Internet Appendix to “The Dynamic Informativeness of Scheduled News”

February 8, 2023

Section A describes our volatility estimator, justifies it, and compares it with alternative ones. Section B analysis whether our results hold using different volatility estimators. Section C addresses the heterogeneity depending on option liquidity. We justofy our measure of the slope in Section D and argue why it serves as an estimate of the error induced by the flat-term structure assumption of previous papers. Section E assesses the effect of assuming different functional forms for the term structure. Section F relaxes the assumption that all announcement dates are known in advance with certainty and uses a proxy for the expected announcement dates instead of the actual ones. Section G extends the model to account for price and announcement volatility jumps. To compute the distribution of the estimator for signals that are uninformative by design, Section H provides a falsification exercise. Section I describes the construction of the alternative measures of informativeness presented in Section 4 of the paper. Section J takes an event-study approach focusing on short windows around the market signal. We provide the numbers used to create the figures in the paper in Section K. We use alternative information measures to study prior signals in Section L. Section M takes potential heterogeneity in informativeness by firm and by quarter into account.

A Estimating implied volatility

The main dependent variable in the paper is the variance under the risk-neutral measure. To extract this quantity, most of the previous literature focuses on three methods: the non-parametric method proposed by Bakshi et al. (2003) (BKM), the non-parametric method proposed by Demeterfi et al. (1999) (DDKZ) and used in the computation of the Chicago Board Options Exchange's Volatility Index (VIX), and the implied volatility computed by OptionMetrics, which relies on the log-normality of returns as Black-Scholes formula. This appendix explains how we applied each of the methods and discusses their advantages and disadvantages. Nonetheless, any methodology delivers similar results.

Regardless of the method, to avoid major effects of illiquidity and to be able to compute the implied variance, we drop observations (firm-date-maturity-strike quadruplets) that satisfy one of these conditions:

- There is no information about the underlying price.
- The bid price is zero.
- The ask price is lower or equal to the bid price.
- OptionMetrics does not provide the implied volatility (this is a signal of non-standard options).

We also net the discounted dividends from the underlying spot price using the projected ex-dividend date and dividend amount provided by OptionMetrics. We use as rate of discount the zero-coupon yield provided by OptionMetrics linearly interpolated across the available maturities.

Non-parametric

The non-parametric methods assume that we observe a continuum of strikes and we integrate the weighted option prices across all strikes to obtain the risk-neutral variance. Unfortunately, we only observe a finite number of strikes and, for most of them liquidity is low. There are two ways to proceed using OptionMetrics data. The first one consists of using the quoted midpoints of each available option, similar to BKM. The second one relies on the volatility surface provided by OptionMetrics and has also been used extensively (e.g., Driessen et al., 2009). Although the second approach provides smoother estimates, the interpolation algorithm used by OptionMetrics across strikes and maturities eliminates any discontinuity across strikes or along the term structure. Hence, by construction, it eliminates the variation from which we identify the effect. As a consequence, we rely on quoted midpoints. In-the-money and out-of-the money options carry the same information due to the put-call parity; hence, following the literature, we keep out-of-the-money options to reduce the impact of early exercise. Since we need to assume a wide range of strikes, we drop any date-firm-maturity triplet with less than six out-of-the-money options to compute the non-parametric measures. Then we apply the following discretized version of the original BKM formula:

$$IV_{i,t,\tau}^{BKM^2} = \frac{(e^{r\tau}V - \mu^2)}{\tau}$$

$$\mu = e^{r_{t,\tau}\tau} - 1 - \frac{e^{r_{t,\tau}\tau}}{2V_{i,t,\tau}} - \frac{e^{r_{t,\tau}\tau}}{6W_{i,t,\tau}} - \frac{e^{r_{t,\tau}\tau}}{24X_{i,t,\tau}}$$

$$V_{i,t,\tau} = \sum_{K_{i,t,\tau,k}>S_{i,t,\tau}} \frac{1 - ln\left(\frac{K_{i,t,\tau,k}}{S_{i,t,\tau}}\right)}{K^2_{i,t,\tau,k}}(C_{i,t,\tau,k} + C_{i,t,\tau,k-1})(K_{i,t,\tau,k} - K_{i,t,\tau,k-1}) + \sum_{K_{i,t,\tau,k}\leq S_{i,t,\tau}} \frac{1 + ln\left(\frac{S_{i,t,\tau}}{K_{i,t,\tau,k}}\right)}{K^2_{i,t,\tau,k}}(P_{i,t,\tau,k} + P_{i,t,\tau,k-1})(K_{i,t,\tau,k} - K_{i,t,\tau,k-1})$$

$$W_{i,t,\tau} = \sum_{K_{i,t,\tau,k}>S_{i,t}} \frac{6\,ln\left(\frac{K_{i,t,\tau,k}}{S_{i,t,\tau}}\right) - 3\left(ln\left(\frac{K_{i,t,\tau,k}}{S_{i,t,\tau}}\right)\right)^2}{K^2_{i,t,\tau,k}} \frac{(C_{i,t,\tau,k} + C_{i,t,\tau,k-1})}{2}(K_{i,t,\tau,k} - K_{i,t,\tau,k-1}) + \sum_{K_{i,t,\tau,k}\leq S_{i,t}} \frac{6\,ln\left(\frac{K_{i,t,\tau,k}}{S_{i,t,\tau}}\right) - 3\left(ln\left(\frac{K_{i,t,\tau,k}}{S_{i,t,\tau}}\right)\right)^2}{K^2_{i,t,\tau,k}} \frac{(P_{i,t,\tau,k} + P_{i,t,\tau,k-1})}{2}(K_{i,t,\tau,k} - K_{i,t,\tau,k-1})$$

$$X_{i,t,\tau} =$$

$$\sum_{K_{i,t,\tau,k}>S_{i,t,\tau}} \frac{6\left(ln\left(\frac{K_{i,t,\tau,k}}{S_{i,t,\tau}}\right)\right)^2 - 2\left(ln\left(\frac{K_{i,t,\tau,k}}{S_{i,t,\tau}}\right)\right)^3}{K_{i,t,\tau,k}^2}(C_{i,t,\tau,k} + C_{i,t,\tau,k-1})(K_{i,t,\tau,k} - K_{i,t,\tau,k-1}) +$$

$$\sum_{K_{i,t,\tau,k}\leq S_{i,t,\tau}} \frac{6\left(ln\left(\frac{K_{i,t,\tau,k}}{S_{i,t,\tau}}\right)\right)^2 - 2\left(ln\left(\frac{K_{i,t,\tau,k}}{S_{i,t,\tau}}\right)\right)^3}{K_{i,t,\tau,k}^2}(C_{i,t,\tau,k} + C_{i,t,\tau,k-1})(K_{i,t,\tau,k} - K_{i,t,\tau,k-1})$$

where $C_{i,t,\tau,k}$ refers to the midpoint of call option prices, $P_{i,t,\tau,k}$ refers to put option prices, and K is the strike price. $r_{t,\tau}$ is the zero-coupon yield provided by OptionMetrics interpolated linearly. $S_{i,t,\tau}$ is the spot price minus the discounted expected dividends from t to τ. The subscripts indicate the firm (i), the day (t), the maturity (τ), and the strike (k). Strikes are numbered from the lowest to the highest such that $K_{i,t,\tau,k} > K_{i,t,\tau,k-1} \forall k$. We also construct the DDKZ measure using the following discretized formula:

$$IV_{i,t,\tau}^{DDKZ^2} = \frac{1}{\tau}\left(\sum_{k=1}^{N_{i,t,\tau}} \frac{e^{r_{t,\tau}\tau}(Q_{i,t,\tau,k} + Q_{i,t,\tau,k-1})}{K_{i,t,\tau,k}^2}(K_{i,t,\tau,k} - K_{i,t,\tau,k-1}) - \left(\frac{e^{r_{t,\tau}\tau}Si,t,\tau}{K_{i,t,\tau,0}} - 1\right)\right)$$

where $Q_{i,t,\tau,k}$ is the midpoint quote of the option (puts or calls). K_0 is the strike closest to the spot price. $k = \{1, ..., N_{i,t,\tau}\}$ indeces both out-of-the-money put and call options.

The discrete approximation takes two arbitrary decisions: i) prices across strikes are interpolated linearly and ii) prices below the minimum strike or above the maximum strike are not considered. Both of these decisions, as well as any alternative one, create noise in our implied volatility estimator. However, this noise is likely to be unrelated to the term structure, and more importantly, unrelated to ex ante signals. Nonetheless, to avoid extremely noisy observations, we drop those firm-date-maturity triplets from the sample for which:[1]

- DDKZ volatility exceeds 200% (573 triplets)
- BKM volatility exceeds 200% (186 triplets)
- OptionMetrics at-the-money volatility exceeds 200% (3,850 triplets)
- One of the measures doubles the mean of the three measures (97 triplets)

[1]These filters do not change the results as they exclude 0.13% of the sample.

In the paper we focus on the BKM measure because it measures the implied quadratic variation in the presence of jumps while DDKZ captures the integrated variance if the process is continuous. Nonetheless, we repeat all the results using the DDKZ measure and the closest-to-at-the-money OptionMetrics volatility for the same set of firm-date-maturity triplets and results are almost identical (see Tables in this section).

Parametric

Patell and Wolfson (1979) and Dubinsky et al. (2019), among others, hinge on the implied volatility provided by OptionMetrics. This volatility is the result of discretizing Black-Scholes into a binomial model and computing the volatility of an American option. This approach has the advantage that we can obtain the implied volatility with just one option per firm-date-maturity. But it carries some disadvantages. First, note that discretizing is not an issue anymore but it translates into an aggregation issue. In particular, the implied volatility across strikes is different. We follow Dubinsky et al. (2019) and use the closest to at-the-money available option. This option has the highest Vega and, therefore, its price is most affected by the earnings announcement risk. As a consequence, the identification would be cleaner.

The second disadvantage is the parametric assumption. The above-mentioned papers assumed the Black-Scholes model holds, at least to some extent. However, if insiders exploit their private information, the Black-Scholes model does not hold because the signal the market receives from these trades is extremely asymmetric (see illustrative example below). Therefore, the methodology would be incorrect under the alternative hypothesis. Nonetheless, given the consistency of results for the subset of firm-day-maturity triplets in which we can compute the non-parametric volatility, this disadvantage does not seem to play a major role. Hence, we re-estimate the main results with every observation for which we observe the parametric implied volatility to increase the sample size and assess the consequences of sample selection.

Illustrative example

This example illustrates why Black-Scholes implied volatility might provide wrong conclusions in the presence of informed traders. In particular, we show that the implied volatility computed using Black-Scholes increases after the market observes other signals such as insider trading, even if the risk-neutral volatility decreases.

Assume that at time 0 there is an asset with price S_0 and payoff at T equal to V_T. Consider the canonical model in which the risk-neutral probability of the payoff is such that $V_T = e^{r-\frac{\sigma^2}{2}T+\sigma\epsilon_T}S_0$ and $\epsilon_T \sim \mathcal{N}(0,T)$. Following Glosten and Milgrom (1985), a risk-neutral informed investor, who knows v_T with certainty, trades one unit of the asset at time 1. Consider for simplicity that investors know she is indeed informed and the information investors learn does not change the Radon-Nikodym derivative that links the risk-neutral and physical probability measures. For instance, this is the case if the information is idiosyncratic to the firm and the marginal investor is fully diversified.

Due to risk-neutrality, the informed investor always trades. She buys if the liquidation value exceeds the forward price, $V_T > e^{r(T-1)}S_0 \equiv F_0$, and sells otherwise. Therefore, the asset prices after the informed agent buys are given by:

$$S_1 = e^{-r(T-1)}\mathbb{E}(V_T|V_T > F_0) \qquad C_1(K) = e^{-r(T-1)}\mathbb{E}\left((V_T - K)^+ |V_T > F_0\right)$$

where $C_1(K)$ indicates the price of a call option with strike price K, and $\mathbb{E}$ denotes the expectation under the risk-neutral measure. To ease the exposition, we use $(a)^+$ to denote the maximum between a and 0. Since we aim to show a counterexample in which Black-Scholes provides the wrong prediction, we focus on the call option after the informed investor buys. Nonetheless, a similar procedure will provide counterexamples in the other situations.

First, we prove the intuitive result that the risk-neutral variance of the asset decreases with the new information. To ease the exposition we refer to the logarithm of the price, liquidation value and forward price as s, v, and f respectively. We define $\tau = T - 1$.

Lemma 1. *The risk-neutral variance is lower after updating the beliefs with the new information*

$$\mathbb{V}\left(v_T - s_1|v_T > f_0\right) < \mathbb{V}(v_T - v_1) = \sigma^2\tau$$

Proof. $v_T - v_1 = r - \frac{\sigma^2}{2}T - v_1 + \sigma\epsilon_T$. Hence the conditional distribution $v_T - v_1|v_T > f_0$ is a truncated normal whose variance is given by:

$$\mathbb{V}\left(v_T - s_1|v_T > f_0\right) = \sigma^2 T\left[1 - \frac{\phi(\alpha)}{1-\Phi(\alpha)}\left(\frac{\phi(\alpha)}{1-\Phi(\alpha)} - \alpha\right)\right]$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ denote the pdf and cdf of the standard normal distribution. α is the standardized truncation threshold: $\alpha = \dfrac{f_0 - r - \frac{\sigma^2}{T}T - v1}{\sigma\sqrt{T}}$. Therefore, the variance is lower iff

$\dfrac{\phi(\alpha)}{1-\Phi(\alpha)} > \alpha$. The left-hand side of the equation is the inverse Mills ratio; hence, the inequality is true for all α (see Gordon, 1941). $\square$

Then, we prove that Black-Scholes implied variance is higher than the initial one. To do that, we show that the Black-Scholes formula using the initial implied volatility (σ) results in a lower call price than the one based on risk-neutral pricing under the truncated distribution. Since the derivative of the Black-Scholes formula with respect to volatility, named Vega, is positive for the whole support, the implied volatility must be higher to equal the call price.

Lemma 2. *The call price is higher than the one predicted by Black-Scholes using the unconditional risk-neutral volatility σ.*

$$C_1(K) > BS(K, \sigma, v_1, r, \tau)$$

where $BS(k, s, v, r, \tau)$ refers to the Black-Scholes function with strike price k, volatility s, spot price v, risk-free rate r, and maturity τ.

Proof. Denote as $g(v, r, \tau)$ and $G(v, r, \tau)$ the pdf and cdf of v_T given v_1 assumed by the Black-Scholes model for a maturity equal to τ and an interest rate equal to r. Then,

$$BS(K, \sigma, v_1, r, \tau) = e^{-r\tau}\int_{K}^{\infty}(v-K)^+ g(v)dv < e^{-r\tau}\int_{max\{F_0,K\}}^{\infty}(v-K)^+\frac{g(v)}{G(F_0)}dv = C_1(K)$$

$\square$

This example illustrates the problem of using Black-Scholes in an extreme setting. The more symmetric the posterior signal received from the trade is, the more reliable is Black-Scholes. There are many missing ingredients that would contribute to relaxing the problem and are likely to play a role. For instance, investors might not be able to distinguish informed an uninformed agents; informed agents might not know the actual liquidation value but just a noisy signal of that value, etc.

Comparison

Table A.1 compares the informativeness of the earnings announcement across the three different volatility measures. We observe that BKM provides the highest estimate, while there are mild differences with the other two volatility measures. Nonetheless, if we expand the sample and consider the whole OptionMetrics sample, the average relevance of earnings announcements decreases. This evidence suggests that investors rely less on accounting information to price those firms outside our original sample. Yet, earnings announcements explain 9% (2.26×4) of the total variance of an average firm.

Table A.1: The informativeness of earnings announcements - Different volatility measures

The first column of this table repeats the third column of Table 4 which includes the baseline specification to estimate λ. Then, column (2) repeats the estimation using the implied volatility measure developed by Demeterfi et al. (1999). Column (3) and (4) use the implied volatility provided by OptionMetrics. While column (3) uses the same sample as the other measures, column (4) includes every other option for which we have implied volatility. Standard errors are clustered at both the day and the firm-quarter level and presented in parentheses. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level respectively.

Dep. var.: implied volatility	(1)	(2)	(3)	(4)
$\mathbf{1}(T > t_R)\dfrac{1}{T-t}$ (γ)	2.665***	2.517***	2.639***	2.258***
	(0.023)	(0.022)	(0.022)	(0.022)
Maturity pol.	Yes	Yes	Yes	Yes
Learning pol.	No	No	No	No
Fixed Effects	Day × firm	Day × firm	Day × firm	Day × firm
Ajusted R2	0.949	0.960	0.969	0.925
Obs.	3,039,877	3,039,877	3,039,877	6,148,923

B Alternative measures of volatility and prior signals

Although Section A shows that the selection of one volatility measure instead of the alternatives has a small impact on the average relevance of the announcement, it might be the case that the choice of the measure matters for conclusions on how the signals affect the informativeness of the announcement. In this section, we explore this possibility. Tables B.1 and B.2 provide the results of the estimation using the alternative volatility measures. We observe that the effects are very similar across measures. Table B.3 implements the model on the whole sample using the parametric volatility. In this case, we also observe similar results. These results suggests that our sample is not fully representative of the OptionMetrics universe while it constitutes a close approximation.

Table B.1: Earnings information disclosed by other signals: Demeterfi et al. (1999)

This table reports the results of the regression shown in Equation (3). The dependent variable is twice the log of implied volatily. Buys (Sales) is the number of days with net buying (selling) by corporate insiders since the last EA. $Forecast^{+}$ ($Forecast^{-}$) is the number of upward (downward) forecast revisions since the last EA. $Recom^{+}$ ($Recom^{-}$) is the number of upward (downward) recommendation revisions since the last EA. Standard errors are clustered at both the day and the firm-quarter level and presented in parentheses. Table 6 describes the variables. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level respectively.

Dep. var.: implied vol.	(1)	(2)	(3)	(4)
$\frac{\mathbf{1}(T > t_R)}{T-t}$	2.373***	2.311***	2.429***	2.313***
	(0.023)	(0.026)	(0.027)	(0.030)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Forecast^{+}$	-0.053***		-0.049***	-0.050***
	(0.005)		(0.005)	(0.005)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Forecast^{-}$	-0.069***		-0.065***	-0.056***
	(0.004)		(0.004)	(0.004)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Recom^{+}$		-0.062***	-0.038***	-0.053***
		(0.015)	(0.014)	(0.014)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Recom^{-}$		-0.101***	-0.062***	-0.057***
		(0.015)	(0.015)	(0.015)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Buys$				-0.107***
				(0.020)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Sales$				0.050***
				(0.004)
Maturity pol.	Yes	Yes	Yes	Yes
Signal × maturity pol.	Yes	Yes	Yes	Yes
Learning pol.	Yes	Yes	Yes	Yes
Fixed effects	Day × firm	Day × firm	Day × firm	Day × firm
Ajusted R2	0.961	0.960	0.961	0.961
Obs.	3,039,877	3,039,877	3,039,877	3,039,877

Table B.2: Earnings information disclosed by other signals: OptionMetrics

This table reports the results of the regression shown in Equation (3). The dependent variable is twice the log of implied volatily. Buys (Sales) is the number of days with net buying (selling) by corporate insiders since the last EA. $Forecast^{+}$ ($Forecast^{-}$) is the number of upward (downward) forecast revisions since the last EA. $Recom^{+}$ ($Recom^{-}$) is the number of upward (downward) recommendation revisions since the last EA. Standard errors are clustered at both the day and the firm-quarter level and presented in parentheses. Table 6 describes the variables. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level respectively.

Dep. var.: implied vol.	(1)	(2)	(3)	(4)
$\frac{\mathbf{1}(T>t_R)}{T-t}$	2.377***	2.296***	2.422***	2.293***
	(0.023)	(0.026)	(0.027)	(0.030)
$\frac{\mathbf{1}(T>t_R)}{T-t} \times Forecast^{+}$	-0.055***		-0.052***	-0.052***
	(0.005)		(0.005)	(0.005)
$\frac{\mathbf{1}(T>t_R)}{T-t} \times Forecast^{-}$	-0.072***		-0.068***	-0.057***
	(0.004)		(0.004)	(0.004)
$\frac{\mathbf{1}(T>t_R)}{T-t} \times Recom^{+}$		-0.060***	-0.035**	-0.052***
		(0.015)	(0.014)	(0.014)
$\frac{\mathbf{1}(T>t_R)}{T-t} \times Recom^{-}$		-0.097***	-0.056***	-0.050***
		(0.016)	(0.016)	(0.015)
$\frac{\mathbf{1}(T>t_R)}{T-t} \times Buys$				-0.114***
				(0.021)
$\frac{\mathbf{1}(T>t_R)}{T-t} \times Sales$				0.057***
				(0.004)
Maturity pol.	Yes	Yes	Yes	Yes
Signal × maturity pol.	Yes	Yes	Yes	Yes
Learning pol.	Yes	Yes	Yes	Yes
Fixed effects	Day × firm	Day × firm	Day × firm	Day × firm
Ajusted R2	0.970	0.970	0.970	0.971
Obs.	3,039,877	3,039,877	3,039,877	3,039,877

Table B.3: Earnings information disclosed by other signals: Whole OptionMetrics

This table reports the results of the regression shown in Equation (3). The dependent variable is twice the log of implied volatily. Buys (Sales) is the number of days with net buying (selling) by corporate insiders since the last EA. $Forecast^{+}$ ($Forecast^{-}$) is the number of upward (downward) forecast revisions since the last EA. $Recom^{+}$ ($Recom^{-}$) is the number of upward (downward) recommendation revisions since the last EA. Standard errors are clustered at both the day and the firm-quarter level and presented in parentheses. Table 6 describes the variables. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level respectively.

Dep. var.: implied vol.	(1)	(2)	(3)	(4)
$\frac{\mathbf{1}(T > t_R)}{T-t}$	1.935***	1.910***	1.985***	1.806***
	(0.023)	(0.025)	(0.026)	(0.028)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Forecast^{+}$	-0.021***		-0.019***	-0.028***
	(0.004)		(0.004)	(0.004)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Forecast^{-}$	-0.031***		-0.028***	-0.020***
	(0.004)		(0.004)	(0.004)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Recom^{+}$		-0.027**	-0.016	-0.044***
		(0.012)	(0.011)	(0.011)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Recom^{-}$		-0.065***	-0.048***	-0.050***
		(0.013)	(0.013)	(0.012)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Buys$				0.036*
				(0.022)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Sales$				0.118***
				(0.005)
Maturity pol.	Yes	Yes	Yes	Yes
Signal × maturity pol.	Yes	Yes	Yes	Yes
Learning pol.	Yes	Yes	Yes	Yes
Fixed effects	Day × firm	Day × firm	Day × firm	Day × firm
Ajusted R2	0.925	0.925	0.926	0.927
Obs.	6,148,923	6,148,923	6,148,923	6,148,923

C Option liquidity

Section A shows that extending the sample to the whole OptionMetrics universe changes slightly the magnitude of the effect. This evidence suggests that option liquidity might correlate with the informativeness of the earnings announcement. In this section we investigate how informativeness varies with option liquididy within our restricted sample and if option liquidity affects the estimation of the effect of insider trading. First, we examine how the number of options and maturity varies over time until the next earnings announcement. Further, we calculate the average value of total open interest of each firm-day-maturity-triplet in a given firm-quarter. We then sort the observations by open interest for each quarter and create groups.

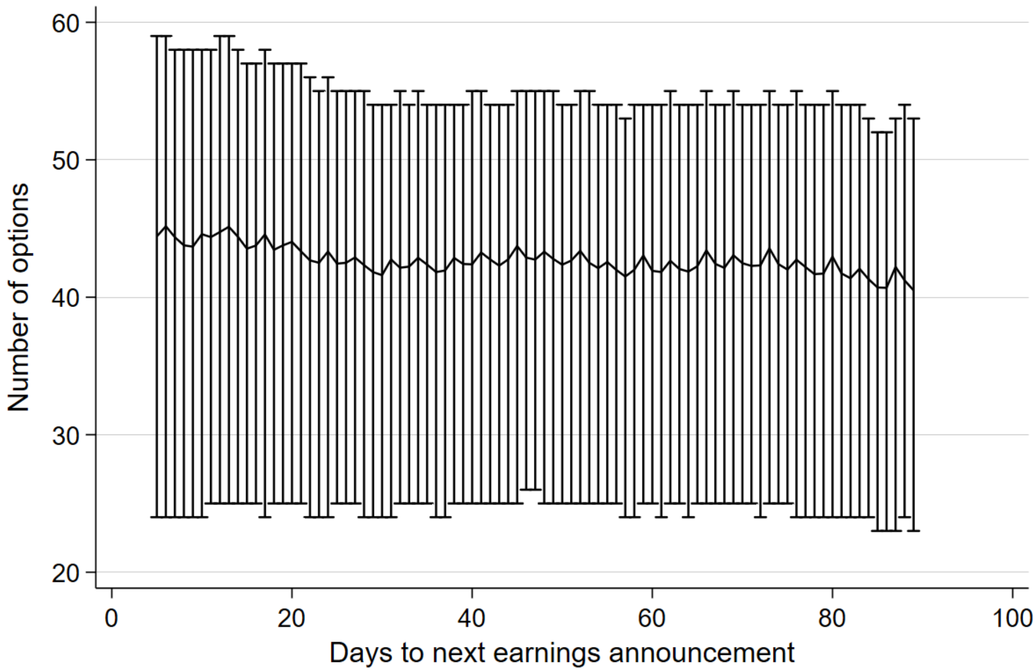
If the proximity to the next earnings announcement affects the availability of observable option prices or there is a systematic relation between days to maturity and the days left until the next announcement, one might be concerned about a potential bias in our measure. Panel A of Figure C.1 shows the average number of options as well the top and bottom quartile by days until the next earnings announcement, indicating that the number of options is relatively stable over time. Panel Panel B presents the average days to maturity by days until the next announcements, also suggesting that there is no systematic relation over time.

Figure C.2 shows how our measure of earnings announcement informativeness varies over open interest deciles. We find that the measure of earnings announcement informativeness decreases with open interest. This may be a consequence of liquidity but it may also be the result of firms without a liquid option market being less monitored; thus, relying more on earnings announcements.

Figure C.1: Number of options and maturity over time to the next announcement

These graphs show the average number of options (Panel Panel A) and the average number of days to maturity (Panel Panel B) over the days until the next earnings announcement, as well as the lower and upper quartiles.

Panel A: Number of options



Panel B: Days to maturity

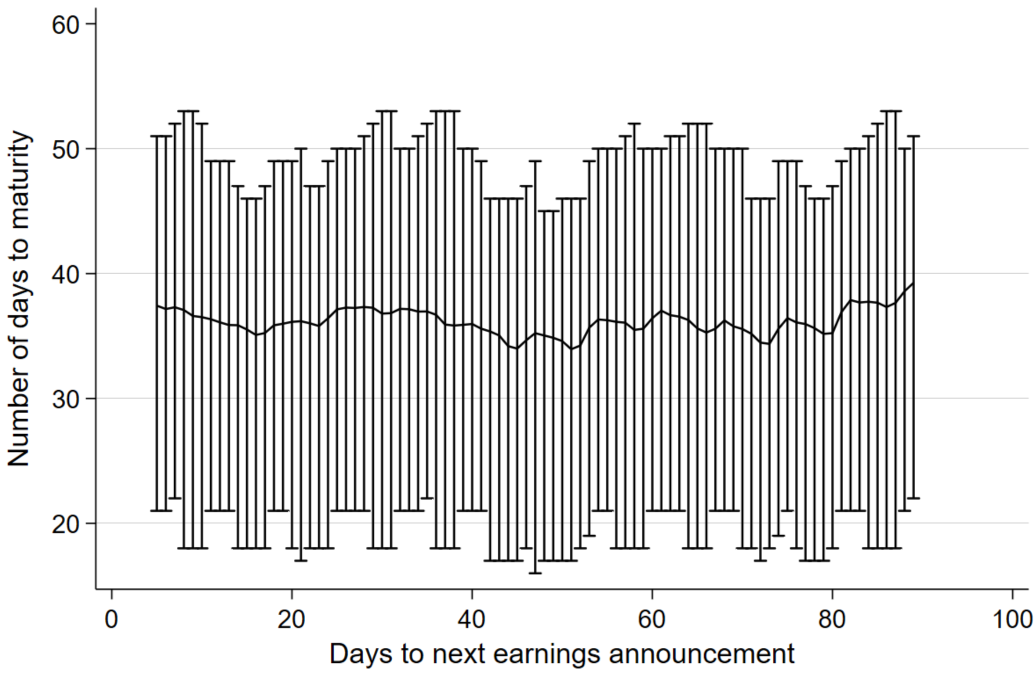
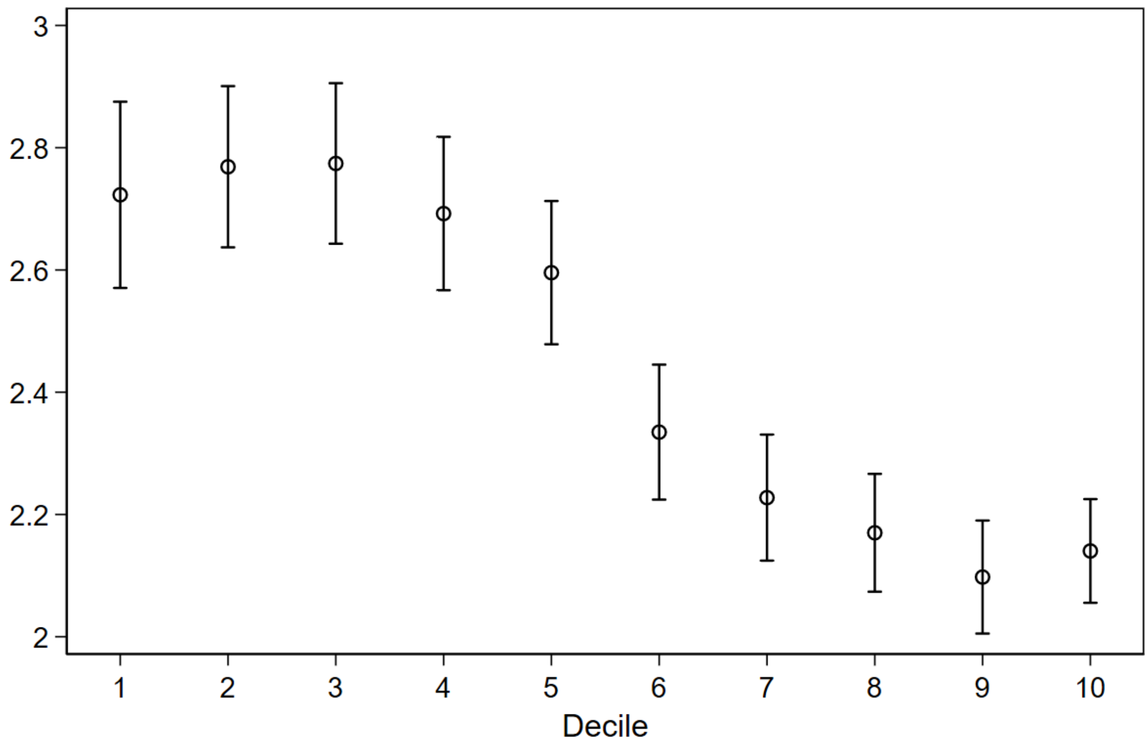


Figure C.2: EA informativeness by open interest deciles

These plots depict the estimate of the informativeness of earnings announcements, and the 95% con dence intervals across deciles of open interest. Standard errors are clustered at both the day and the firm level.



D Error due to the term structure

Section 3 analyzes how our estimator of the bias of the measure proposed by Dubinsky et al. (2019) correlates with different signals. In this section, we explain in further detail how we construct the measure and provide evidence of its use as an estimate of the error induced by the flat term structure assumption. Because Dubinsky et al. (2019) do not use options expiring before the announcement, we use them to estimate the slope of the variance term structure and define the error due to the flat term-structure assumption for firm i on date t as:

$$Error_{i,t} = \frac{1}{M-1}\sum_{j=2}^{M}\frac{IV^2_{\tau_{j-1}} - IV^2_{\tau_j}}{\tau^{-1}_{j-1} + \tau^{-1}_{j}}$$

where M is the number of options expiring before the announcement, τ indicates an available time to maturity such that $\tau_1 < \tau_2 < ... < \tau_M$, and IV is the Black-Scholes volatility. Any measure of the term-structure would serve as an estimate of the bias. We select this one for two main reasons. First, this measure would exactly capture the bias if options expiring before and after the announcement had the same time-to-maturity distribution and there was no measurement error. In practice, they do not, but the violation of those assumptions is unlikely related to signals by insiders and analysts. Second, this measure has the same functional form as Dubinsky et al. (2019) measure; hence, it has a nice interpretation as a placebo test. In particular, it corresponds to an exercise in which we assume that the earnings announcement date is before the first expiration date, and we estimate the informativeness considering all options that expire after this false announcement and before any real announcement.

This measure is a proxy for the error due to the flat term-structure assumption, but it does not measure exactly the error. This feature precludes us from making any conclusion about the average error or the size of the error because the measurement error in the variable might influence both. Nonetheless, the measurement error will not affect the estimates when we include our measure as a dependent variable in a regression. To reduce the noise of our error measure and Dubinsky et al. (2019) measure, we aggregate them at the firm-quarter level by taking the median. Table D.1 shows the summary statistics. The low liquidity of long-term options leads to fewer announcements in our sample. Our proxy coincides with the argument by Dubinsky et al. (2019) that the bias induced by the flat-term structure might be close to zero, although it is slightly negative.[2] The remaining question is whether the variability of the bias is independent of the relevant variables or not.

Before answering this question, we must show that our bias measure is related to the bias, not pure noise. To do that, we regress the measure by Dubinsky et al. (2019) on our bias measure. If our proxy was pure noise, or, equivalently, their measure was not biased, there would be no correlation between the two variables. Column 1 of Table D.2 shows that, indeed, these two variables are correlated. One possibility is that the whole correlation occurs at the firm or quarter level; hence firm and quarter fixed effects could absorb the bias. Columns 2 and 3 show that the correlation persists even if we control for firm and quarter fixed effects. We acknowledge there are few extreme outliers in the sample. In column 5, we restrict the sample to observations in which the absolute value of the ratio between the bias and the measure itself does not exceed 100%. The estimate increases considerably despite excluding just 12% of the sample, and statistical significance increases.

To interpret the estimates is useful to consider the following model:

$$\overline{\sigma^{2DJKS}_{\pi,i,q}} = \sigma^{2TRUE}_{\pi,i,q} + b_{i,q} + u_{i,q}; \quad \overline{Error}_{i,q} = b_{i,q} + v_{i,q}$$

where $\overline{\sigma^{2DJKS}_{\pi,i,q}}$ and $\overline{Error}_{i,q}$ represent the estimates of the relevance of the announcement and of the error induced by the flat term-structure assumption respectively. $b_{i,q}$ represents the true error induced by the flat term-structure assumption and u and v are measurement errors independent of each other and independent of $\sigma^{2TRUE}_{\pi,i,q}$. Then, the estimator in the first column of Table D.2 corresponds to:

$$\frac{cov(\sigma^{2TRUE}_{\pi,i,q}, b_{i,q}) + Var(b_{i,q})}{Var(b_{i,q}) + Var(v_{i,q})}$$

If the bias and the true relevance are uncorrelated, the estimate is the signal-to-noise ratio of our estimator for the error induced by the flat term-structure assumption. Consequently, 66% of the variation of our estimator would correspond to variation of the error due to the flat-term structure. Once we eliminate the variation across firms and quarters through the fixed effects, and outliers, 107% of the variation of our estimator would correspond to variation of the error

[2] Dubinsky et al. (2019) varies significantly depending on how we aggregate. In Figure 3 of the paper we use the average across firms or years. The former weights more recent years while the later weight more firms with more liquid options. This selection explains the difference between the figure in the paper and the results in this table.

due to the flat-term structure. If the error due to the flat-term structure and the true relevance are positively (negatively) correlated, 107% is an upper (lower) bound of the variation of our measure corresponding to the bias. Unfortunately, without observing the true relevance, we cannot estimate this correlation. Nonetheless, in any case, if the error due to the flat-term structure is a constant or our estimator is pure noise, the parameter estimate of the regression will be zero.

Table D.1: Summary statistics Dubinsky et al. (2019) and bias at the firm-quarter level

This table present the date-firm level summary statistics of $\sigma_{\pi}^{2\ DJKS}$ and $Error$. $\sigma_{\pi}^{2\ DJKS}$ is the measure of informativeness by Dubinsky et al. (2019) as described in Section I. $Error$ is our estimate of the bias of their measure estimated as described in Section D.

	Obs	Mean	std	P10	P50	P90
Option-level						
Error	1221125	-0.065	1.131	-0.390	-0.017	0.249
σ_{π}^{2DJKS}	643183	0.160	2.037	-0.563	0.116	1.048
Day-firm level (mean)						
Error	443612	-0.119	0.705	-0.374	-0.044	0.093
σ_{π}^{2DJKS}	312555	0.001	1.769	-0.566	0.055	0.720
Announcement level (mean)						
$\overline{Error}$	17643	-0.150	0.518	-0.404	-0.065	0.051
$\overline{Rel.Error}$	14351	-4.116	2804.935	-118.053	2.062	150.108
$\overline{\sigma_{\pi}^{2DJKS}}$	17138	-0.018	1.389	-0.539	0.034	0.590
Announcement level (median)						
$\overline{Error}$	17643	-0.153	0.479	-0.393	-0.066	0.027
$\overline{Rel.Error}$	14351	-49.694	4485.859	-124.810	-0.142	152.884
$\overline{\sigma_{\pi}^{2DJKS}}$	17138	0.005	1.204	-0.476	0.043	0.575

Table D.2: Validation of our bias measure

This table presents the results of the regression:

$$\overline{\sigma_{\pi}^{2DJKS}}_{i,q} = \alpha_i + \delta_q + \beta \overline{Error}_{i,q} + \varepsilon_{i,q}$$

where α_i and δ_q are firm and quarter fixed effects, $\overline{\sigma_{\pi}^{2\ DJKS}}$ is the median measure of informativeness by Dubinsky et al. (2019) as described in Section I. *Bias* is our estimate of the bias of their measure estimated as described in Section D. Rel. Bias corresponds to the ratio between *Bias* and σ_{π}^{2DJKS}. Standard errors are computed using Huber-White formula and presented in parentheses. Table 6 describes the variables. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level respectively.

Dep. var.: Dubinsky et al. (2019)	(1)	(2)	(3)	(4)
Error	0.668***	0.586***	0.419**	1.072***
	(0.134)	(0.155)	(0.166)	(0.308)
Fixed effects	No	Firm	Quarter & firm	Quarter & firm
Rel Error support	$(-\infty, \infty)$	$(-\infty, \infty)$	$(-\infty, \infty)$	(-1,1)
Adjusted R2	0.057	0.120	0.170	0.237
Obs.	14,351	14,320	14,320	10,559

E Functional form

We acknowledge that the functional form of the term structure that we consider is arbitrary. In this section, we assess the fit of the functional form and the consequences of alternative functional forms. Because our estimation strategy requires a model that is linear in parameters, we consider the term structure can be represented by:

$$\delta_{i,t} + \sum_{m=1}^{M} \lambda_m (T-t)^{\frac{m}{n}} + \sum_{m=1}^{M} \theta_m (T-t_R)^{\frac{m}{n}}$$

where $\delta_{i,t}$ is the firm-date fixed effect, T is the expiration date, and t_R is the time of the announcement. The case in the main text is $M = n = 2$.

The first panel of Table E.1 considers a reduction to one polynomial term and extensions to three or four terms ($0 < M \leq 4$) while keeping $n = 2$. The biggest impact is when we only consider one polynomial term. In this case, the estimated informativeness decreases from 2.37 to 2.31, and the R^2 drops from 95.33% to 95.30%. Extending the polynomial barely affects the estimate and R^2. Therefore, we choose $M = 2$ for the sake of parsimony. Then, we consider if the functional form might affect the results. The second panel of Table E.1 fixes $M = 2$ and considers the term structure can be represented by:

$$\delta_{i,t} + \lambda_1 (T-t)^{\frac{1}{n}} + \lambda_2 (T-t)^{\frac{m}{n}} + \theta_1 (T-t_R)^{\frac{m}{n}} + \theta_2 (T-t_R)^{\frac{m}{n}}$$

for all possible combinations of $n \in \mathbb{N}$ and $m \in \mathbb{N}$ such that $0 < n \leq 4$ and $0 < m \leq 4$, which includes the quadratic polynomial ($m = 2, n = 1$). The results are very similar across functional forms.

The lack of relevance of the functional form derives from the identification strategy. Our model hinges on comparing options before and after the announcement; therefore, as long as the functional form captures the average of each of these two option groups appropriately, the results will be similar. Moreover, since we restrict our sample to options expiring in fewer than 90 days, low-degree polynomials capture the differences across maturities.

Table E.1: Fit of the term-structure functional form

This table reports the results of the regression shown in Equation (2) using different functional forms for the term structure. Panel A considers the following functional form:

$$\delta_{i,t} + \sum_{m=1}^{M} \lambda_m (T-t)^{\frac{m}{n}} + \sum_{m=1}^{M} \theta_m (T-t_R)^{\frac{m}{n}}$$

for different values of M. Panel B considers the term structure follows:

$$\delta_{i,t} + \lambda_1 (T-t)^{\frac{1}{n}} + \lambda_2 (T-t)^{\frac{m}{n}} + \theta_1 (T-t_R)^{\frac{m}{n}} + \theta_2 (T-t_R)^{\frac{m}{n}}$$

For different values of n and m. The baseline is $m = n = 2$. Adjusted-R^2 are presented in parenthesis.

Extending the polynomial ($n = m = 2$)

	$M = 1$	$M = 3$	$M = 4$
$\mathbf{1}\,(T > t_R)\,\dfrac{1}{T-t}$ (γ)	2.256	2.375	2.404
$Adjusted - R^2$	(94.912)	(94.972)	(94.996)

Different Polynomials ($M = 2$)

	$m = 2$	$m = 3$	$m = 4$
n = 1	2.344	2.339	2.337
	(94.963)	(94.962)	(94.961)
n = 2	2.363	2.349	2.337
	(94.969)	(94.966)	(94.962)
n = 3	2.379	2.367	2.355
	(94.974)	(94.971)	(94.968)
n = 4	2.387	2.379	2.369
	(94.977)	(94.974)	(94.972)

F Actual versus expected earnings announcement dates

Our analysis rests on the implicit assumption that market participants know the earnings announcement dates with sufficient precision, so they can know which options are treated and which are not. In line with this assumption, Johnson and So (2018) show that options react to changes in the earnings announcement date. Market expectations about the announcement date are not observable directly, so instead we need to rely on a proxy. In our main analysis we use the actual earnings announcement dates as such proxy. This decision creates a concern for insider trading as managers might have private information about the earnings date and transact accordingly or they might displace the earnings date to transact over more days reducing the price impact.

Typically, market participants are informed about the earnings announcement date via so-called earnings notifications. These notifications are mandatory since Reg FD became effective in 2001. However, most earnings notifications occur relatively close to the earnings announcement date, approximately 10 trading days (see Chapman (2018)). Market participants are likely to have formed expectations about the timing of the next earnings announcement date even before the official earnings notifications. In our analysis we analyze up to 90 calendar days before the next earnings announcement. Even if we precisely know the date of the earnings notification, we would need a proxy for market expectations in the remaining time, which represents the bulk of our sample.

In the extreme event that earnings announcement dates are unpredictable, we would not expect that the earnings announcement produces a wedge in implied volatility between options maturing before or after the next earnings announcement. In the event that earnings announcement dates are fairly predictable, the actual announcement dates would be a reliable proxy for the expected dates. We evaluate the plausibility of this assumption in the following and investigate the sensitivity of our findings with respect to this assumption.

First, we examine the deviation between the expected and the actual earnings date. We estimate expected earnings announcement dates based on the current year's end of the fiscal quarter and add the number of business days between the end of the fiscal quarter and the earnings announcement date from the same quarter of the firm's last fiscal year. Table F.1 summarizes the deviation from the actual earnings announcement date and the expected date for each quarter, and the average across a given firm year. The deviations between the expected and the actual earnings announcement dates are small, as the mean value is 0. Even the top and bottom 10% are small with values of -2 and 4.[3] We cross-tabulate the number of options classified as 'treated' and 'control' under either the expected or the actual earnings announcement dates. Given these small deviations, it is not surprising that the treatment status assigned to daily option observations that depends on whether a given option expires before or after the next earnings announcement date does not change much irrespective of whether we use the expected or the actual earnings announcement dates. As shown in Table F.2 the majority of option days, to be precise 97.7%, that are classified as treated under expected earnings dates would also be classified as treated under the actual earnings dates. Similarly, 98.4% of option days classified as control according to expected dates would be classified as such according to the actual dates.

Second, we use expected instead of actual earnings announcement dates as a further robustness check. Table F.3 shows the results using the expected earnings announcement dates. We find similar estimates estimate for the signals by analysts and insiders, though we note that the economic magnitudes of recommendations are larger and the magnitude of insider buys is smaller.

Table F.1: Summary statistics

This table shows the summary statistics for the number of business days between the expected earnings announcement date and the actual earnings announcement date. The expected earnings announcement date is calculated as the the current year's end of the fiscal quarter plus the number of business days between the end of the fiscal quarter and the earnings announcement date from the same quarter of the firm's last fiscal year.

Variable	Obs.	Mean	S.D.	10pct	50pct	90pct
Deviation Q1	4,273	0	3	-2	0	4
Deviation Q2	4,080	0	3	-2	-1	4
Deviation Q3	4,351	0	3	-2	-1	4
Deviation Q4	4,247	0	4	-2	0	4
Mean firm-year deviation	3,201	0	2	-2	-0	2
Mean absolute firm-year deviation	3,201	2	1	1	2	4

[3]The number of observations decreases because we do not observe the deviation for the first year in the sample, and because some earnings announcements could be missing.

Table F.2: Treatment under actual and expected earnings announcements

This table tabulates the number of daily options that are treated, as they expire after the next earnings announcement, and control, as they expire before the next earnings announcement, based on actual and expected earnings announcement dates.

	Control (expected)	%	Treated (expected)	%	Sum
Control (actual)	1,662,160	98.4%	22,268	2.3%	1,684,428
Treated (actual)	26,388	1.6%	964,384	97.7%	990,772

Table F.3: Expected versus actual earnings announcement dates

This table shows the results of a regression of implied volatility on corporate insider purchases and sales. The treatment status of option day observations is based on expected earnings announcement dates rather than the actual dates. Column 1 shows the results of a regression of implied volatility on the square root of the time to maturity interacted with a dummy variable indicating whether the option expires before the next earnings announcement and a dummy variable that is Columns 2 to 4 add different sets of fixed effects or control variables. Maturity pol. refers to controlling for the time to maturity of the option measured in years and its square root as well as the interaction of the linear and the square root term with the insider buy or sell variables. Standard errors are clustered at both the day and the firm-quarter level and presented in parentheses. Table 6 describes the variables. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level respectively.

Dep. var.: implied vol.	(1)	(2)	(3)	(4)
$\frac{\mathbf{1}(T > t_R)}{T-t}$	2.277***	2.303***	2.416***	2.296***
	(0.031)	(0.034)	(0.036)	(0.039)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Forecast^{+}$	-0.057***		-0.051***	-0.051***
	(0.007)		(0.007)	(0.007)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Forecast^{-}$	-0.070***		-0.064***	-0.055***
	(0.005)		(0.005)	(0.005)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Recom^{+}$		-0.116***	-0.092***	-0.103***
		(0.018)	(0.018)	(0.018)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Recom^{-}$		-0.125***	-0.083***	-0.078***
		(0.020)	(0.020)	(0.020)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Buys$				-0.087***
				(0.025)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Sales$				0.051***
				(0.006)
Maturity pol.	Yes	Yes	Yes	Yes
Signal × maturity pol.	Yes	Yes	Yes	Yes
Learning pol.	Yes	Yes	Yes	Yes
Fixed effects	Day × firm	Day × firm	Day × firm	Day × firm
Ajusted R2	0.943	0.943	0.943	0.943
Obs.	2,762,767	2,762,767	2,762,767	2,762,767

G Extended Model

In the model in equation (1), we assume a constant volatility of the announcement jump for simplicity and to ease the comparison with alternative models. However, investors might expect information about the announcement before it occurs and the volatility might depend on the time to the next announcement. In particular, investors might expect analyst forecasts or insider transactions, and consequently, changes in stock price and the informativeness of the variance. In this section, we extend the model to include these dynamics of prices although limiting the analysis to a simple model.

Consider the price follows a simplified version of Merton's jump-diffusion process:

$$\frac{dP(t)}{P(t-)} = r(t) + \sigma dW(t) + \beta dJ(t) + \pi 1\{t = t_R\}$$

where $J(t)$ is a Poisson process with intensity λ up to the announcement date (t_R) and remains constant thereafter. β is constant and represents how much prices move when there is a signal prior to the earnings announcement. We assume that the jump size on the announcement date is distributed according to a normal distribution: $\pi \sim N(\frac{-\sigma_\pi^2}{2}, \sigma_\pi^2)$, in which the expectation ensures that the process is a martingale. Meanwhile, the variance itself is subject to Poisson jumps of size θ:

$$d\sigma_\pi^2 = \mu + \theta dJ(t)$$

Note that the process is subject to the same counting process as before reflecting that signals such as a positive analyst forecast revision affect the variance of the announcement but also the price of the asset. Including more Poisson processes in the price equation or adding a diffusion term to the dynamics of σ_π^2 do not change the conclusions and complicate the expressions. Using other processes for σ_π^2 to ensure non-negativity (e.g. exponential) mainly change the functional forms.

In this model, the scaled risk-neutral variance is given by:

$$IV^2 = \sigma_\pi^2 + \lambda\mu \frac{t_R - t}{T - t} + 1\{T > t_R\} \left(-\frac{1}{2}\theta\beta\lambda \frac{t_R - t}{T - t} + V(\pi) \right)$$

where $V(\pi) = \frac{1}{4}\lambda\theta^2 + \mu + \lambda\theta$. Note that we control for a polynomial in $(t_R - t)$ and another one in $(T - t)$, and the interaction with their treated variable $1\{T > t_r\}$. Therefore, we identify $V(\pi)$. We use the learning polynomial based on $(t_R - t)$ instead of $\frac{t_R - t}{T - t}$ because it mimics the other polynomial and the factor $\frac{t_R - t}{T - t}$ depends on the model we choose (e.g., an exponential model for the variance of the announcement would lead to a different functional form). Nonetheless, we re-estimate our main analysis in Table 5 using a polynomial on $\frac{t_R - t}{T - t}$ and results are almost identical. Table G.1 presents the results.

Table G.1: Earnings information disclosed by other signals

This table reports the results of the regression shown in Equation (3). The dependent variable is twice the log of implied volatily. Buys (Sales) is the number of days with net buying (selling) by corporate insiders since the last EA. $Forecast^{+}$ ($Forecast^{-}$) is the number of upward (downward) forecast revisions since the last EA. $Recom^{+}$ ($Recom^{-}$) is the number of upward (downward) recommendation revisions since the last EA. Standard errors are clustered at both the day and the firm-quarter level and presented in parentheses. Table 6 describes the variables. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level respectively.

Dep. var.: implied vol.	(1)	(2)	(3)	(4)
$\frac{\mathbf{1}(T>t_R)}{T-t}$	2.475***	2.369***	2.548***	2.374***
	(0.030)	(0.035)	(0.035)	(0.039)
$\frac{\mathbf{1}(T>t_R)}{T-t} \times Forecast^{+}$	-0.050***		-0.048***	-0.048***
	(0.006)		(0.006)	(0.006)
$\frac{\mathbf{1}(T>t_R)}{T-t} \times Forecast^{-}$	-0.067***		-0.064***	-0.054***
	(0.004)		(0.004)	(0.004)
$\frac{\mathbf{1}(T>t_R)}{T-t} \times Recom^{+}$		-0.050***	-0.028*	-0.043***
		(0.016)	(0.015)	(0.015)
$\frac{\mathbf{1}(T>t_R)}{T-t} \times Recom^{-}$		-0.095***	-0.058***	-0.052***
		(0.017)	(0.017)	(0.016)
$\frac{\mathbf{1}(T>t_R)}{T-t} \times Buys$				-0.110***
				(0.022)
$\frac{\mathbf{1}(T>t_R)}{T-t} \times Sales$				0.054***
				(0.004)
Maturity pol.	Yes	Yes	Yes	Yes
Signal × maturity pol.	Yes	Yes	Yes	Yes
Learning pol. (fraction)	Yes	Yes	Yes	Yes
Fixed effects	Day × firm	Day × firm	Day × firm	Day × firm
Ajusted R2	0.950	0.950	0.950	0.950
Obs.	3,039,877	3,039,877	3,039,877	3,039,877

H Falsification exercise

We acknowledge that the asymptotic distribution of the estimator that we use in the paper assumes that the firm-date fixed effects and the two-way cluster variance correctly take into account the time series properties of the implied volatility process. If the implied volatility of different maturities do not share a cointegration relationship or if the measurement error of the implied volatility is highly persistent, our inference would be incorrect. Similarly, we base our analysis on an asymptotic approximation, which might be problematic when using the two-way cluster variance if the within-cluster correlation is high with respect to the number of clusters (Villacorta, 2015).

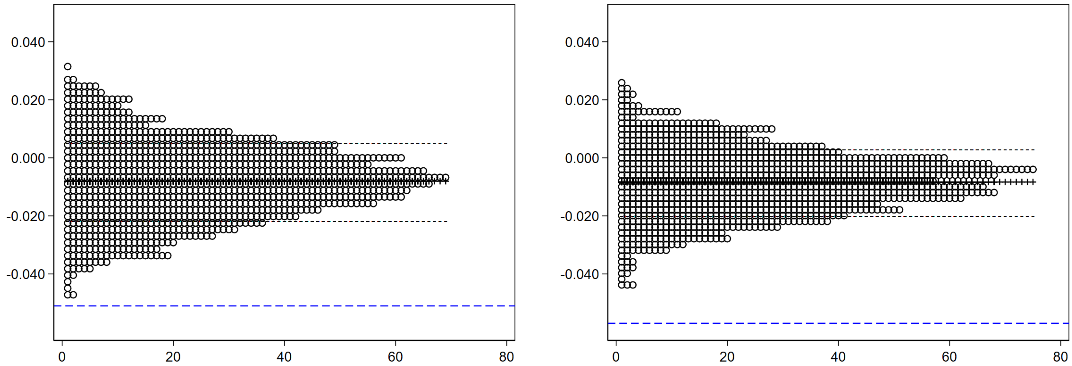
To tackle these issues, in this section we obtain the finite-sample distribution of our estimators under the null hypothesis that the signals are uninformative. Since we would like to maintain the properties of the implied volatility across time, we keep the sample implied volatility and the distribution and timing of the signals, and we randomly assign upward and downward signals to trading days, keeping the respective number of upward and downward signals for each agent we consider fixed. For example, in Panel A we randomize upward and downward forecasts by analysts, while maintaining the actual occurence of all other signals. For each signal, We repeat the process 1,000 times to create 1,000 placebo samples. These samples closely represent samples in which the signals have no effect on earnings announcement informativeness by design. Hence, applying our estimation in each sample, we recover the finite-sample distribution of our estimator under the null hypothesis. The advantage of this approach compared with bootstrap or parametric simulation methods lies in the possibility of maintaining the complete correlation structure of implied volatility over time and across firms. The main disadvantage consists of the small tilt towards our estimates that the empirical distribution will have; nonetheless, this disadvantage works against validating our approach.

Figure H.1 shows the empirical distribution under the null hypothesis of the baseline estimators, $\widehat{\gamma^+}$ and $\widehat{\gamma^-}$. The blue dotted lines in the graphs show the actual estimates presented in Table 5. For all simulated signals, the mean values of $\widehat{\gamma^+}$ and $\widehat{\gamma^-}$ are close to zero. We find that the simulated estimates are substantially smaller than the estimates based on the actual data in Table 5. For example, for analyst forecasts the mean value of $\widehat{\gamma^+}$ is -0.008, while the mean value of $\widehat{\gamma^-}$ is -0.008. These values are much smaller than the estimates we observe for the actual timing of analyst forecast revisions. More importantly, the p-value of our actual estimates using the simulated distribution is zero for all signals, consistent with the high significance that we report in the main analysis.

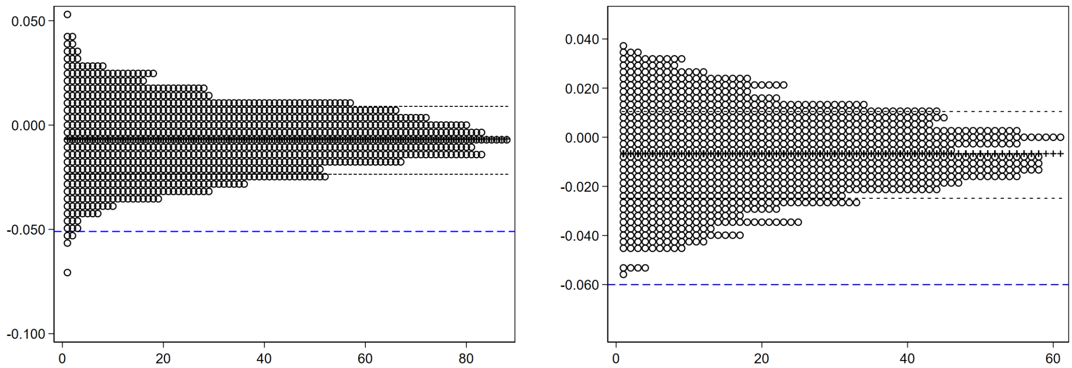
Figure H.1: Simulated distribution under the null of uninformative signals

This figure shows the estimates of γ^+ (left graph) and γ^- (right graph). The dots are based on simulating the upward and downward signals for each type of signal 1,000 times and repeating the analysis of Table 5, while keeping the remaining actual distribution of the other signals. The black crosses indicate the respective mean value of $\widehat{\gamma^+}$ and $\widehat{\gamma^-}$, while the distance from the mean to the dotted lines show one standard derviation. The dashed blue line shows the actual estimates from Table 5 in the main paper.

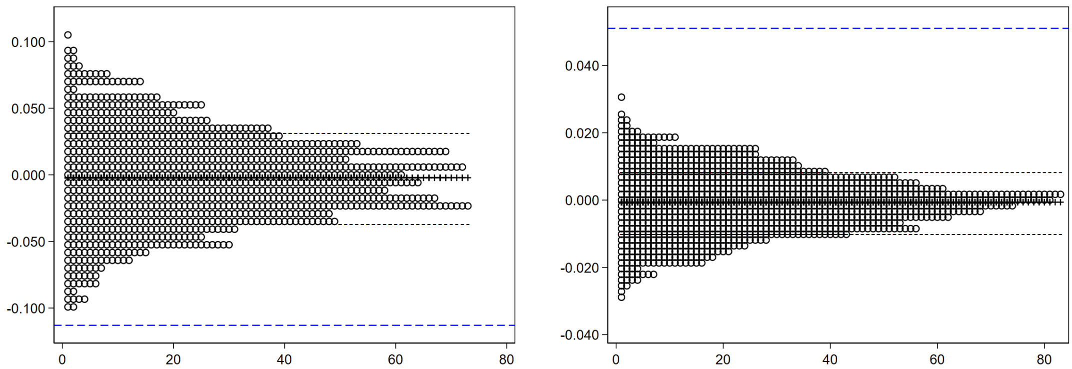
Panel A: Distributions of $\widehat{\gamma^+}$ and $\widehat{\gamma^-}$ for analyst forecasts



Panel B: Distributions of $\widehat{\gamma^+}$ and $\widehat{\gamma^-}$ for analyst recommendations



Panel C: Distributions of $\widehat{\gamma^+}$ and $\widehat{\gamma^-}$ for corporate insider transactions



I Comparison with other informativeness measures

One of the contributions of the paper is to suggest an exante measure of earnings announcement informativeness that varies at a daily frequency and is valid under mild assumptions. In Figure 3, we compare our measure of earnings announcement informativeness with alternative measures across different firms and across different years. In general, every measure correlates significantly with our proposed measure and they share the same time-series pattern, which provides support to our measure. This section describes how we construct each measure.

To construct our measure, we estimate the following regression equation using the 90 days prior to each announcement:

$$ln(IV^2_{i,t,T}) = \mu_{i,t} + \sum_{j=1}^{2} \lambda^a_j (T-t)^{j/2} + \gamma^a \mathbf{1}\left(T > t_{R_{i,t}}\right) \frac{1}{T-t} + \varepsilon_{i,t,T}$$

where subscripts i, t, T denote firm, time, and maturity; and the superscript a emphasizes that we estimate it per firm (scatter plot) or per year (line plots). IV is the nonparametric risk-neutral volatility estimator proposed by Bakshi et al. (2003), t_R is the day of the announcement, and γ^a is the average informativeness of the earnings announcement as a proportion of the annual variance. Note that this modeling is much more general and robust than the baseline model because it considers a different term structure (λ^a_j) per firm or year. Yet, the results are very similar.

As explained in the main paper, Patell and Wolfson (1981) propose measuring the informativeness of the announcement by exploiting the time-series variation of implied volatility before the announcement. Precisely, the estimator is given by:

$$\hat{\sigma}^2_{\pi,PW} = \frac{IV^2_{t_2,T} - IV^2_{t_1,T}}{(T-t_2)^{-1} - (T-t_1)^{-1}}, \ (t_1 < t_2 < t_R \text{ and } T > t_R).$$

To implement it, for each day and maturity, we compute the weekly change in OptionMetrics implied variance of the at-the-money options. Then, we average across all days and maturities to obtain the scatter plot and across all days in a given year and all maturities to obtain the line plots. We use weekly changes and the OptionMetrics estimator to follow PW; however, these decisions are not crucial. Finally, $\hat{\sigma}^2_{\pi,PW}$ measures the informativeness in absolute terms instead of relative to the annual variance; hence we normalize the estimator by dividing it by the mean of the implied variance of options that expire before the earnings announcement.

Dubinsky et al. (2019) propose a similar estimator using the term structure:

$$\hat{\sigma}^2_{\pi,DJKS} = \frac{IV^2_{t,T_1} - IV^2_{t,T_2}}{(T_1 - t)^{-1} - (T_2 - t)^{-1}}, \ (t_R < T_1 < T_2).$$

In this case, for each day we compute the difference between the at-the-money OptionMetrics implied variance of each option and the one with a longer maturity as long as both maturities are posterior to the announcement. We then average across maturities and days for a given announcement. Similar to the previous case, we normalize the estimator by the implied variance of options that expire before the earnings announcement.

Beaver et al. (2018) construct a test of significance of earnings announcement whose intuition closely relates to our definition of informativeness. We follow their procedure:

1. We create an estimation period of 130 days before the announcement until 10 days before, and 10 to 130 days after the announcement.

2. We aggregate the data to 3-days cumulative returns.

3. We estimate the market model using the S&P500 as benchmark and data of the estimation period.

4. We construct the abnormal return as the cumulative return from the day before to the day after the announcement minus the predicted return from the market model.

5. We construct the U-statistic as the squared abnormal return over the residual variance of the market model in the estimation period.

Finally, we subtract one to make it comparable to the other measures. The interpretation is similar to our γ since it is the ratio of the squared abnormal return on the announcement date over the idiosyncratic variance. The main difference is that this measure focuses on the idiosyncratic part while ours is the ratio of the total variance of returns.

J Event study analysis

The analysis in the main paper uses the whole time series of each firm to estimate the effect of each signal, e.g. insiders' sales and buys. The benefits of this approach are threefold. First, we obtain more precise estimates by including more data. Second, we account for the correlation across signals. Third, the model accommodates downward and upward signals of the same stock in subsequent days. In an event study jargon, the pre-event period length varies depending on the timing of the last signal and, similarly, the post-event window length widens as the next transaction delays.

Compared to an event study analysis, our main analysis also owns several disadvantages. First, we implicitly assume that the effect of two upward signals doubles the effect of one. Second, we consider that our measure of informativeness remains similar across days and firms. These concerns are important if there is a spurious correlation between the informativeness of the earnings announcement and the propensity of insiders to buy or sale. For instance, if in the 2000s we had less sales and less earnings informativeness than in the 2010s, we would erroneously conclude that sales increase the earnings informativeness.

Our main analysis also differs from an event study in the estimated effect that we recover. Consider for example downward forecast revisions. Moreover, consider that the effect of those revisions varies across firms and days. Because we use a panel data of options, the average effect we recover does not weight equally all firms and days with the same number of downward revisions. Instead, firms and days with more options would have a higher weight. This feature is an advantage if the effect of downward revisions is similar because we put more weight on those firm-days for which our identification is more suitable. However, if prior downward forecast revisions affect firms or periods with more options differently, our estimates would not reflect the average effect of downward revisions.

To take into account the different frequency of signals across firms and dates and ensure that our results are not driven by these differences, we estimate the same model using an event study approach. Precisely, we identify the date of each signal (e.g., of an insider transaction) as $\tau = 0$ and include the implied volatility of the firm transacted only for the days in the final sample such that $|\tau| \leq \overline{\tau} = 10$ We explore $\overline{\tau} \in \{1, 2, 5, 10\}$ and the conclusions are similar. Then, we estimate by OLS:

$$2log(IV_e, \tau, T) = \delta_{e,\tau} + \frac{\mathbf{1}\{T > t_{R_{i,t}}\}}{T-t}\left(\gamma + 1\{\tau \geq 0\}(\sum_a \gamma_a^+ \Delta Upward_e^a + \gamma_a^- \Delta Downward_e^a)\right) \tag{1}$$

$$+ \sum_{j=1}^{2} \lambda_j (T-t)^{j/2} + \sum_{j=1}^{2} \theta_j (t_R - t)^{j/2}$$
$$+ \frac{\mathbf{1}\{T > t_{R_{i,t}}\}}{T-t} \sum_a \sum_{j=1}^{2} \lambda_{a,j} (T-t)^{j/2} (\sum_a \lambda_a^+ \Delta Upward_e^a + \lambda_a^- \Delta Downward_e^a) + \varepsilon_{e,\tau,T} \tag{2}$$

where e indexes the events and τ is the event time. $\Delta Downward_e^a$ is a dummy variable that takes the value one if the event is a negative signal (e.g., an insider sale) and zero if it is a a positive signal (e.g., an insider purchase). Recall that T is the maturity of the option, t_R is the announcement date in calendar time, and t is the calendar time that corresponds to event e and event time τ. We cluster the standard errors at the firm and calendar date levels.

Table J.1 presents the results. We observe that results are stronger than in the main paper. A significant part of this difference arises because there are signals in the estimation window that we disregard because of the setup. However, the difference might also be due to the weighting difference we describe before or they arise from a better or worse fit of the term structure, a different composition of firms in terms of option liquidity, or the dynamic effect in which one signal leads or lags another one.

Table J.1: Earnings information disclosed by other signals - Event Study analogy

This table reports the results of the regression shown in Equation (3). The dependent variable is twice the log of implied volatily. Buys (Sales) is the number of days with net buying (selling) by corporate insiders since the last EA. $Forecast^{+}$ ($Forecast^{-}$) is the number of upward (downward) forecast revisions since the last EA. $Recom^{+}$ ($Recom^{-}$) is the number of upward (downward) recommendation revisions since the last EA. Standard errors are clustered at both the day and the firm-quarter level and presented in parentheses. Table 6 describes the variables. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level respectively.

Dep. var.: implied vol.	(1)	(2)	(3)	(4)
$\frac{\mathbf{1}(T > t_R)}{T-t}$	0.906***	0.807***	0.979***	0.899***
	(0.160)	(0.166)	(0.143)	(0.134)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Forecast^{+}$	-0.080***		-0.131***	-0.209***
	(0.022)		(0.022)	(0.023)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Forecast^{-}$	-0.189***		-0.238***	-0.313***
	(0.020)		(0.021)	(0.023)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Recom^{+}$		0.025	0.181***	0.097***
		(0.027)	(0.030)	(0.030)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Recom^{-}$		-0.125***	0.048	-0.027
		(0.030)	(0.032)	(0.032)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Buys$				-0.375***
				(0.116)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Sales$				0.518***
				(0.037)
Maturity pol.	Yes	Yes	Yes	Yes
Signal $\times$ maturity pol.	Yes	Yes	Yes	Yes
Learning pol.	Yes	Yes	Yes	Yes
Fixed effects	Day $\times$ firm	Day $\times$ firm	Day $\times$ firm	Day $\times$ firm
Ajusted R2	0.949	0.951	0.949	0.950
Obs.	2,330,713	1,164,230	3,290,033	5,063,366

K Tables underlying figures

Table K.1: Insider Position (Figure 4)

This table shows the estimates and standard errors used to construct Figure 4 in the main paper. Standard errors are clustered at both the day and the firm-quarter level and presented in parentheses. Table 6 describes the variables. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level respectively.

Dep. var.: implied volatility	(1)
Officer $\times \mathbf{1}(T > t_R)\,(1/T-t)\,CBuys$	0.015
	(0.054)
Officer $\times \mathbf{1}(T > t_R)\,(1/T-t)\,CSales$	0.047***
	(0.005)
Director $\times \mathbf{1}(T > t_R)\,(1/T-t)\,CBuys$	-0.194***
	(0.032)
Director $\times \mathbf{1}(T > t_R)\,(1/T-t)\,CSales$	0.046***
	(0.013)
Beneficial owner $\times \mathbf{1}(T > t_R)\,(1/T-t)\,CBuys$	-0.110***
	(0.030)
Beneficial owner $\times \mathbf{1}(T > t_R)\,(1/T-t)\,CSales$	0.017
	(0.024)
Other $\times \mathbf{1}(T > t_R)\,(1/T-t)\,CBuys$	-0.380
	(0.267)
Other $\times \mathbf{1}(T > t_R)\,(1/T-t)\,CSales$	0.001
	(0.050)

Table K.1: Insider Position (Figure 4) continued

Difference in coefficients	
Buys: officer - director	0.209***
F-value	(9.66)
Buys: officer - beneficial owner	0.125*
F-value	(3.39)
Buys: officer - other	0.395
F-value	(2.05)
Buys: director - beneficial owner	-0.084 *
F-value	(3.73)
Buys: director - other	0.186
F-value	(0.48)
Buys: beneficial owner - other	0.270
F-value	(1.01)
Sales: officer - director	0.001
F-value	(0.01)
Sales: officer - beneficial owner	0.030
F-value	(1.47)
Sales: officer - other	0.046
F-value	(0.82)
Sales: director - beneficial owner	0.029
F-value	(1.10)
Sales: director - other	0.029
F-value	(0.76)
Sales: beneficial owner - other	0.016
F-value	(0.08)
Maturity Pol.	Yes
Signal × maturity pol.	Yes
Learning pol.	Yes
Fixed effects	Day × firm
Adjusted R2	0.950
Obs	3,039,877

Table K.2: By months to EA (Figure 5)

This table shows the estimates and standard errors used to construct Figure 5 Panels D-F in the main paper. Standard errors are clustered at both the day and the firm-quarter level and presented in parentheses. Table 6 describes the variables. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level respectively.

Dep. var.: implied volatility	(1)
1m $\times \mathbf{1}(T > t_R)\,(^1\!/_{T-t})\,CBuys$	-0.184***
	(0.071)
1m $\times \mathbf{1}(T > t_R)\,(^1\!/_{T-t})\,CSales$	-0.084***
	(0.015)
2m $\times \mathbf{1}(T > t_R)\,(^1\!/_{T-t})\,CBuys$	-0.233***
	(0.041)
2m $\times \mathbf{1}(T > t_R)\,(^1\!/_{T-t})\,CSales$	0.027**
	(0.012)
3m $\times \mathbf{1}(T > t_R)\,(^1\!/_{T-t})\,CBuys$	-0.035
	(0.037)
3m $\times \mathbf{1}(T > t_R)\,(^1\!/_{T-t})\,CSales$	0.112***
	(0.009)
Difference in coefficients	
Buys: month 1 - month 2	0.049
F-value	(0.33)
Buys: month 1 - month 3	-0.149*
F-value	(3.14)
Buys: month 2 - month 3	-0.198***
F-value	(10.47)
Sales: month 1 - month 2	-0.111***
F-value	(23.59)
Sales: month 1 - month 3	-0.196***
F-value	(103.53)
Sales: month 2 - month 3	-0.085***
F-value	(24.17)
Maturity Pol.	Yes
Signal × maturity pol.	Yes
Learning pol.	Yes
Fixed effects	Day × firm
Adjusted R2	0.951
Obs	3,039,877

L Alternative measures of earnings informativeness and prior signals

Figure 3 shows that our measure of earnings announcement informativeness correlates significantly with previous measures proposed in the literature. Some of these measures (PW and DJKS) are daily and ex-ante measures. As a consequence, we can use them to test the effect of signals observed before the announcement and check if our main results emanate from our new measure and estimating method or whether they are robust to other measures. As mentioned before, these measures implicitly assume a flat term structure and are computed just using the information of a given firm-day. Although, at first sight, the last feature looks like an advantage, in practice, it leads to very noisy measures of earnings announcement informativeness as we observe in Table L.1 in which we present the summary statistics of the two alternative measures. For instance, DJKS and PW estimates of earnings informativeness are negative more than 25% of day-firm pairs. We can see in Figure 3 that when aggregated at the firm or yearly level, they are mostly positive as the original papers show.

We construct these measures as described in Section I with the only exception of the measure proposed by PW for which we have changed the weekly change to a daily change to have a more timely measure of earnings informativeness. The unit of observation is the duple firm-day although some measures cannot be computed everyday. More precisely, the normalized measured by PW requires options that mature before and after the announcement, which constitutes a likely scenario. Additionally, the method by DJKS requires another option that matures after the announcement. Since we consider options with maturity below 90 days, days with two options maturing after the announcement and one before are far less common; hence, number of observations is lower. Likewise, there is a selection issue since three months before the announcement we cannot compute DJKS measure and we know the effect of the signals differ depending on the distance to the earnings announcement (see Figure 5 of the main paper).

Once we have the different daily measures of informativeness, which we label γ^{PW} and γ^{DJKS}, we estimate the following equation by OLS:

$$\gamma^j_{j;i,t+1} - \gamma^j_{j;i,t-1} = \alpha_j + \sum_a \gamma^-_{a,j} \Delta Downward^a_{i,t} + \gamma^+_{a,j} \Delta Upward^a_{i,t} + \delta_j \gamma^j_{j;i,t-1} + \varepsilon_{j;i,t} \qquad (3)$$

where the j subscript indicates which of the methods we consider (PW and DJKS) and the

Table L.1: Summary Statistics Alternative Measures (daily)

This table presents the summary statistics of the alternative measures of earnings announcement informativeness proposed by Dubinsky et al. (2019) (DJKS) and Patell and Wolfson (1979) (PW). These methods require a measure of implied volatility as input and we consider two nonparametric and one parametric.

Estimator	Obs	Mean	S.D.	P10	P50	P90
γ^{DJKS}	162,948	1.158	10.426	-9.129	2.128	10.272
γ^{PW}	370,206	-3.451	128.180	-112.827	1.131	100.551

subscripts i and t refer to the firm and trading date. $\Delta Upward^{a}_{i,t}$ is a dummy variable that takes the value 1 if agent a produces a positive signal, for instance if buys by corporate insiders of firm i reported on date t exceed, in value, sales by corporate insiders of the same firm reported on the same date. We purposely use a similar notation for the coefficient of these variables as the one for our main parameters in the main paper to emphasize their similarity. Concretely, γ_j^+ (γ_j^-) represents the change in the proportion of variance explained by the next earnings announcement attributed to an insider buy (sale). Lastly, if the informativeness of the announcement is not an integrated series of order one, the past level of informativeness affects the growth. We add the lag of the corresponding measure to control for this mechanism generated by mean-reversion.

Table L.2 presents the effect of the different signals. We observe that results are non robust. They not only change when we include the lag of the earnings informativeness but they also change from one measure to the other. The only significant result with both measures is the effect of insider sales.

Table L.2: Baseline Results using Alternative Measures

This table presents estimates of Equation (3) using the two alternative measures of earnings announcement informativeness proposed by Dubinsky et al. (2019) (DJKS) and Patell and Wolfson (1979) (PW). The implied volatility is computed using Bakshi et al. (2003). Standard errors are clustered at both the day and the firm level and presented in parentheses. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level respectively.

Estimator	(1) DJKS	(2) PW	(3) DJKS	(4) PW
Dep. var: Nonparametric implied volatility (Bakshi et al., 2003)				
Constant	0.567	-4.305**	0.615***	-4.634**
	(5.270)	(2.130)	(0.051)	(2.121)
$\Delta Fore^{+}$	-0.149	0.106	-0.135	-0.101
	(0.104)	(2.026)	(0.106)	(2.045)
$\Delta Fore^{-}$	-0.179	-2.859	-0.144	-2.706
	(9.307)	(2.061)	(0.093)	(2.064)
$\Delta Recom^{+}$	0.264*	-1.408	0.247	-2.024
	(0.157)	(3.352)	(0.159)	(3.330)
$\Delta Recom^{-}$	-0.081	0.974	-0.072	1.525
	(0.153)	(4.008)	(0.155)	(4.063)
$\Delta Buys$	-0.166	10.763	-0.213	10.152
	(72.315)	(12.567)	(0.731)	(12.605)
$\Delta Sales$	0.137	5.190**	0.173	5.383**
	(11.131)	(2.235)	(0.113)	(2.237)
Lagged Relevance	No	No	Yes	Yes
Ajusted R2	0.000	0.000	0.004	0.000
Obs.	81,312	188,235	80,272	187,244

M Unobserved heterogeneity in earnings announcement informativeness

In the main paper, we exploit the variation in announcement informativeness across firms and quarters. Nonetheless, it is possible that some of this variation is spurious. One robustness check we implement to support our finding is to estimate the model using an event study (Section J). In this section, we take a different approach by maintaining the same model but adding firm and fiscal quarter heterogeneity. Since the results are qualitatively the same, we exclude the heterogeneity from the main model because it adds another layer of complexity, which seems unnecessary. Moreover, there is no obvious reason why the number of insider trades would be higher for firms with high (or low) announcement informativeness besides the channels we propose in the main paper.

M.1 Firm heterogeneity

The first heterogeneity we consider is across firms. To implement this estimation, we estimate Equation (3) of the main paper but we interact the informativeness term $\left(\mathbf{1}\left(T > t_{R_{i,t}}\right)\left(\frac{1}{T-t}\right)\right)$ with firm-fixed effects. This specification provides an extra burden to the identification; nonetheless, the main conclusions of the analysis remain unchanged. We note that the economic magnitude of the effects of analysts forecasts and corporate insiders drops. Unfortunately, this specification does not allow to compute the proportion of informativeness that increases or decreases with the trades because the benchmark is firm-specific.

Table M.1: Earnings information disclosed by other signals: Firm heterogeneity

This table reports the results of the regression shown in Equation (3) complemented with the interaction of the informativeness term $\left(\mathbf{1}\left(T > t_{R_{i,t}}\right)\left(\frac{1}{T-t}\right)\right)$ and firm-fixed effects. The dependent variable is twice the log of implied volatily. Buys (Sales) is the number of days with net buying (selling) by corporate insiders since the last EA. $Forecast^{+}$ ($Forecast^{-}$) is the number of upward (downward) forecast revisions since the last EA. $Recom^{+}$ ($Recom^{-}$) is the number of upward (downward) recommendation revisions since the last EA. Standard errors are clustered at both the day and the firm-quarter level and presented in parentheses. Table 6 describes the variables. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level respectively.

Dep. var.: implied vol.	(1)	(2)	(3)	(4)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Forecast^{+}$	-0.018***		-0.011*	-0.013**
	(0.006)		(0.006)	(0.006)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Forecast^{-}$	-0.035***		-0.028***	-0.026***
	(0.004)		(0.004)	(0.004)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Recom^{+}$		-0.072***	-0.068***	-0.066***
		(0.011)	(0.011)	(0.010)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Recom^{-}$		-0.085***	-0.075***	-0.070***
		(0.020)	(0.020)	(0.020)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Buys$				-0.038***
				(0.014)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Sales$				0.020***
				(0.004)
Maturity pol.	Yes	Yes	Yes	Yes
Signal × maturity pol.	Yes	Yes	Yes	Yes
Learning pol.	Yes	Yes	Yes	Yes
Firm × info.	Yes	Yes	Yes	Yes
Fixed effects	Day × firm	Day × firm	Day × firm	Day × firm
Ajusted R2	0.954	0.954	0.954	0.955
Obs.	3,039,877	3,039,877	3,039,877	3,039,877

M.2 Fiscal quarter heterogeneity

The second dimension of heterogeneity we consider is across fiscal quarters. The information content of fourth-quarter announcements might differ from interim announcements, because, for example, more information is released together the full fiscal year results. Conversely, interim quarter results are typically released in a more timely fashion. Further, differences can also arise because of greater manager discretion over interim-period cost formulations, potentially allowing them to defer bad news (e.g., Mendenhall and Nichols, 1988). Table M.2 splits the analysis by fiscal quarter and indicates that the main effects persist within each of the four quarters. The only notable difference we observe is that downward analyst recommendations are more informative about earnings in the fourth quarter relative to interim quarters, as the economic nearly doubles.

Table M.2: Trades by insiders and the informativeness of earnings announcements

This table shows the results of the regression on column (3) of Table 3 in the main paper where we split the sample into interim quarters and the fourth quarter. Standard errors are clustered at both the day and the firm-quarter level and presented in parentheses. Table 6 describes the variables. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level respectively.

Dep. var.: implied vol.	(1)	(2)
Quarter	Interm	Fourth quarter
$\frac{\mathbf{1}(T > t_R)}{T-t}$	2.427***	2.615***
	(0.038)	(0.061)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Forecast^{+}$	-0.048***	-0.057***
	(0.007)	(0.010)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Forecast^{-}$	-0.058***	-0.052***
	(0.005)	(0.007)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Recom^{+}$	-0.047***	-0.059**
	(0.018)	(0.028)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Recom^{-}$	-0.047**	-0.088***
	(0.019)	(0.031)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Buys$	-0.111***	-0.130***
	(0.026)	(0.044)
$\frac{\mathbf{1}(T > t_R)}{T-t} \times Sales$	0.052***	0.046***
	(0.005)	(0.009)
Maturity pol.	Yes	Yes
Signal × maturity pol.	Yes	Yes
Learning pol.	Yes	Yes
Firm × info.	Yes	Yes
Fixed effects	Day × firm	Day × firm
Ajusted R2	0.954	0.954
Obs.	3,039,877	3,039,877

References

G. Bakshi, N. Kapadia, and D. Madan. Stock return characteristics, skew laws, and the differential pricing of individual equity options. *Review of Financial Studies*, 16(1):101–143, 2003.

W. H. Beaver, M. F. McNichols, and Z. Z. Wang. The information content of earnings announcements: New insights from intertemporal and cross-sectional behavior. *Review of Accounting Studies*, 23:95–135, 2018.

K. Chapman. Earnings notifications, investor attention, and the earnings announcement premium. *Journal of Accounting and Economics*, 66(1):222–243, 2018.

K. Demeterfi, E. Derman, M. Kamal, and J. Zou. More than you ever wanted to know about volatility swaps. *Goldman Sachs Quantitative Strategies Research Notes*, 41:1–56, 1999.

J. Driessen, P. J. Maenhout, and G. Vilkov. The price of correlation risk: Evidence from equity options. *The Journal of Finance*, 64(3):1377–1406, 2009.

A. Dubinsky, M. Johannes, A. Kaeck, and N. J. Seeger. Option pricing of earnings announcement risks. *Review of Financial Studies*, 32(2):646–687, 2019.

L. R. Glosten and P. R. Milgrom. Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of Financial Economics*, 14(1):71 – 100, 1985.

R. D. Gordon. Values of mills' ratio of area to bounding ordinate and of the normal probability integral for large values of the argument. *Ann. Math. Statist.*, 12(3):364–366, 09 1941.

T. L. Johnson and E. C. So. Time will tell: Information in the timing of scheduled earnings news. *Journal of Financial and Quantitative Analsysis*, 53(6):2431 – 2464, 2018.

R. R. Mendenhall and W. D. Nichols. Bad news and differential market reactions to announcements of earlier-quarters versus fourth-quarter earnings. *Journal of Accounting Research*, 26: 63–86, 1988.

J. M. Patell and M. A. Wolfson. Anticipated information releases reflected in call option prices. *Journal of Accounting and Economics*, 1(2):117–140, 1979.

J. M. Patell and M. A. Wolfson. The ex ante and ex post price effects of quarterly earnings announcements reflected in option and stock prices. *Journal of Accounting Research*, 19(2): 434–458, 1981.

L. Villacorta. Robust standard errors to spatial and time dependence when neither n nor t are very large. Technical report, CEMFI, Mimeo, 2015.