55
Q2	0.87	0.59	0.25	0.20
Q3	0.99	0.71	0.35	0.37
Q4	0.53	0.25	−0.14	−0.08
High VoV (EAD in formation month)	0.41	0.13	−0.26	−0.09
High minus low difference		0.11	0.04	0.45
t-statistic		(0.27)	(0.10)	(1.40)
C. Univariate sort by VoV (no EAD in formation month)				
Low VoV (no EAD in formation month)	1.04	0.76	0.43	0.28
Q2	1.03	0.74	0.38	0.29
Q3	0.96	0.68	0.30	0.24
Q4	0.76	0.47	0.08	0.07
High VoV (no EAD in formation month)	−0.05	−0.33	−0.77	−0.71
High minus low difference		−1.09	−1.20	−0.99
t-statistic		(−3.61)	(−4.56)	(−4.04)

The first portfolio (Low VoV) contains stocks with the lowest monthly Vol-of-Vol in the previous month and portfolio 5 (High VoV) contains stocks with the highest monthly Vol-of-Vol in the previous month. We equally weight stocks in each quintile portfolio and rebalance monthly. For each portfolio Columns 2 to 5 report the average raw returns, the CAPM and four-factor Fama-French-Carhart (FFC-4F) alphas. Panel A includes all stocks; panel B uses only stocks with an earnings announcement during the portfolio formation month; and panel C imposes the restriction that no earnings announcements occur during the portfolio formation month.

First, interpolated constant-maturity IVs have the advantage of mitigating the deterministic upward drift, which is particularly pronounced in short-term options. Using interpolated data, measures based on IV changes may be constructed by removing only a handful of trading days: the EAD and potentially days on which the announcement enters the calculation for the first time. Despite the widespread use of interpolated IVs from OptionMetrics, it is also worth noting, however, that OptionMetrics interpolated volatilities and use a log transformation of the time to maturity in their interpolation method. Our model-based results imply that the most reasonable interpolation is linear in variances (like in, for instance, Carr and Wu 2009).

Second, depending on the application, it may be useful to separate diffusive and EAD jump volatility (as we do in Section 3). While this approach has theoretical advantages, it requires the earnings dates and times and may suffer from noise due to database errors and missing EAD information. Third, an important consideration is the choice of option maturity. While many studies rely on short-term IVs due to higher liquidity and trading volume, longer term IVs are far less affected by EADs than short-term options. For instance, when we repeat the analysis of BBG with longer-term options, we find that the difference between announcing firms and nonannouncing firms narrows substantially and that the vol-of-vol effect exhibits the same sign in both groups with only minor differences in the alphas for the spread portfolios. For instance, using options with 1 year to maturity, the CAPM alpha of the high-minus-low portfolio for announcing firms is -0.81% compared to -0.79% for nonannouncing firms (untabulated). This result is theoretically expected and supports our claim that earnings releases are the main driver of the empirical results in panel B of Table 11. Depending on the research question, longer dated IVs may be sufficient. Finally, it is essential to provide robustness checks by removing EADs and/or announcing firms unless the research question explicitly deals with earnings announcements. Han and Zhou (2012) and Vasquez (2017), for example, split the sample into announcing and nonannouncing firms (as we do in this section). Earnings announcements are not only important because of the variation they cause in IVs, but they also affect returns through different channels (Beaver 1968; Cohen et al. 2007; Frazzini and Lamont 2007; Savor and Wilson 2016).

3.7 Option pricing implications

This section analyzes earnings announcement jumps in standard SV models with randomly timed jumps in prices. This allows us to quantify the economic impact on option prices and compare the impact of EADs to other components such as randomly timed jumps.

The literature on individual equity options is relatively small compared to the literature on index options. One reason for this is the computational difficulty present in calibrating SV models on many firms. Bakshi, Cao, and Zhong (2012) study the performance of option pricing specifications nested in the double jump model of Duffie et al. (2000) and conclude that "in contrast to index-options, [jump] model generalizations are unable to produce a large improvement for near-the-money individual equity options." They find that there is greater improvement for deep OTM options. Further studies on individual equity options include Christoffersen et al. (2018), who model the joint dynamics of index and individual equity options, and Carr and Wu (2017), who propose a self-exciting jump model and estimate it on equity options of five individual firms. This paper is the first to explicitly account for earnings announcements in the data-generating process and to quantify the impact.

We consider a number of nested versions of the earnings jump model developed in Section 1: SVJEJ is the full specification with SV, randomly timed jumps and earnings jumps; SVJ is the model without EAD jumps; SVEJ is the model with earnings jumps; and SV is a purely diffusive SV model. For all four models, we estimate parameters and filter the latent variance process using the unscented Kalman filter of Julier and Uhlmann (1997) and Wan and Van Der Merwe (2000).[22] To describe our approach, we let $IV\left(S_t, V_t, \Upsilon^{\mathbb{Q}}, T_n, K_n\right)$ denote the model-based IV of an option with strike K_n and time to maturity T_n, and let $\Upsilon^{\mathbb{Q}} = \left(\kappa^{\mathbb{Q}}, \theta^{\mathbb{Q}}, \sigma_v, \rho, \widehat{\sigma}^{\mathbb{Q}}, \bar{\lambda}^{\mathbb{Q}}, \bar{\mu}_y^{\mathbb{Q}}, \bar{\sigma}_y^{\mathbb{Q}}\right)$ denote the structural parameters. For simplicity we assume that the EAD jump volatility $\sigma_j^{\mathbb{Q}}$ is constant over time, that is, $\sigma_j^{\mathbb{Q}} = \widehat{\sigma}^{\mathbb{Q}}$ for all j, and hence our deterministic jump models require only one additional parameter. Extensions to time-changing jump volatilities are left to future research.

The observation equation is given by

$$IV_t^m(T_n, K_n) = IV\left(S_t, V_t, \Upsilon^{\mathbb{Q}}, T_n, K_n\right) + e_{t,n} \qquad \forall n = 1, \ldots, n_t, t = 1, \ldots, T, \quad (8)$$

where IV_t^m is the observed IV at time t and n_t is the number of options available at time t.[23] The error term $e_{t,n}$ is assumed to be i.i.d. normal with mean zero and standard deviation σ_e. The state evolution is given by a time discretization of the $\mathbb{P}$-dynamics of the square-root variance process. This approach provides estimates of the spot variances, the SV and jump parameters under the $\mathbb{Q}$-measure, and the $\mathbb{P}$-measure parameters of the SV process.

We construct a sample of option prices by averaging the IV for the put/call option pair closest to the money for each maturity and day and also for the option pairs with moneyness closest to 0.90 and 1.10. To our knowledge and due to computational burdens, few calibration procedures use daily data over long time samples, most studies focus on weekly data (see, for instance, Bates 2000, Christoffersen et al. 2010, or Andersen et al. 2015).[24] For our sample, the computational burden of using daily data, multiple options and several firms is extreme: we have to numerically compute around 150,000 option prices for each objective function evaluation. Because of these computational burdens, we restrict our empirical analysis to all firms that remain in our sample throughout entire period: AMZN, GE, IBM, INTC, MSFT, and QCOM.[25] These firms vary substantially in terms of the earnings jump volatilities reported in Section 3.3.

To understand the impact of earnings jumps, consider first option pricing errors as a measure of overall fit. Figure 2 provides the difference between the average absolute IV pricing errors for SV and SVEJ for the days surrounding EADs, in addition to pricing errors by option maturity. To economize on space,

[22] This procedure imposes that the model parameters remain constant during the whole sample period. Ideally, one would estimate the model using, in addition to option prices, the time series of returns. Other 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 (2007). These approaches are in principle statistically efficient; however, the computational demands of pricing options for each simulated latent volatility path and parameter vector constrains research short data samples and/or few options contracts (typically 1 per day).

[23] See Christoffersen and Jacobs (2004) for a discussion of choice of loss function.

[24] Pan (2002) uses two option prices sampled weekly over a 5-year period, Eraker (2004) uses a single option price for every day over a 4-year period.

[25] Additionally, we estimate all structural models for all firms that are missing only during 1 year: Cisco Systems (CSCO), Goldman Sachs (GS), JP Morgan/Chase Manhattan Bank (JPM), Wal-Mart Stores (WMT) and Apple (AAPL), which is missing during 2 years. Because of space restrictions, we do note report these additional results, which are qualitatively and quantitatively very similar to the results presented in this section.

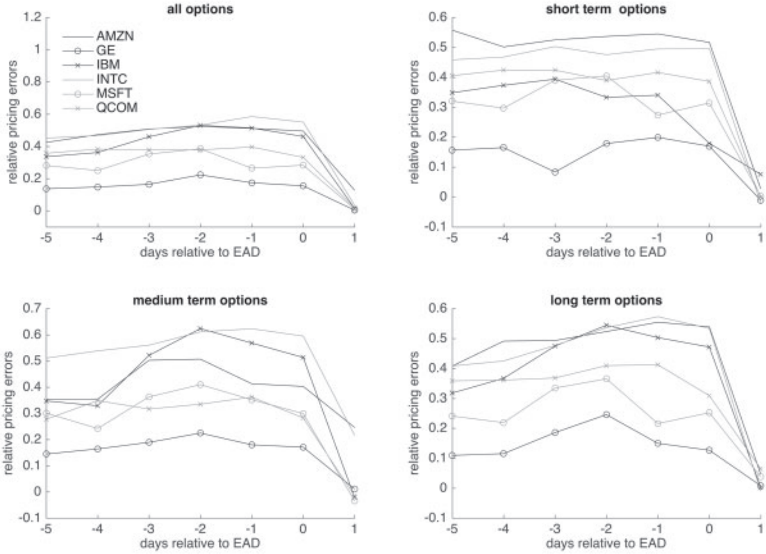

Figure 2
Pricing errors around earnings announcement days
This figure reports the relative difference between the mean absolute pricing errors of the SV and SVEJ model on trading days around earnings announcements: MAPE(SV)/MAPE($SVEJ$)-1, where MAPE(M) denotes the mean absolute pricing error of model M. The data set is a representative daily option sample from January 2000 to August 2015. Pricing errors are grouped into four different categories: all (all options), short (less than 30 days to maturity), medium (between 31 and 90 days to maturity) and long (more than 90 days to maturity). We report estimation results for Amazon (ticker: AMZN), General Electric (GE), Intel Corporation (INTC), International Business Machines Corporation (IBM), Microsoft (MSFT), and Qualcomm (QCOM). For exact model definitions, see Sections 1 and 3.7.

we focus on SV and SVEJ and provide detailed results for other models upon request. A relative pricing error of 0.4 in Figure 2 implies that the SVEJ model reduces pricing errors by 40%. Accounting for jumps on EADs leads to a significant pricing improvement: in the week before an EAD, overall pricing errors across all firms can fall by more than 50%, and the pricing errors fall in all cases after incorporating earnings jumps. To provide further intuition, for Intel the mean absolute pricing errors fall in the 3 days prior to earnings announcements from 4.111, 3.911, and 4.554 in the SV model to 1.925, 1.623, and 2.047 in the SVEJ model, respectively (untabulated). The earnings announcement effect is most pronounced in short-dated options, given their sensitivity to earnings jumps, but there is also a significant improvement in long-dated option prices. In SV models, IVs are only driven by spot volatility, V_t, and, intuitively, if spot volatility increases enough to match short-dated IVs, it will massively overshoot longer-dated IVs, a tension released by accounting for earnings jumps. Although not reported, models incorporating randomly timed jumps do not add any further pricing improvements around EADs (we provide further details below).

Table 12
Option pricing error by moneyness and maturity

		Option Categories						
Firm	Model	All	OTM	ATM	ITM	short	medium	long
AMZN	BSEJ	2.40	2.84	1.88	2.51	3.40	2.00	2.03
	SV	2.66	2.73	2.63	2.61	3.92	2.35	2.15
	SVEJ	1.99	2.10	1.87	2.01	2.95	1.55	1.70
	SVJ	2.59	2.61	2.61	2.56	3.75	2.29	2.16
	SVJEJ	1.94	1.98	1.90	1.93	2.83	1.48	1.71
AMZN	BSEJ	2.40	2.84	1.88	2.51	3.40	2.00	2.03
	SV	2.66	2.73	2.63	2.61	3.92	2.35	2.15
	SVEJ	1.99	2.10	1.87	2.01	2.95	1.55	1.70
	SVJ	2.59	2.61	2.61	2.56	3.75	2.29	2.16
	SVJEJ	1.94	1.98	1.90	1.93	2.83	1.48	1.71
GE	BSEJ	2.22	2.85	1.51	2.46	3.61	2.31	1.77
	SV	1.60	1.80	1.40	1.65	2.87	1.49	1.28
	SVEJ	1.51	1.68	1.33	1.56	2.70	1.38	1.23
	SVJ	1.55	1.61	1.46	1.62	2.77	1.41	1.26
	SVJEJ	1.51	1.61	1.36	1.58	2.61	1.38	1.24
IBM	BSEJ	2.21	2.77	1.52	2.46	3.42	1.95	1.71
	SV	1.93	2.16	1.74	1.91	2.84	1.39	1.69
	SVEJ	1.61	1.75	1.45	1.67	2.44	1.20	1.41
	SVJ	1.79	1.91	1.72	1.73	2.71	1.24	1.58
	SVJEJ	1.51	1.61	1.43	1.52	2.30	1.14	1.32
INTC	BSEJ	2.10	2.55	1.58	2.23	3.51	1.87	1.68
	SV	1.88	1.97	1.81	1.85	3.28	1.47	1.49
	SVEJ	1.49	1.55	1.40	1.55	2.70	1.18	1.21
	SVJ	1.82	1.84	1.82	1.81	3.17	1.40	1.46
	SVJEJ	1.48	1.49	1.44	1.52	2.64	1.15	1.21
MSFT	BSEJ	1.94	2.40	1.40	2.11	3.10	1.80	1.60
	SV	1.61	1.73	1.47	1.64	2.76	1.30	1.35
	SVEJ	1.46	1.59	1.29	1.52	2.52	1.18	1.23
	SVJ	1.54	1.60	1.46	1.57	2.56	1.22	1.33
	SVJEJ	1.42	1.50	1.31	1.47	2.38	1.12	1.24
QCOM	BSEJ	2.31	2.79	1.68	2.53	3.54	1.98	1.87
	SV	1.92	2.06	1.76	1.98	3.12	1.45	1.62
	SVEJ	1.68	1.82	1.46	1.78	2.73	1.22	1.43
	SVJ	1.87	1.97	1.74	1.94	2.99	1.43	1.58
	SVJEJ	1.66	1.76	1.49	1.74	2.61	1.22	1.44

This table reports the mean absolute pricing errors for the BSEJ, SV, SVEJ, SVJ and SVJEJ models. The data set is a representative daily option sample from January 2000 to August 2015. Pricing errors are grouped into six different categories: OTM (if $M < 0.95$), ATM (if $0.95 \leq M \leq 1.05$), ITM (if $M > 1.05$), short (less than 30 days to maturity), medium (between 31 and 90 days to maturity) and long (more than 90 days to maturity). We report estimation results for Amazon (ticker: AMZN), General Electric (GE), Intel Corporation (INTC), International Business Machines Corporation (IBM), Microsoft (MSFT) and Qualcomm (QCOM). For exact model definitions, see Sections 1 and 3.7.

Table 12 provides pricing errors by moneyness and maturity. In addition to the four SV-based models, for comparison we also provide pricing errors for the Black-Scholes model augmented with earnings jumps (BSEJ). We estimate pricing errors for this model by simply minimizing the squared pricing errors between model and IV.[26] We classify options according to their

[26] To estimate errors, we first fix an earnings jump parameter and optimize on each trading day the diffusive volatility which implies a daily recalibration of the diffusive volatility. We then alternate the earnings jump parameter until an optimum is found. Note that the BSEJ model is less constrained in its minimization of pricing errors as we

moneyness (OTM, ITM, or ATM) and use three different maturity categories. There is a substantial pricing improvement for all firms and categories. For Intel, the improvement is 36%, 14%, and 24%, respectively, for the three maturity categories. SVEJ also offers sizeable improvements for ATM options with errors decreasing from 1.81 to 1.40. Our results contrast with those of Bakshi, Cao, and Zhong (2012), who find that randomly timed jumps in prices or in volatility provide little benefit for pricing ATM options. Overall, our results indicate that incorporating jumps on EADs provides first order pricing improvements not only around EADs, but over the entire sample as it relieves tensions present due to the deterministic movements in IVs around EADs.

Table 13 summarizes fits and parameter estimates for each of the four models. Overall, we find strong evidence for earnings jumps, as well as evidence for leverage effects and randomly timed jumps in returns. In terms of model fits, the final column shows the incremental improvements for each of the components and our results indicate that earnings jumps are far more important than randomly timed price jumps. For example, for Intel, σ_e is 3.34%, 2.54%, 3.28%, and 2.52% for SV, SVEJ, SVJ, and SVJEJ models, respectively, indicative of a modest improvement of randomly timed jumps and a larger improvement of earnings jumps. This result is consistent across firms, and even firms with low anticipated uncertainty on EADs (General Electric for example) provide evidence in favor of SVEJ over a random jump model. Although not reported, a likelihood ratio test overwhelmingly rejects the restrictions that jump volatilities are zero.[27]

In terms of earnings jump estimates, we focus on $\widehat{\sigma}^{\mathbb{Q}}$ and use Intel as an example. The average jump volatility for Intel from the term structure and time-series estimator was 7.04 and 6.17, respectively. The estimates using the formal SV model extensions are similar, although values are lower with slightly more than 5%. Similar results are obtained for the other firms. There are at least two reasons why these estimates may differ. First, 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. If investor's perceptions of $\widehat{\sigma}^{\mathbb{Q}}$ changes in the days and weeks prior to the earnings announcement, this

do not filter the variance path for this model. In addition BSEJ is calibrated using an option pricing error metric whereas the unscented Kalman filter used for the other models includes both a likelihood term for the variance path and observed option prices.

27 Our primary goal is to quantify the pricing improvements generated by jumps on EADs. 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).

Table 13
Parameter estimates

Firm	κ_v	θ_v	σ_v	ρ	$\kappa_v^{\mathbb{Q}}$	$\theta_v^{\mathbb{Q}}$	$\bar{\lambda}_y^{\mathbb{Q}}$	$\bar{\mu}_y^{\mathbb{Q}}(\%)$	$\bar{\sigma}_y^{\mathbb{Q}}(\%)$	$\widehat{\sigma}^{\mathbb{Q}}(\%)$	$\sigma_e(\%)$
AMZN	1.28	0.36	0.80	−0.55	0.88	0.28					3.91
	(0.25)	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)					(0.01)
	1.28	0.36	0.77	−0.63	0.73	0.21				8.77	3.24
	(0.23)	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)				(0.02)	(0.00)
	0.89	0.12	0.94	−0.85	0.52	0.31	38.28	−0.49	3.85		3.81
	(0.13)	(0.02)	(0.00)	(0.01)	(0.01)	(0.00)	(0.06)	(0.00)	(0.01)		(0.00)
	1.15	0.36	0.76	−0.89	0.60	0.18	6.70	−0.17	7.33	8.70	3.13
	(0.04)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.03)	(0.00)	(0.04)	(0.02)	(0.00)
GE	3.22	0.10	0.98	−0.43	0.85	0.14					2.57
	(0.51)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)					(0.00)
	3.46	0.10	1.11	−0.45	0.53	0.21				2.95	2.44
	(0.73)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)				(0.01)	(0.00)
	0.69	0.05	0.86	−0.65	0.72	0.10	4.59	0.10	5.60		2.50
	(0.34)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)
	0.63	0.06	0.78	−0.66	0.85	0.09	0.69	0.34	13.02	2.86	2.41
	(0.33)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.01)	(0.00)
IBM	4.07	0.09	1.00	−0.44	1.70	0.09					3.21
	(0.83)	(0.02)	(0.01)	(0.00)	(0.01)	(0.00)					(0.00)
	0.75	0.12	1.07	−0.47	1.16	0.10				4.15	2.59
	(0.65)	(0.10)	(0.00)	(0.00)	(0.00)	(0.00)				(0.00)	(0.00)
	1.75	0.04	0.81	−0.69	1.29	0.05	6.59	−1.17	5.62		3.01
	(0.46)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)		(0.00)
	0.75	0.09	0.62	−0.78	1.16	0.05	2.30	−1.52	7.40	4.03	2.46
	(0.12)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
INTC	2.68	0.17	0.96	−0.38	1.46	0.13					3.34
	(0.55)	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)					(0.00)
	1.78	0.16	0.88	−0.47	1.05	0.13				5.07	2.54
	(0.63)	(0.05)	(0.01)	(0.00)	(0.01)	(0.00)				(0.00)	(0.00)
	0.63	0.11	0.90	−0.65	1.16	0.09	9.67	−0.10	5.45		3.28
	(0.40)	(0.07)	(0.00)	(0.00)	(0.01)	(0.00)	(0.08)	(0.01)	(0.02)		(0.00)
	0.63	0.14	0.76	−0.71	0.97	0.10	4.16	0.10	6.26	5.01	2.52
	(0.27)	(0.06)	(0.00)	(0.01)	(0.01)	(0.00)	(0.07)	(0.00)	(0.06)	(0.00)	(0.00)
MSFT	2.20	0.11	0.76	−0.39	1.04	0.11					2.64
	(0.69)	(0.04)	(0.01)	(0.00)	(0.01)	(0.00)					(0.00)
	2.23	0.11	0.82	−0.41	0.74	0.13				3.93	2.39
	(0.33)	(0.02)	(0.01)	(0.00)	(0.01)	(0.00)				(0.00)	(0.00)
	0.63	0.06	0.65	−0.72	0.85	0.08	6.43	0.05	5.72		2.54
	(0.22)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)	(0.01)		(0.00)
	0.75	0.07	0.61	−0.74	0.79	0.08	3.01	0.24	7.11	3.79	2.32
	(0.34)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)	(0.01)	(0.00)	(0.00)
QCOM	0.68	0.36	0.86	−0.47	0.71	0.23					3.01
	(0.16)	(0.07)	(0.00)	(0.00)	(0.00)	(0.00)					(0.00)
	0.53	0.34	0.89	−0.52	0.56	0.25				5.02	2.72
	(0.10)	(0.06)	(0.00)	(0.00)	(0.00)	(0.00)				(0.01)	(0.00)
	0.05	0.16	0.79	−0.67	0.53	0.21	5.16	−0.69	6.78		2.92
	(0.01)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.03)		(0.00)
	0.52	0.22	0.74	−0.70	0.56	0.18	2.22	−1.12	8.89	4.92	2.65
	(0.09)	(0.04)	(0.00)	(0.01)	(0.00)	(0.00)	(0.04)	(0.02)	(0.10)	(0.01)	(0.00)

This table reports the estimation results for the SV, SVEJ, SVJ and SVJEJ models. The parameters are estimated using the unscented Kalman filter on a representative daily option sample from January 2000 to August 2015. For each parameter, we report estimates and asymptotic standard errors in parenthesis. We report estimation results for Amazon (ticker: AMZN), General Electric (GE), Intel Corporation (INTC), International Business Machines Corporation (IBM), Microsoft (MSFT) and Qualcomm (QCOM). For exact model definitions, see Sections 1 and 3.7.

would result in slightly lower estimates. And second, the SV model imposes that the parameters in the model are constant through time, whereas the term-structure and time-series estimators allow volatility to differ at each announcement. Because of this, the estimates based on the extension of the Black-Scholes model are less constrained and less subject to potential misspecification. For robustness, we have experimented with additional calibration methodologies and find that our earnings announcement jump volatility estimators are indeed very close if the same option data is used in the estimation. Provided our estimation routine provides a lower bound, the impact of EADs on option pricing applications that we report is conservative. A further discussion of structural model parameters is relegated to Online Appendix A.7.

4. Conclusions

This paper develops models incorporating earnings announcements for pricing options and for learning about the uncertainty embedded in an individual firm's earnings announcement. We develop a model and pricing approach with predictably timed price jumps on EADs and estimators of the price uncertainty associated with earnings announcements. Empirically, there is strong evidence that earnings announcements are important components of option prices, and we find evidence supporting an earnings jump risk premium. To quantify the impact on option prices and to compare to other benchmark specifications, we calibrate SV models 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 SV model incorporating earnings jumps drastically lowers the pricing errors and reduces misspecification in the volatility process.

There are a number of interesting extensions. First, our approach applies to other predictably timed events such as macroeconomic announcements (e.g., employment or inflation reports), crop reports, energy inventory data, 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.[28] Second, it would be interesting to explore how investors form expectations about anticipated earnings uncertainty and timing of information gathering. Do investor's beliefs about earnings uncertainty change leading into EADs? Third, markets take time to digest information, and it would be interesting to use high frequency data to quantify how options markets digest earnings information after the announcement. We leave these projects for future research.

[28] Ederington and Lee (1996) focus on the Treasury bond, Eurodollar, and Deutsche Mark options, whereas Beber and Brandt (2006) study the U.S. Treasury option market.

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