A Online Appendix:

Option Pricing of Earnings Announcement Risks

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Abstract. 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, G15, C53)

A.1 Transform Analysis

This section provides details on the option transforms. To price options, we need to evaluate the conditional transform of $\log(S_T)$. In our framework, the logarithm of the stock price consists of two independent, additive components. First, an affine process for which the characteristic function is well-defined and provided in Duffie et al. (2000). The second component is a simple discrete process with deterministic jumps at known times. Since the two components are independent, the characteristic function of the log stock price is given by the product of the characteristic functions of the two components. It follows that the discounted transform for $c \in \mathbb{C}$ is exponentially affine:

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

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

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

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

with

$$
\begin{aligned}
\alpha^*(c,t,T) &= r\tau(c-1) + \frac{-\kappa_v^{\mathbb{Q}}\theta_v^{\mathbb{Q}}}{\sigma_v^2}\left[\left(\alpha_v - \kappa_v^{\mathbb{Q}}\right)\tau + 2\ln\left(1 - \frac{\alpha_v - \kappa_v^{\mathbb{Q}}}{2\gamma_v}\left(1-e^{\gamma_v\tau}\right)\right)\right], \\
\overline{\alpha}(c,t,T) &= \bar{\lambda}_y^{\mathbb{Q}}\tau\left[e^{\bar{\mu}_y^{\mathbb{Q}}c + \frac{1}{2}\left(\bar{\sigma}_y^{\mathbb{Q}}\right)^2 c^2} - 1\right] - \bar{\lambda}_y^{\mathbb{Q}}\tau\left[e^{\bar{\mu}_y^{\mathbb{Q}} + \frac{1}{2}\left(\bar{\sigma}_y^{\mathbb{Q}}\right)^2} - 1\right],
\end{aligned}
$$

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

The transform with deterministic jumps has a particularly simple structure under our assumptions. To see this, note that

$$
\begin{aligned}
\log\left(S_T\right) = \log\left(S_t\right) &+ \int_t^T \left(r - \tfrac{1}{2}V_s - \bar{\lambda}_y^{\mathbb{Q}} E_t^{\mathbb{Q}}\left[e^{\bar{Z}_j(\mathbb{Q})} - 1\right]\right) ds + \int_t^T \sqrt{V_t} dW_t^s(\mathbb{Q}) \\
&+ \sum_{j=\bar{N}_t(\mathbb{Q})+1}^{\bar{N}_T(\mathbb{Q})} \bar{Z}_j(\mathbb{Q}) + \sum_{j=N_t^d+1}^{N_T^d} Z_j(\mathbb{Q}) \\
&= \log\left(\widetilde{S}_T\right) + \sum_{j=N_t^d+1}^{N_T^d} Z_j(\mathbb{Q})
\end{aligned}
$$

where $\log\left(\widetilde{S}_T\right)$ is the standard affine component. Assuming deterministic jumps are conditionally independent of the affine state variables, the transform of $\log\left(S_T\right)$ is just the product of the traditional affine transform and the transform of the deterministic jumps:

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

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

Our model structure is particularly simple as deterministic jumps do not affect the persistent stochastic volatility process which is completely independent of the jump. In a recent paper, Kim and Wright (2014) propose multi-factor term-structure models with deterministic jumps in the state variables on economic announcement days. In their model, the deterministic jump leads to time-inhomogeneous ODEs as the jump in a mean reverting process affects the mean-reversion behavior after the announcement and hence one has to account for this additional feature.

A.2 Black-Scholes and Stochastic Volatility

This appendix analyzes the impact of SV on the earnings announcement jump estimators. Standard SV models imply that volatility has predictable components and potentially large and asymmetric shocks. The time-series and term structure estimators formally assume a constant expected diffusive volatility, which could result in a systematic bias.

The first issue can be addressed using the insights of Hull and White (1987) and Bates (1996). Under mild conditions on SV, if shocks to volatility and returns are independent, then the SV option price is the expectation of the Black-Scholes price where the Black-Scholes implied variance is the expected integrated risk-neutral variance $EIV_{t,T} = E_t^{\mathbb{Q}}\left[\int_t^{t+T} V_s ds\right]$. Based on this, it is common to assume that Black-Scholes implied variance is an accurate proxy for expected risk neutral variance, that is, $\left(\sigma_{t,T}^{BS}\right)^2 \approx EIV_{t,T}$. The errors in assuming that $\left(\sigma_{t,T}^{BS}\right)^2 \approx EIV_{t,T}$ are generally small for ATM index options, and will be even smaller for individual equity options. For ATM options, Hull and White (1987) find the errors are less than 1% with no leverage and only 1.6% when $\rho = -0.6$. The errors are even smaller for shorter maturities which we use in our empirical analysis. Of course, approximation errors can be quite large for out-of-the-money options.

Price jumps also do not lead to a substantial bias. Merton (1976) finds that the errors of using the Black-Scholes model with a properly adjusted variance are extremely small for ATM options.[29] Chernov (2007) quantifies the approximation in models for index option

[29] Merton was surprised how small the errors were: "What I did find rather surprising is the general level of the magnitudes of the errors. For the smallest frequency value examined, the percentage of variation caused by the jump component had to exceed forty percent before an error of more than five percent could be generated... In summary, the effect of specification error in the underlying equity returns on option prices will generally be rather small... However, there are some important exceptions...deep out-of-the-money

pricing with non mean-zero jumps in prices, non-zero correlation, and jumps in volatility and concludes the bias, for at-the-money options, is negligible. Errors are even smaller here, as the references cited above indicate that the leverage effect is smaller for individual equity than for indices. Since all of our estimators rely on differences between Black-Scholes implied variances, any level biases are differenced out. Thus we conclude that assuming $\left(\sigma_{t,T}^{BS}\right)^2 = EIV_{t,T}$ does not introduce any substantive biases.

Assume that there are two ATM options available at maturities T_1 and T_2 and there is one earnings announcement between time t and $T_2 > T_1$. For generality, consider a square-root SV model with Poisson jumps in variance:

$$dV_t = \kappa_v^{\mathbb{Q}} \left(\theta_v^{\mathbb{Q}} - V_t\right) dt + \sigma_v \sqrt{V_t} dW_t^v(\mathbb{Q}) + d\left(\sum_{j=1}^{\bar{N}_t(\mathbb{Q})} \bar{Z}_j^v(\mathbb{Q})\right),$$

where the shocks are all independent, $\bar{Z}_j^v(\mathbb{Q}) > 0$ with mean $\bar{\mu}_v^{\mathbb{Q}}$, $\bar{N}_t(\mathbb{Q})$ is Poisson process with intensity $\bar{\lambda}_v^{\mathbb{Q}}$ under $\mathbb{Q}$. It is important to note that there is no evidence that the variance for individual equities jumps, however, we include it here for completeness and to understand its potential impact.

Both the term structure and time-series estimators rely on differences between the implied variances of two option maturities. To understand how SV affects these estimators, first, compute the expected integrated variance:

$$EIV_{t,T_i} = \widetilde{\theta}_v^{\mathbb{Q}} + \frac{1 - e^{-\kappa_v^{\mathbb{Q}} T_i}}{\kappa_v^{\mathbb{Q}} T_i} \left(V_t - \widetilde{\theta}_v^{\mathbb{Q}}\right), \tag{9}$$

where $\widetilde{\theta}_v^{\mathbb{Q}} = \bar{\lambda}_v^{\mathbb{Q}} \bar{\mu}_v^{\mathbb{Q}} / \kappa_v^{\mathbb{Q}} + \theta_v^{\mathbb{Q}}$. The estimators' accuracy depends on how variable $EIV_{t,T}$ is as a function of T (for the term structure estimator) and t (for the time-series estimator). The term structure estimator relies on the difference between Black-Scholes implied variances,

options can have very large percentage errors." (p. 345).

$\left(\sigma_{t,T_1}^{BS}\right)^2 - \left(\sigma_{t,T_2}^{BS}\right)^2$. Since volatility jumps merely alter the long-run mean in EIV_{t,T_i}, they have no impact of the term structure estimator above and beyond the mean-reversion term, so they can be ignored. Time-varying volatility can have an impact because $EIV_{t,T_1} \neq EIV_{t,T_2}$.

This implies that there is a predictable difference in expected volatility over, for example, two weeks and six weeks. Independent of any model, this difference is likely minor. As mentioned in the text, since volatility is very persistent, there will be very little difference in forecasts of volatility over the relatively short horizons used here. Moreover, the IV term structure is very flat for both indices (Broadie et al. (2007)) and individual firms, which implies that the variation in expected variance over short horizons tends to be small.

In the SV model above, $V_t - \theta_v^{\mathbb{Q}}$, $\kappa_v^{\mathbb{Q}}$, and T_i could each impact the term structure estimator, while realized jumps in volatility and Brownian shocks have no impact. For each of these, the impact will likely be minor. For example, unless there are large volatility risk premiums (for which there is no evidence for individual firms), $\theta_v^{\mathbb{Q}} \approx \theta_v^{\mathbb{P}}$ which implies that, *on average* $V_t \approx \theta^{\mathbb{Q}}$. This further implies biases will be small, at least on average. Since the IV term structure is very flat, even in periods of very high volatility and especially for the shortest maturities, this implies that V_t is close to $\theta_v^{\mathbb{Q}}$ and/or $\kappa_v^{\mathbb{Q}}$ is small. Volatility is also highly persistent and we use short-dated options, implying that $\kappa_v^{\mathbb{Q}}$ and T_i are small and thus the predictable differences in IV over various maturities is small.

More formally, there is some evidence regarding likely parameter values. For index options, Pan finds that $\kappa_v^{\mathbb{Q}} = -0.05$, which implies explosive volatility, but it is not statistically different from zero.[30] Using time-series models, Cheung and Johannes (2006) analyze square-root SV models with jumps on EADs. They find that individual firm volatility, once earnings announcements are accounted for, is more persistence than index volatility with estimates of κ_v being around 1.5-3. Since it is typically assumed that $\kappa_v^{\mathbb{Q}} < \kappa_v^{\mathbb{P}}$, this implies a relatively

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

modest level of mean-reversion. In section 3.7, we report estimates of $\kappa_v^{\mathbb{Q}}$ of the order of 1.

The term structure of IVs is also very flat. This is true for both indices and individual equity options. For example, Broadie et al. (2007) find that the slope of the IV term structure is less than 1% for S&P 500 options. The same result holds for the firms in our dataset. A flat average term structure indicates that $\theta_v^{\mathbb{Q}} \approx \theta_v^{\mathbb{P}}$ and/or that $\kappa_v^{\mathbb{Q}}$ is small. Further evidence pointing toward mild risk-neutral mean-reversion comes from variation in the slope of the IV term structure for individual options. In addition to little average slope, there is also very little term structure slope even in very high or very low states. For example, Table A.1 shows that for MSFT and INTC the $(5,95)\%$ quantile of the term structure slope is $(-2.86, 1.40)\%$ and $(-3.44, 1.41)\%$, respectively, pointing to a very low value of $\kappa_v^{\mathbb{Q}}$. Last, most trading volume is concentrated in short-dated options, and we use the shortest maturities for estimation. In practice, we almost always have the two near maturity contracts. Putting the pieces together, this implies that any the impact of mean-reversion is small.

To provide some further intuition regarding the size of the errors, consider the following reasonable SV parameters: $\theta_v^{\mathbb{Q}} = (0.3)^2$, $\kappa_v^{\mathbb{Q}} = 2.5$, and $\sigma_j^{\mathbb{Q}} = 0.10$. Compared to the empirical evidence, this is a high level of mean reversion. Computing the term structure based estimator for $\sqrt{V_t} = (0.20, 0.40.0.50)$, assuming the short-dated option matures in 1 week (1/52), 2 weeks (2/52), or 3 weeks (3/52) and assuming the second option matures 1 month later, we have that ${\sigma_j}^{\mathbb{Q}} = (0.0995, 0.1007, 0.1017)$, $(0.0988, 0.1017, 0.1038)$, or $(0.0979, 0.1029, 0.1064)$, respectively. The effect is small as volatility is persistent and option maturities are short, implying that $\left(1 - e^{-\kappa_v^{\mathbb{Q}} T_i}\right) / \kappa_v^{\mathbb{Q}} T_i$ does not vary a lot across maturities.

Next, consider the time-series estimator:

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

and note that EIV_{t,T_i} is a function of V_t while $EIV_{t+\Delta,T_i-\Delta}$ is a function of $V_{t+\Delta}$. If $V_t \approx V_{t+\Delta}$, then the estimator is quite accurate as the effect of mean-reversion over one-day is negligible. Using the parameters from above, the estimates for three weeks (i.e. the estimator with the largest bias) are ${\sigma_j}^{\mathbb{Q}} = (0.10006, 0.09990, 0.09979)$.

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

The effect increases with maturity, so that the bias is greater when long-dated options are used. Intuitively, diffusive volatility is more important for long-dated options, magnifying the impact of the shocks. This effect may cause some of the errors we observe, especially if only options with longer maturities are available. For example, if $\sigma_j^{\mathbb{Q}} = 0.05$, the shortest-dated option has 6 weeks to maturity, and V_t increases from 30% to 35%, $\left(\sigma_{t,T_i}^{BS}\right)^2 - \left(\sigma_{t+\Delta,T_i-\Delta}^{BS}\right)^2$ is negative. Long-dated options, combined with close-price issues are, in our opinion, the major cause of the problematic dates for the time series estimator.

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

A.3 Close/open and open/close behavior

We assume that earnings announcements generate a discontinuity in the sample path of equity prices. An alternative assumption is that the diffusion coefficient increases on days following earnings announcements, as in Patell and Wolfson (1979, 1981). Thus, the main difference between our model and of the model in Patell and Wolfson (1979, 1981) is the discontinuity of the sample path. With discretely sampled prices, it is impossible to identify when jumps occurred with certainty. It is common to use statistical methods (see, e.g., Johannes (2004), Barndorff-Nielsen and Shephard (2006), or Huang and Tauchen (2005)) to identify jumps. Identifying jumps on EADs is even more difficult in our setting as earnings are announced outside of normal trading hours.[31]

Since it is impossible to ascertain with discretely sampled prices whether or not there is a jump, we consider the following intuitive metric. Strictly speaking, there will almost always be a "jump" from close-to-open, as the opening price is rarely exactly equal to the

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

Table A.1
Term Structure

Firm	All	5%	95%	High vol	5%	95%	Low vol	5%	95%
AMZN	-1.31	-7.01	1.87	0.36	-5.74	8.91	-2.25	-7.76	0.22
AIG	-0.61	-3.72	2.01	-0.94	-6.36	4.26	-0.75	-2.64	0.89
AMGN	-0.54	-4.09	2.31	0.87	-2.73	4.98	-0.95	-4.06	0.43
AAPL	-1.82	-5.93	0.84	-1.05	-5.18	1.97	-1.97	-4.15	-0.05
BAC	-0.52	-2.84	1.50	0.86	-3.53	7.23	-0.63	-2.32	0.59
BA	-0.83	-2.87	1.01	0.68	-4.16	5.68	-0.80	-1.98	-0.07
CAT	-0.97	-3.47	1.52	0.24	-4.84	5.40	-1.41	-3.31	0.04
JPM	-0.03	-2.44	3.03	2.20	-1.63	7.94	-0.63	-2.07	0.50
CVX	-0.08	-1.74	1.78	1.87	-1.23	7.45	-0.51	-1.66	0.22
CSCO	-1.10	-5.27	2.20	0.67	-3.05	3.92	-2.78	-5.95	0.01
C	-0.23	-2.38	2.11	1.19	-1.27	4.53	-0.57	-2.11	0.51
DELL	-1.00	-4.88	2.94	1.44	-2.95	5.93	-1.75	-4.93	0.04
EBAY	-0.96	-4.97	2.53	0.83	-2.63	5.62	-1.81	-4.56	0.01
XOM	-0.20	-1.54	1.06	1.03	-1.01	4.20	-0.51	-1.40	0.09
FCX	-0.24	-2.63	2.67	1.18	-3.42	7.74	-1.15	-2.81	0.13
GE	-0.25	-2.40	2.01	1.34	-1.99	6.22	-0.61	-2.10	0.81
GS	-0.00	-1.95	2.52	2.76	-0.21	11.41	-0.68	-1.61	0.08
INTC	-0.83	-3.44	1.41	0.29	-3.05	3.74	-1.55	-3.37	0.03
IBM	-0.77	-3.00	0.70	0.11	-2.05	2.82	-1.17	-3.04	0.09
JNJ	-0.35	-1.85	0.86	0.60	-0.83	3.73	-0.58	-1.76	0.24
MRK	-0.48	-2.55	1.25	0.51	-0.85	2.42	-1.22	-2.70	-0.03
MSFT	-0.53	-2.86	1.40	0.67	-1.92	4.13	-0.86	-2.93	0.59
MS	1.14	-1.44	5.17	8.85	-1.15	28.63	-0.10	-1.62	1.77
NEM	-0.38	-2.56	1.28	0.81	-0.77	3.53	-2.98	-5.34	-0.21
PFE	-0.40	-2.27	1.64	1.25	-0.35	3.88	-1.12	-2.43	-0.06
MO	-0.42	-3.20	1.70	0.21	-2.17	2.66	-0.91	-3.52	0.25
COP	-0.70	-3.17	1.62	1.31	-2.22	5.24	-1.54	-4.75	0.29
PG	-0.36	-1.96	0.88	0.09	-1.75	1.90	-0.70	-2.53	0.31
QCOM	-0.80	-4.04	1.68	0.70	-4.27	7.15	-1.69	-4.35	-0.02
T	-0.61	-2.11	0.62	0.30	-2.81	3.29	-1.01	-2.34	-0.15
X	0.04	-3.21	4.01	3.11	-2.49	12.15	-2.50	-5.24	-0.42
UPS	-0.23	-1.82	1.12	0.80	-0.39	2.88	-0.49	-2.02	-0.00
VZ	-0.48	-2.32	1.18	0.43	-1.71	2.58	-1.08	-2.74	0.06
WMT	-0.35	-1.97	1.32	0.71	-1.79	4.42	-0.88	-1.93	0.25
WFC	-0.47	-3.55	3.52	2.85	-2.74	12.08	-1.19	-2.67	-0.06
YHOO	-1.07	-5.63	3.56	0.74	-5.32	8.56	-2.20	-5.84	0.30
NFLX	-2.74	-11.58	1.97	2.30	-0.99	6.72	-4.81	-11.74	-0.16
SHLD	-2.37	-7.16	1.44	-5.33	-14.81	0.83	-2.92	-6.76	1.24
GOOGL	-1.22	-5.16	2.34	1.70	-2.63	6.07	-2.81	-5.03	-0.63
MA	-0.91	-5.74	1.56	1.00	-7.15	9.42	-1.14	-3.85	0.00
FSLR	-0.86	-6.58	4.14	4.58	-0.41	11.69	-1.94	-7.16	1.55

This table provides the average term structure slope calculated as the difference between 30 and 60 days ATM implied volatilities on trading days that are not strongly affected by earnings announcements (we remove all data from 30 days prior to 5 days after an earnings announcement). The columns *High Vol* use only trading dates on which the short-term ATM implied volatility is at least 50% above its average, the columns *Low Vol* use only trading dates on which the short-term ATM implied volatility is more than 30% below its average. The columns *5%* and *95%* provide the 5 and 95% percentiles, respectively.

close price. For example, there are many events that could cause relatively minor overnight movements in equity prices and result in a non-zero close-to-open movement: movements of related equity and bond markets (e.g., Europe and Japan), macroeconomic announcements such as employment or inflation (typically announced at 8:30 a.m. EST, an hour before the formal market open), or earnings announcements of related firms to name a few. The main difference, however, is that if our assumption of a jump on earnings dates is true, the magnitude of the moves should be much bigger for earnings dates versus non-earnings dates. Statistically, the movements should appear as outliers.

To analyze this issue, we compare the standard deviation of close-to-open to returns on announcement and non-announcement days over our sample.[32] Table A.2 provides the standard deviation of close-to-open and open-to-close returns for earnings and non-earnings dates and the ratios comparing earnings and non-earnings dates for all firms with at least 7 years of data. Note first that the results indicate that the close-to-open returns on earnings dates are, on average, much more volatile. Average volatility of close-to-open returns on earnings days was 5.93% compared to 1.59% on non-earnings dates. An F-test for equal variances is rejected against the one-sided alternative at the one-percent critical level for all but two cases for which the p-values are 3% and 6%. Since we usually identify outliers as movements greater than three standard deviations, this is clear evidence of abnormal or jump behavior.

Second, note that open-to-close returns are slightly more volatile on earnings dates than non-earnings dates, on average 3.00% compared to 2.03% which indicates that returns are slightly more volatile during the day following announcements. This could be due to a number of factors, such as price discovery through trading, liquidity, or inefficient opening procedures. Regarding the last point, Barclay et al. (2003) argue that the Nasdaq opening procedure introduces more noise than the opening procedure on the NYSE and the effect is

[32]We remove days on which dividends are paid from the sample.

Table A.2
Close-to-open and Open-to-close Return Standard Deviation

Ticker	EAD Close-Open	Non-EAD Close-Open	Ratio	F-Test	EAD Open-Close	Non-EAD Open-Close	Ratio	F-Test
AAPL	6.26	1.47	4.27	0.00	2.46	2.12	1.16	0.05
AIG	3.11	0.91	3.41	0.00	2.15	1.72	1.25	0.02
AMGN	3.71	1.22	3.04	0.00	2.79	2.10	1.33	0.00
AMZN	10.87	1.67	6.51	0.00	5.47	2.89	1.89	0.00
BA	2.61	1.06	2.46	0.00	2.25	1.62	1.39	0.00
BAC	2.61	1.29	2.02	0.00	3.84	1.95	1.97	0.00
C	2.55	0.99	2.58	0.00	1.84	1.55	1.19	0.04
CAT	4.58	1.01	4.55	0.00	2.57	1.68	1.53	0.00
COP	1.31	1.07	1.22	0.06	2.16	1.82	1.19	0.09
CSCO	6.71	1.28	5.23	0.00	2.60	2.20	1.18	0.03
CVX	1.02	0.83	1.23	0.03	1.46	1.44	1.01	0.43
DELL	5.80	1.42	4.08	0.00	2.94	2.37	1.24	0.04
EBAY	7.03	1.46	4.81	0.00	4.87	3.23	1.51	0.00
FCX	2.95	1.78	1.66	0.00	3.12	2.56	1.22	0.02
FSLR	12.57	1.98	6.34	0.00	5.00	3.69	1.36	0.01
GE	2.55	1.11	2.29	0.00	2.75	1.67	1.65	0.00
GOOGL	6.62	0.89	7.43	0.00	2.45	1.53	1.60	0.00
GS	2.97	1.23	2.41	0.00	3.56	1.86	1.92	0.00
IBM	4.40	0.81	5.41	0.00	2.06	1.37	1.50	0.00
INTC	5.18	1.31	3.95	0.00	2.84	2.00	1.42	0.00
JNJ	1.25	0.69	1.81	0.00	1.38	0.99	1.39	0.00
JPM	2.48	1.30	1.90	0.00	2.63	2.22	1.19	0.02
MA	4.76	1.16	4.11	0.00	4.18	2.04	2.05	0.00
MO	1.17	0.83	1.41	0.00	1.59	1.40	1.14	0.10
MRK	2.10	0.97	2.18	0.00	1.62	1.40	1.16	0.08
MS	4.69	2.44	1.92	0.00	3.64	2.86	1.27	0.02
MSFT	5.18	0.92	5.62	0.00	2.29	1.60	1.43	0.00
NEM	1.75	1.09	1.60	0.00	3.19	1.80	1.77	0.00
NFLX	19.50	1.62	12.02	0.00	5.94	2.75	2.16	0.00
PFE	2.69	0.91	2.94	0.00	1.90	1.32	1.44	0.00
PG	2.04	0.84	2.45	0.00	2.22	1.12	1.98	0.00
QCOM	5.70	1.39	4.11	0.00	2.99	2.41	1.24	0.00
SHLD	7.84	1.29	6.06	0.00	5.09	2.74	1.86	0.00
T	1.93	0.75	2.58	0.00	1.57	1.23	1.28	0.01
UPS	1.82	0.60	3.04	0.00	1.97	1.08	1.82	0.00
VZ	1.54	0.74	2.10	0.00	1.82	1.29	1.41	0.00
WFC	5.27	1.79	2.94	0.00	4.01	2.68	1.50	0.00
WMT	2.10	0.69	3.03	0.00	1.16	1.21	0.96	0.64
X	3.70	1.79	2.07	0.00	3.66	3.23	1.13	0.16
XOM	1.46	0.75	1.95	0.00	1.48	1.33	1.12	0.12
YHOO	7.71	1.94	3.97	0.00	3.86	2.80	1.38	0.00
Pooled	5.34	1.25	4.28	0.00	3.00	2.03	1.48	0.00

This table provides a comparisons of close-to-open and open-to-close return standard deviation on earnings (EAD) and non-earnings (non-EAD) announcements dates. We provide standard deviations, the ratio of standard deviations and p-values of one-sided F-tests.

Table A.3
Wilcoxon and Fisher tests (by calendar year)

	Increase Prior to EAD		**Term Structure on EAD**		**Decrease after EAD**	
Year	Wilcoxon	Fisher	Wilcoxon	Fisher	Wilcoxon	Fisher
2000	7.29e-20	3.24e-19	2.31e-30	6.23e-43	2.06e-22	4.90e-17
2001	1.54e-11	7.83e-11	1.11e-29	8.95e-42	7.46e-25	5.68e-22
2002	1.59e-16	1.04e-12	3.36e-30	6.09e-41	2.16e-24	2.09e-20
2003	4.52e-10	0.00027	2.02e-26	3.19e-31	1.54e-29	1.35e-39
2004	3.15e-19	3.19e-19	1.56e-20	1.31e-20	5.76e-26	3.88e-37
2005	9.77e-15	4.01e-11	2.12e-23	1.35e-25	6.96e-29	3.95e-31
2006	8.15e-26	3.38e-25	8.44e-33	3.72e-44	1.01e-28	2.57e-35
2007	4.10e-22	1.12e-18	1.09e-31	2.78e-40	4.00e-29	2.78e-40
2008	2.12e-17	1.04e-15	1.26e-31	6.71e-50	1.14e-24	1.89e-32
2009	0.00248	0.12221	7.71e-31	1.79e-42	3.75e-28	7.77e-39
2010	1.05e-08	1.55e-05	2.90e-29	6.22e-31	9.55e-29	2.03e-33
2011	3.34e-14	1.25e-09	4.16e-32	9.90e-39	2.81e-28	1.28e-35
2012	3.12e-23	5.98e-20	6.25e-33	2.53e-46	1.07e-30	3.43e-45
2013	7.43e-29	4.81e-31	1.69e-34	3.22e-54	1.66e-32	4.86e-46
2014	9.34e-23	1.18e-28	2.25e-34	4.98e-60	7.04e-33	3.86e-49
2015	2.06e-15	1.05e-19	1.24e-25	1.57e-41	1.62e-24	8.30e-37
Pooled	1.55e-235	5.69e-191	0.00e+00	0.00e+00	0.00e+00	0.00e+00

This table provides the p-values for the Wilcoxon and Fisher nonparametric test, pooled by calendar year. We use one-sided versions to test the increase in implied volatility in the two weeks prior to an earnings announcement (Increase Prior to EAD), the decreasing term structure of implied volatility before the earnings announcements (Term Structure on EAD), and the decrease in implied volatility after the earnings announcement (Decrease after EAD).

exacerbated for smaller firms.

A.4 Nonparametric Tests: Empirical Results

This section provides further details on the nonparametric tests described in Section 3.2. Table A.3 provides p-values (by calendar year and for the entire sample) for the Wilcoxon and Fisher nonparametric test for our three main hypothesis: (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. Table A.4 provides the statistical tests on the firm level. A detailed discussion of our empirical results is provided in the main body of the paper (Section 3.2).

Table A.4
Wilcoxon and Fisher tests (by firm)

	Increase Prior to EAD		**Term Structure on EAD**		**Decrease after EAD**	
Ticker	Wilcoxon	Fisher	Wilcoxon	Fisher	Wilcoxon	Fisher
AAPL	3.31e-08	3.80e-09	2.65e-10	4.44e-16	2.81e-10	2.31e-14
AIG	0.00095	0.02139	1.83e-07	1.84e-08	1.17e-06	9.71e-07
AMGN	0.21198	0.16200	1.36e-07	9.29e-08	2.27e-07	7.28e-11
AMZN	6.92e-10	8.77e-11	1.84e-11	6.94e-18	5.17e-12	2.19e-16
BA	0.04441	0.27860	5.22e-05	2.82e-06	3.50e-05	0.00076
BAC	3.90e-08	2.86e-08	1.02e-09	1.21e-10	7.48e-05	9.90e-05
C	2.97e-07	4.48e-06	8.75e-09	1.39e-09	0.00217	0.00154
CAT	0.00060	0.00014	1.82e-09	1.42e-14	3.75e-09	1.54e-11
COP	0.52395	0.64945	1.20e-05	9.00e-05	0.00018	0.00046
CSCO	1.23e-11	1.73e-18	8.36e-12	8.67e-19	8.79e-12	5.29e-17
CVX	0.46441	0.24343	0.00096	0.01441	0.00050	0.00567
DELL	0.00028	1.37e-05	2.00e-06	3.73e-09	3.54e-05	1.52e-06
EBAY	0.00028	0.00125	9.13e-07	9.31e-10	9.13e-07	9.31e-10
FCX	0.08249	0.16839	1.25e-08	1.08e-10	1.30e-07	1.08e-10
FSLR	1.20e-05	7.75e-07	4.28e-05	2.09e-07	5.20e-06	2.09e-07
GE	2.44e-07	9.58e-06	8.45e-11	8.62e-15	4.92e-09	1.69e-08
GOOGL	4.04e-07	6.17e-08	5.80e-09	1.14e-13	7.17e-09	5.00e-12
GS	3.17e-09	2.90e-09	6.36e-11	1.55e-15	4.66e-10	4.28e-14
IBM	1.43e-11	4.24e-16	2.65e-12	1.08e-19	4.08e-12	6.94e-18
INTC	3.15e-11	2.82e-12	3.88e-12	2.17e-19	1.36e-11	4.24e-16
JNJ	7.99e-05	0.00299	9.30e-07	9.71e-09	4.22e-06	6.46e-06
JPM	5.56e-09	3.76e-07	2.05e-11	5.95e-14	2.30e-09	9.53e-12
MA	0.00039	0.00077	2.97e-06	7.45e-09	4.65e-06	2.09e-07
MO	0.03858	0.20252	0.16203	0.22569	2.50e-05	2.65e-06
MRK	0.23189	0.50000	6.93e-05	2.11e-05	3.69e-06	4.18e-06
MS	0.00022	0.00016	2.86e-06	2.32e-06	0.00062	0.00016
MSFT	5.52e-07	9.58e-06	3.88e-12	2.17e-19	6.06e-10	8.62e-15
NEM	0.47730	0.42528	0.00222	0.00468	0.00069	0.00046
NFLX	1.06e-05	7.75e-07	2.97e-06	7.45e-09	7.24e-06	2.09e-07
PFE	0.00034	0.00805	4.20e-07	1.23e-08	7.11e-05	2.77e-06
PG	0.00060	0.01785	2.28e-10	3.06e-13	3.08e-08	6.42e-10
QCOM	2.41e-06	1.04e-05	4.08e-12	1.37e-17	4.96e-12	4.24e-16
SHLD	0.00168	0.00732	2.15e-05	2.38e-07	0.00016	7.63e-06
T	0.05037	0.19576	1.15e-06	1.73e-06	3.20e-06	2.09e-07
UPS	0.02985	0.14314	1.79e-05	1.37e-05	6.36e-05	0.00016
VZ	0.24858	0.63583	1.07e-05	0.00016	9.54e-08	5.38e-10
WFC	0.00131	0.00166	6.17e-07	4.66e-10	0.00011	2.31e-07
WMT	3.53e-09	3.80e-09	3.36e-10	5.89e-13	9.58e-09	6.06e-08
X	0.62661	0.50000	9.91e-06	5.25e-06	0.00037	0.00076
XOM	0.06640	0.05864	1.78e-06	2.85e-05	4.00e-07	3.43e-07
YHOO	1.17e-08	8.09e-10	1.24e-09	7.11e-15	7.28e-09	3.41e-13

This table provides the p-values for the Wilcoxon and Fisher nonparametric test for all firms with more than seven years of EAD data from January 2000 until August 2015. We use one-sided versions to test the increase in implied volatility in the two weeks prior to an earnings announcement (Increase Prior to EAD), the decreasing term structure of implied volatility before the earnings announcements (Term Structure on EAD), and the decrease in implied volatility after the earnings announcement (Decrease after EAD).

A.5 Error Analysis

In this section we study the *error* occurrences in Tables 4 and 6 in more detail. Our main goal is to provide quantitative evidence whether errors can be linked to the presence of SV and other market-microstructure effects. To understand the effect of SV on the likelihood of errors, we first consider the term-structure estimator. It is clear from Equation (4) that a low level of SV would bias $\sigma_{term}^{\mathbb{Q}}$ downward due to the increasing volatility term structure that would result from the mean-reversion of variance. Our model therefore predicts more errors during low volatility regimes. For the time-series estimator, the main driver of errors is expected to be the level of vol-of-vol as higher vol-of-vol adds further noise to the change of IV on EADs.

Our model also predicts that the probability of an error increases for firms with low variance ratios (provided in Table 3). This is because an EAD jump is much easier to identify if the jump size standard deviation is large relative to the average day-to-day variation in returns. Similarly, the signal-to-noise ratio is higher for options with shorter maturities as their annualized return variance is dominated by EAD jump volatility. More errors are therefore expected for estimators based on longer-term options and for firms with a low variance ratio. Another interesting possibility is to test whether the actually reported earnings per share (EPS) affect the likelihood of an error. This is particularly relevant for the time series estimator as it is based on ex-post data. It is intuitively plausible that a lower than expected EPS leads to an increase in the perceived riskiness of the company, hence IV after the earnings announcement may not drop as much as expected or may even increase.

We use a logit model to estimate the impact of aforementioned variables on the likelihood of errors. We measure the volatility as the 30-day implied ATM volatility 10 days prior to the announcement. The vol-of-vol is measured as the standard deviation of 30-day ATM IV changes over 60 trading days prior to the announcement (the last volatility used is 10

Table A.5
Error Analysis: Logit Regression

Estimator	Volatility	VarRatio	Earnings Surprise	DTM	VolofVol
Term Structure Estimator	-5.87	-0.26	9.37	0.02	27.57
	(-7.85)	(-6.45)	(0.55)	(5.18)	(3.35)
	-4.33	-0.27		0.02	
	(-7.80)	(-6.66)		(5.58)	
Time Series Estimator	-0.16	-0.07	1.25	0.01	3.72
	(-0.68)	(-4.17)	(0.30)	(2.99)	(1.01)
		-0.07	1.20	0.01	2.26
		(-4.28)	(0.29)	(2.99)	(0.72)

This table provides results for a logit regression of the occurrences of errors in the time-series and term-structure estimator of Section 1 on a range of explanatory variables. We measure the volatility as the 30-day implied ATM volatility 10 days prior to the announcement. The vol-of-vol (*VolofVol*) is measured as the standard deviation of 30-day ATM IV changes over 60 trading days prior to the announcement (the last volatility used is 10 days before the EAD). The variance-ratio is defined as in Table 3 and DTM measures the days to maturity of the options used in the calculation of the time-series and term-structure estimator.[33] The *earnings surprise* is given by the actual reported EPS minus the analyst consensus in the month before the announcement, normalized by the equity price ten days prior to the EAD.

days before the EAD). The variance-ratio is defined as in Table 3 and DTM measures the days to maturity of the options used in the calculation of the time-series and term-structure estimator.[34] Finally, the earnings-surprise is given by the actual reported EPS minus the analyst consensus in the month before the announcement, normalized by the equity price ten days prior to the EAD. This definition coincides with DellaVigna and Pollet (2009).

Our findings are reported in Table A.5. We provide two sets of results for each estimator, one with all aforementioned explanatory variables and one with a subset of variables. We find broad support for our model predictions and that some of the errors are driven by market-microstructure effects. The signs of DTM and the variance ratio variables are as predicted and highly significant. The sign of the volatility variables is negative for the term structure estimator indicating that lower levels of volatility increase the likelihood of an error. For the time series estimator, we find that higher-vol-of-vol leads indeed to a higher error occurrence, although the parameter is insignificant. Similarly, we find no significant effect of earnings surprises which is reassuring as our estimator does not take into account reactions to earnings announcement news.

A.6 Impact of Stochastic Volatility

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

[34] For the term-structure estimator DTM is the maturity of the shorter-term option.

anticipated uncertainty plays a dominant role (as Figure 1 would suggest), SV should have a minor effect as the time or maturity variation in EIV_{t,T_i} is swamped by the impact of anticipated uncertainty.

One potential concern is that the increase in IV and the declining term structure of IV prior to earnings could be driven by issues related to expiration cycles: as the time to maturity decreases, option IV tends to increase. There are three reasons this is not a major concern. First, and most importantly, if this is the case, it would have a mixed impact on our tests. While it would bias the pre-earnings increase and term structure test towards rejection, it would have the *opposite* effect on the time series test subsequent to earnings, as the maturity bias would increase IV rather than decrease it. The fact that the time series test of no decrease in IV subsequent to an EAD is rejected, and that the p-values for the decrease are very low, implies that this is not a particularly important issue. Second, none of our conclusions change if we remove all options with a maturity of less than one week.

It is difficult to imagine an alternative to our explanation for the strong predictable behavior in IV. One potential explanation is Mahani and Poteshman (2008), who document that retail investors increase holdings of options on growth firms prior to EADs. If supply is not perfectly elastic, increases in investor demand translate into increases in prices and IV (see also Garleanu et al. (2009)). If, for some reason, retail investors were to sell their entire positions the following day (and there is no evidence this occurs), prices and IV would similarly fall subsequent to the earnings announcement. Could the demand of retail investors generate the magnitudes observed in the data? For example, in the Intel example, could retail investor behavior generate the pattern in IVs in the introduction?

We find it implausible that retail investors have such strong impact for three reasons. First, returns on EADs are far more volatile than returns on other dates. This naturally leads to an increase in IV prior to and decrease in IV subsequent to an EAD as shown by our model. Second, retail investors make up a small portion of option market volume (about

10-15% according to Mahani and Poteshman (2008)). Third, while net demand factors are statistically important, it is unlikely that they could explain the large movements in IV around earnings dates. The results in Bollen and Whaley (2004) indicate that net buying pressure of calls and puts significantly impacts changes in IV, but Garleanu et al. (2009) find that the magnitude of the effect to be quite small. For the S&P 500 index, doubling open interest in a day increases IV by 1.8%, which is within the bid-ask spread, and they find the impact is smaller for individual firms. We conclude that our results provide strong statistical evidence in support of our reduced-form model and its main implications. Option IV increases leading into earnings announcements, the term structure declines for the first two maturities, and IV decreases subsequent to the earnings announcement.

A.7 Parameter Estimates in Stochastic Volatility Models

This section provides further discussion of the estimates of structural parameters in the stochastic volatility models presented in Section 3.7 (Table 13).

In terms of structural parameters, the estimates of $\kappa_v^{\mathbb{Q}}$ are similar, between 0.52 and 1.70. The corresponding parameters under the $\mathbb{P}$-measure tend to be slightly larger, but smaller compared to values reported for equity indices. This low level of risk neutral persistence is intuitive, especially over our sample period from 2000 to 2015. Volatility was high at the beginning and end, but low in the middle. A high $\kappa_v^{\mathbb{Q}}$ implies that volatility rapidly mean-reverts, which would make it difficult to fit high and low volatility periods with a constant $\theta_v^{\mathbb{Q}}$. For example, since $\theta_v^{\mathbb{Q}}$ is an average of the two periods, when spot V_t is high, a high value of $\kappa_v^{\mathbb{Q}}$ would imply a lower IV for longer dated options. As mentioned in the main body of the paper, the volatility term structure (outside of months with EADs) is quite flat. The only way to fit these periods is to decrease the level of mean reversion.

The estimates for $\theta_v^{\mathbb{Q}}$ imply plausible long-run volatility means. Long-run volatility in SV and SVEJ is roughly similar, decreasing when random jumps are added. The values for σ_v are mainly identified by the time series of variance and from OTM options. The estimates are consistent with prior work but are generally higher than estimates based on time series data only (see the discussion in Broadie et al. (2007)). The parameters of the random jump process imply between 1 to 10 jumps per year (with the exception of AMZN for which we estimate a higher jump intensity), with average jump sizes close to zero and jump size volatilities of 3.85% to 13.02%. Interestingly, the number of jumps decreases from SVJ to SVJEJ, often by roughly the number of EADs indicating that some of the EAD jumps may be incorrectly classified as random jumps in these models. Overall, our estimations provide economically plausible parameters.