Internet Appendix to "Trading by Insiders and the Informativeness of Earnings Announcements"

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Section A compares our measure of informativeness with alternative ones. Section B performs a simulation analysis, in which we randomly allocate purchases and sales, in order to derive a benchmark for the results when trades are uninformative by design. Section C examines how the estimates evolve over an increasing number of purchases and sales. In Section D we take an event study approach, restricting attention to the days around the respective insider transaction. Section E discusses the different implied volatility measures and investigates the sensitivity of the results with respect the choice of this measure. Section F describes how we filter EDGAR log files. Section G present the results of the joint estimation of the analyst and insider effect, and the effect of 13D filings and insiders. To estimate how the informativeness of earnings announcement changes with negative corporate news more generally, Section H studies large negative daily returns. Section I distinguishes opportunistic and routine trades. Section J differentiates between trades that are reported with a larger or smaller delay relative to the trading date. Section K examines how the results might be affected by using expected rather than actual earnings announcement dates. We control for potential heterogeneity in Section L. Section M examines results in the cross-section of option liquidity. Section N shows the regression tables that underlie the figures in the paper.

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A Comparison with other informativeness measures

A.1 Alternative measures

One of the contributions of the paper is to suggest a forward looking measure of earnings announcement informativeness that can be easily related to daily variables and is valid under mild assumptions. In Figure A.1, we compare our measure of earnings announcement informativeness with alternative measures across different firms and across different years. Each row of subfigures refers to a different alternative measure out of the three we consider: the option-based measures by Patell and Wolfson (1981) (PW) and Dubinsky et al. (2019) (DJKS), and the ex-post measure based on abnormal returns proposed by Beaver et al. (2018) (TCU). The left graph scatters the alternative measure computed for every firm in the sample for which we have at least 20 earnings announcements against our proposed measure. On the other side, we plot the yearly median of each measure. In general, every measure correlates significantly with our proposed measure and they share the same time-series pattern, which provides support to our measure. The rest of the section describes how we construct each measure and how to interpret the differences with our measure. Finally, we estimate the effect of insider trading using the alternative measures.

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

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

where subscripts i, t, T denote firm, time, and maturity; and the subscript a_i emphasizes that we estimate it per announcement. 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_i} is the informativeness of the earnings announcement a as a proportion of the annual variance. Then, we use the median of the estimates of γ^{a_i} for a given firm to construct the scatter plots, and the median of the same estimates by year to construct the time-series plots. Note that this modeling is much more general and robust than the baseline model because it considers a different term structure ($\lambda_j^{a_i}$) per announcement. Yet, the results are very similar.

As explained in the main text, 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 the 90 days before an earnings announcement and across all expiration dates after the announcement. 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.

In the scatter plot we observe that both measures are highly correlated (65.6%). Nonetheless, the time-series estimator is on average 1.5 times higher than our estimator. Besides, this estimator provides several negative informativeness estimates while there is only one using our proposed estimator. The line graph provides more insight on how this estimator works. We observe how in 2008 as volatility raised, this estimator doubled, this is due to the peak in market volatility and not necessarily due to more informative earnings announcements. Due to the mean reversion of volatility, volatility decreased during 2009 leading to even a negative estimated informativeness of the 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.

The scatter plot shows that this measure closely resembles our measure, indeed their correlation is 78.6%. Moreover, we observe that there are very few firms with negative earnings announcements. In the time-series graph, we observe a peak in 2008 as we did in the previous case but of smaller magnitude. This peak arises because after the huge jump in volatility in 2008, investors expected a reversion; therefore, we observe a steep downward sloping term-structure.

As discussed in the main text, a downward sloping term structure leads to a positive bias in the measure proposed by DJKS.

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.

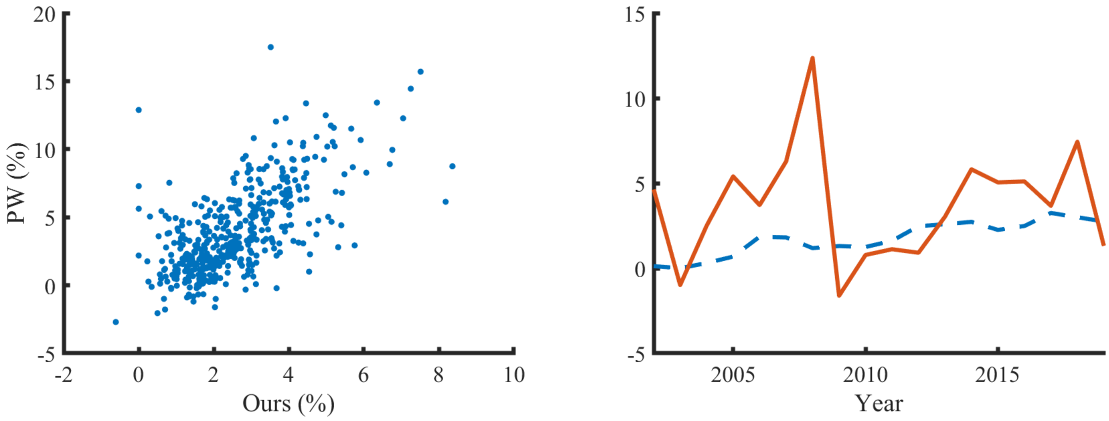
Finally, we subtract one to make it comparable to the other measures. The interpretation is similar to our γ since it is the ratio of the squared abnormal return on the announcement date over the idiosyncratic variance. The main difference is that this measure focuses on the idiosyncratic part while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

Although calculated ex-post, the measure correlates strongly with our ex-ante measure (63.5%). However, their magnitudes are hard to compare. The time-series plot replicates the increasing trend found by Beaver et al. (2018) and shows that informativeness kept increasing after the end of their sample period (December 2011). A very similar pattern arises using our measure.

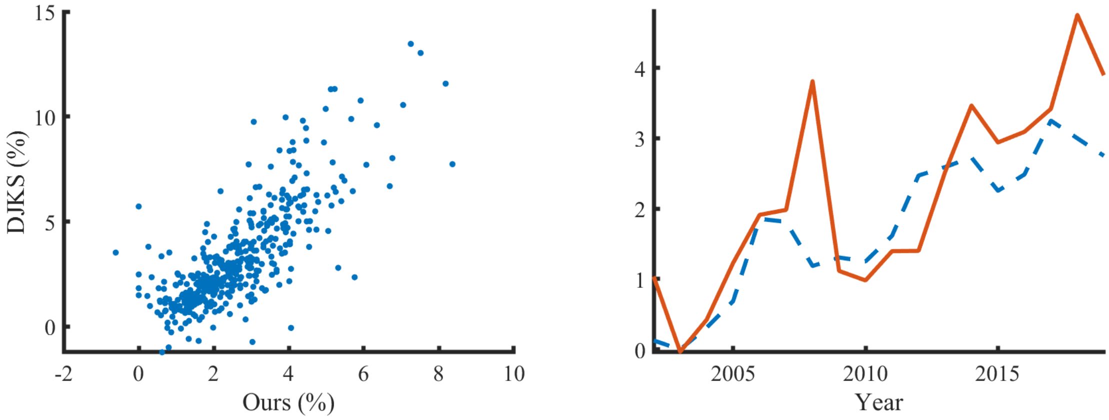
Figure A.1: Comparison earnings announcement informativeness measures

Left-hand figures plot the median informativeness of earnings announcement for each firm according to alternative measures (y-axis) with respect to the measure we use in the paper (x-axis). Right-hand figures plot the median informativeness per year using three different measures (solid orange line) and our measure as benchmark (dashed blue line).

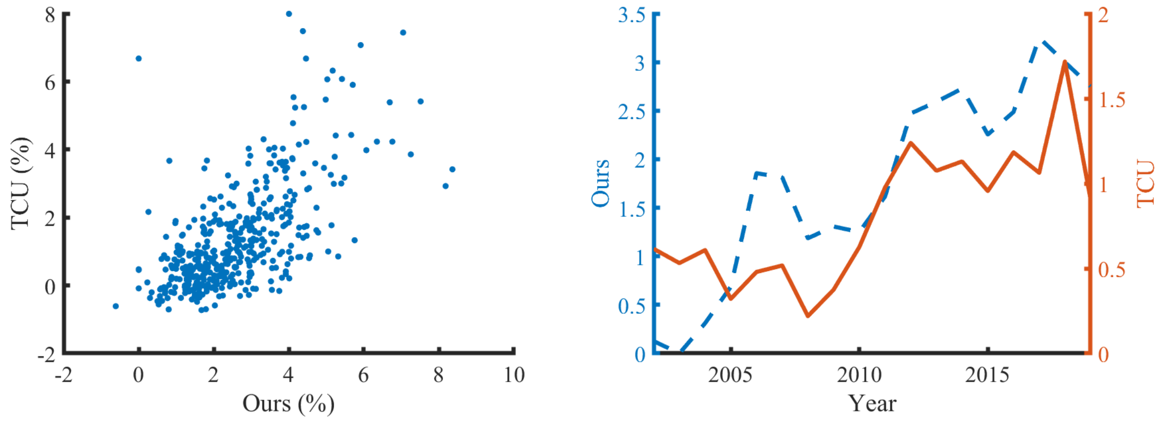
Option-based measure by Patell and Wolfson (1981)



Option-based measure by Dubinsky et al. (2019)



Expost measure by Beaver et al. (2018)



A.2 Alternative measures and insider trading

We have demonstrated 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 exante measures; hence, we can use them to test the effect of insider trading and check if our main results emanate due to our new measure and estimating method or they are robust to other measures. As commented before, these measures assume, implicitly, 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 A.1 in which we present the summary statistics of the two measures constructed as described at the beginning of the section. The only exception is 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. 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 without two options maturing after the announcement and one before are common; hence, the lower number of observations.

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

$$\gamma^j_{i,t+1} - \gamma^j_{i,t-1} = \alpha^j + \gamma^j_S \mathbf{1}\{Sale_{i,t}\} + \gamma^j_B \mathbf{1}\{Buy_{i,t}\} + \delta^j \gamma^j_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

where the j superscript indicates which of the methods we consider (PW and DJKS) and the subscripts i and t refer to the firm and trading date. $\mathbf{1}\{Sale_{i,t}\}$ ($\mathbf{1}\{Buy_{i,t}\}$) is a dummy variable that takes the value 1 if sales (buys) by corporate insiders of firm i reported on date t exceed, in value, buys (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 text to emphasize their similarity. Concretely, γ^j_B (γ^j_S) 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

Table A.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
Dep. var: Nonparametric implied volatility (Bakshi et al., 2003)						
γ^{DJKS}	156,290	1.168	10.294	-9.070	2.086	10.309
γ^{PW}	350,655	-3.326	129.283	-113.732	1.192	101.679
Dep. var: Nonparametric implied volatility (Demeterfi et al., 1999)						
γ^{DJKS}	156,290	1.654	8.407	-5.409	2.004	8.403
γ^{PW}	350,655	-1.396	110.956	-93.220	2.233	86.711
Dep. var: Parametric implied volatility by OptionMetrics						
γ^{DJKS}	156,290	3.047	6.532	-1.894	2.746	8.801
γ^{PW}	350,655	-3.805	112.200	-105.442	1.253	93.633

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 A.2 presents the results of the estimation using different volatility estimators. Across specifications, the effect confirms the sign of our findings: sales increase the informativeness of earnings announcements while buys decrease it. Moreover, the magnitude of the estimates based on DJKS is of the same order of magnitude as the results in the text although they are mainly statistically insignificant. The magnitude of the estimates based on PW are one or two orders of magnitude higher than the ones we report in the main text.

Table A.2: Baseline Results using Alternative Measures

This table presents estimates of equation 1 using the two alternative measures of earnings announcement informativeness proposed by Dubinsky et al. (2019) (DJKS) and Patell and Wolfson (1979) (PW). 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 (α)	0.502***	-0.709	0.941***	-3.464***
	(0.043)	(1.604)	(0.054)	(1.124)
$\mathbf{1}\{buy\}$ (γ_B)	-0.021	-0.555	-0.911**	3.563
	(0.646)	(9.184)	(0.451)	(5.272)
$\mathbf{1}\{sell\}$ (γ_S)	0.099	6.250***	0.281**	3.328***
	(0.109)	(1.866)	(0.112)	(1.225)
Ajusted R2	-0.000	0.000	0.288	0.547
Obs.	136,445	310,620	136,445	310,620
Dep. var: Nonparametric implied volatility (Demeterfi et al., 1999)				
Constant (α)	0.461***	-0.857	1.125***	-1.441
	(0.043)	(1.467)	(0.056)	(1.026)
$\mathbf{1}\{buy\}$ (γ_B)	-0.128	-3.371	-0.903**	-0.064
	(0.538)	(5.623)	(0.370)	(3.842)
$\mathbf{1}\{sell\}$ (γ_S)	0.180*	6.160***	0.282***	3.583***
	(0.095)	(1.504)	(0.094)	(1.014)
Ajusted R2	0.000	0.000	0.206	0.499
Obs.	136,445	310,620	136,445	310,620
Dep. var: Parametric implied volatility by OptionMetrics				
Constant (α)	0.184***	0.566	1.773***	-2.993***
	(0.020)	(1.618)	(0.091)	(1.103)
$\mathbf{1}\{buy\}$ (γ_B)	-0.940**	-0.202	-1.485***	2.744
	(0.393)	(5.596)	(0.305)	(4.336)
$\mathbf{1}\{sell\}$ (γ_S)	-0.081	3.993***	0.207**	3.763***
	(0.092)	(1.532)	(0.087)	(1.034)
Lagged Relevance	No	No	Yes	Yes
Ajusted R2	0.000	0.000	0.356	0.581
Obs.	136,445	310,620	136,445	310,620

B Simulation analysis

We acknowledge that the asymptotic distribution of the estimator that we use in the paper assumes that the the firm-date fixed effects and the two-way cluster variance take into account correctly 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 of no effect. Since we would like to maintain the properties of the implied volatility across time, we kept the sample implied volatility and we randomly assign purchases and sales to trading days, keeping the total number of sales and purchases fixed. We repeat the process 1,000 times to create 1,000 placebo samples. Due to the low incidence of insider trades, these samples closely represent samples in which insiders have no effect on earnings announcement informativeness. 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 methods lies on 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.

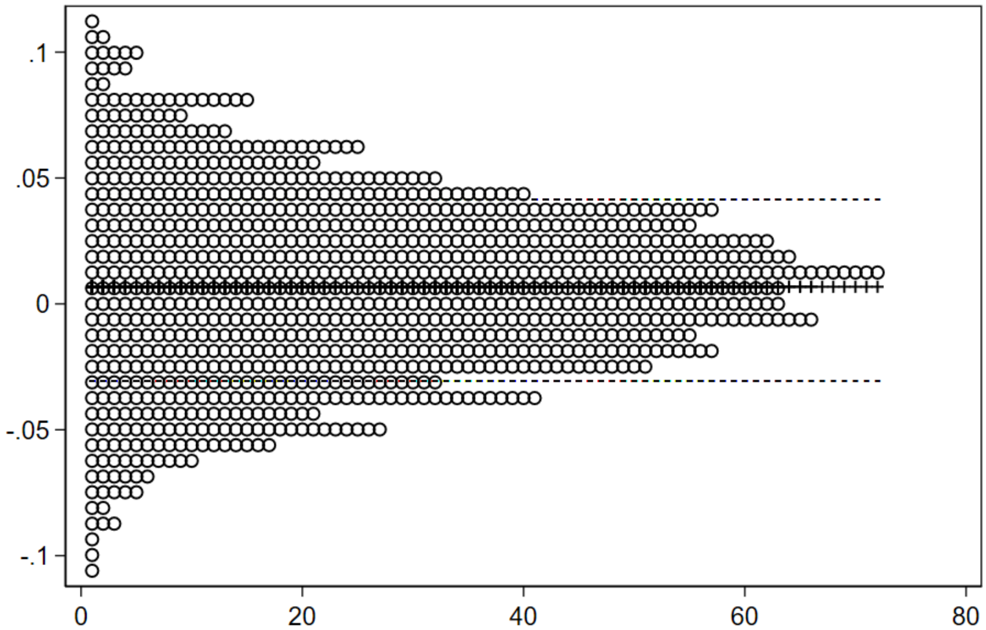
Figure B.1 shows the empirical distribution under the null hypothesis of the baseline estimators, $\widehat{\gamma_B}$ and $\widehat{\gamma_S}$, whose estimates we present in column (3) of Panel A of Table 3. The mean value of $\widehat{\gamma_B}$ is 0.007, while the mean value of $\widehat{\gamma_S}$ is 0.004. These values are close to zero and much smaller than the estimates we observe for the actual timing of insider purchases and insider sales. We interpret these results as evidence that our estimators are indeed unbiased. More importantly, the p-value of our estimates (-0.141 and 0.057) using the simulated distribution is zero, consistent with the highly significance that we report in the main analysis.

Next, in Figure B.2 we repeat the same analysis, while we are not using the cumulative number of purchases or sales, but a dummy variable indicating the presence of insider purchases or sales respectively. Thus, the estimator corresponds to the one presented in column (3) of Panel B of Table 3. The average values are 0.004 for $\widehat{\gamma_B}$ and 0.035 for $\widehat{\gamma_S}$. Once again, the p-value of our estimates (-0.359 and 0.298) is zero.

Figure B.1: Simulated distribution under the null of no effect of insiders (Counting process)

This figure shows the estimates of γ_B (Panel A) and γ_S (Panel B). The dots are based on simulating insider purchases and sales 1,000 times and repeating the analysis in the last column of Panel A of Table 3. The black crosses indicate the respective mean value of $\widehat{\gamma_B}$ and $\widehat{\gamma_S}$, while the distance from the mean to the dotted lines show one standard derviation.

Panel A: Distribution of $\widehat{\gamma_B}$



Panel B: Distribution of $\widehat{\gamma_S}$

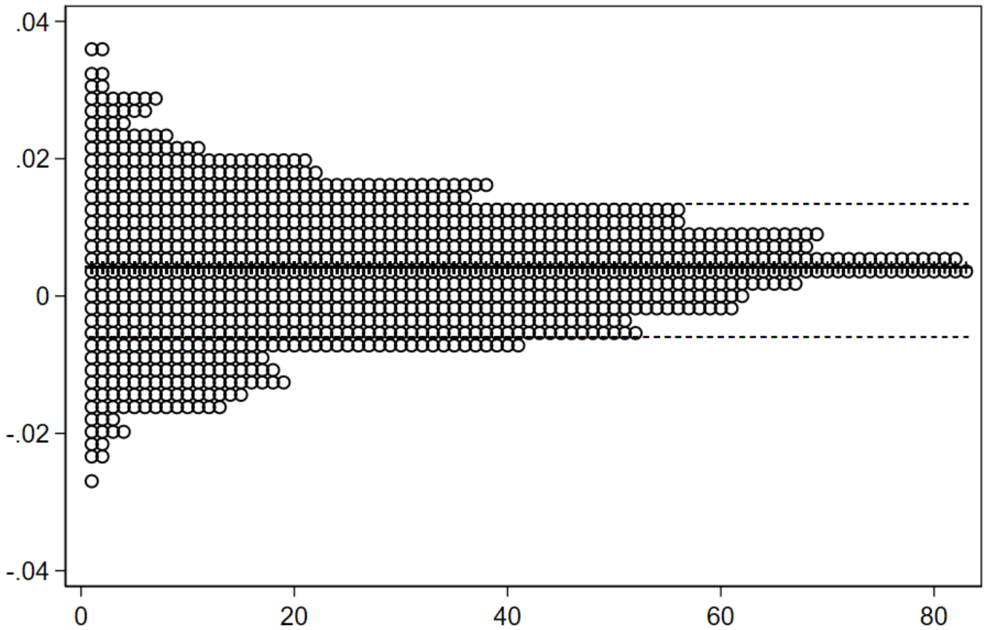
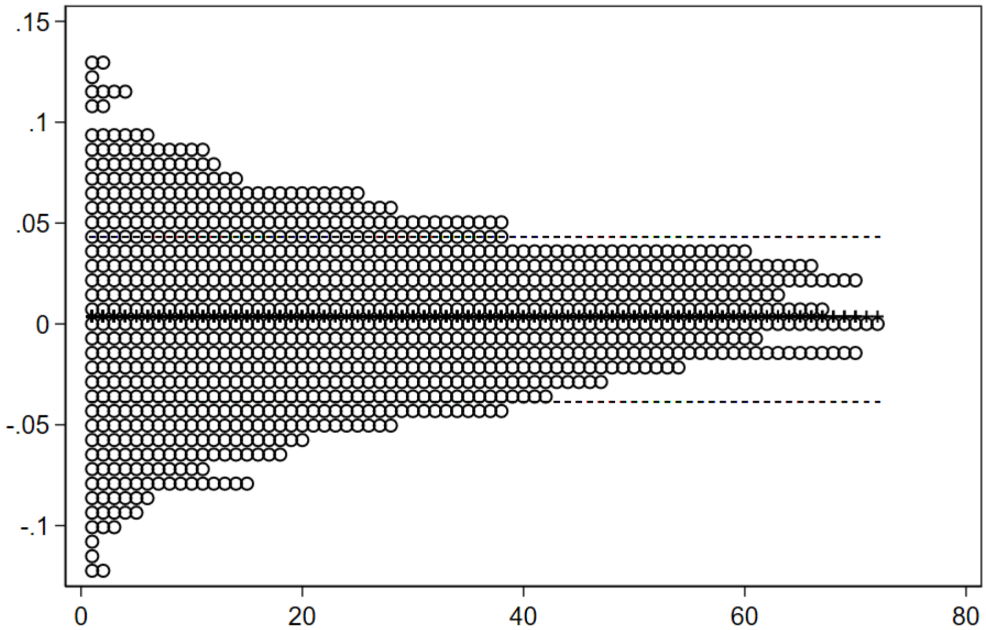


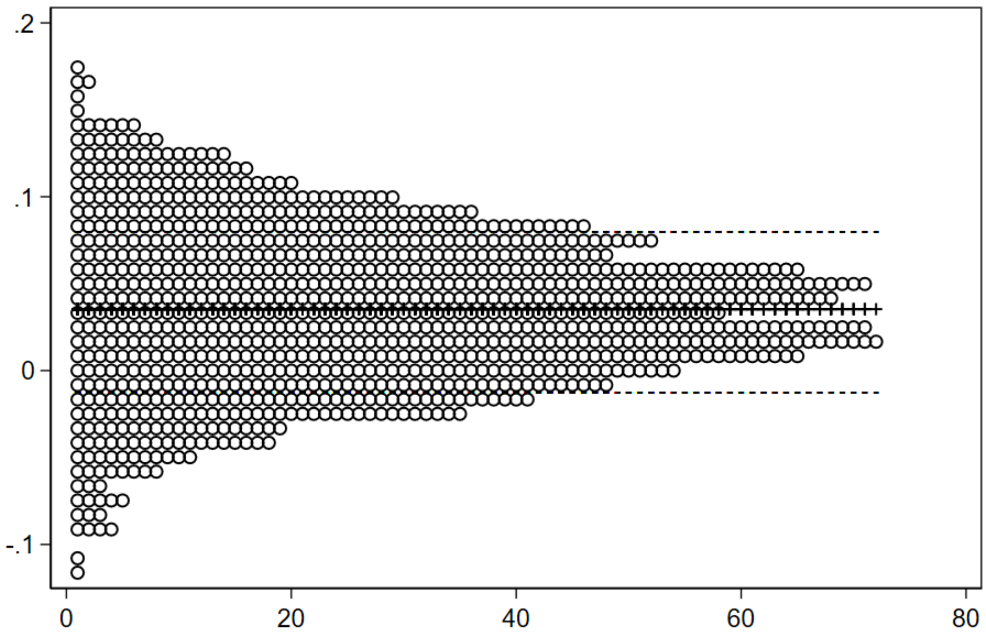
Figure B.2: Simulated distribution under the null of no effect of insiders (Dummy variable)

This figure shows the estimates of γ_B (Panel A) and γ_S (Panel B). The dots are based on simulating insider purchases and sales 1,000 times and repeating the analysis in the last column of Panel A of Table 3. The black crosses indicate the respective mean value of $\widehat{\gamma_B}$ and $\widehat{\gamma_S}$, while the distance from the mean to the dotted lines show one standard derviation.

Panel A: Distribution of $\widehat{\gamma_B}$



Panel B: Distribution of $\widehat{\gamma_S}$



C Evolution with number of purchases and sales

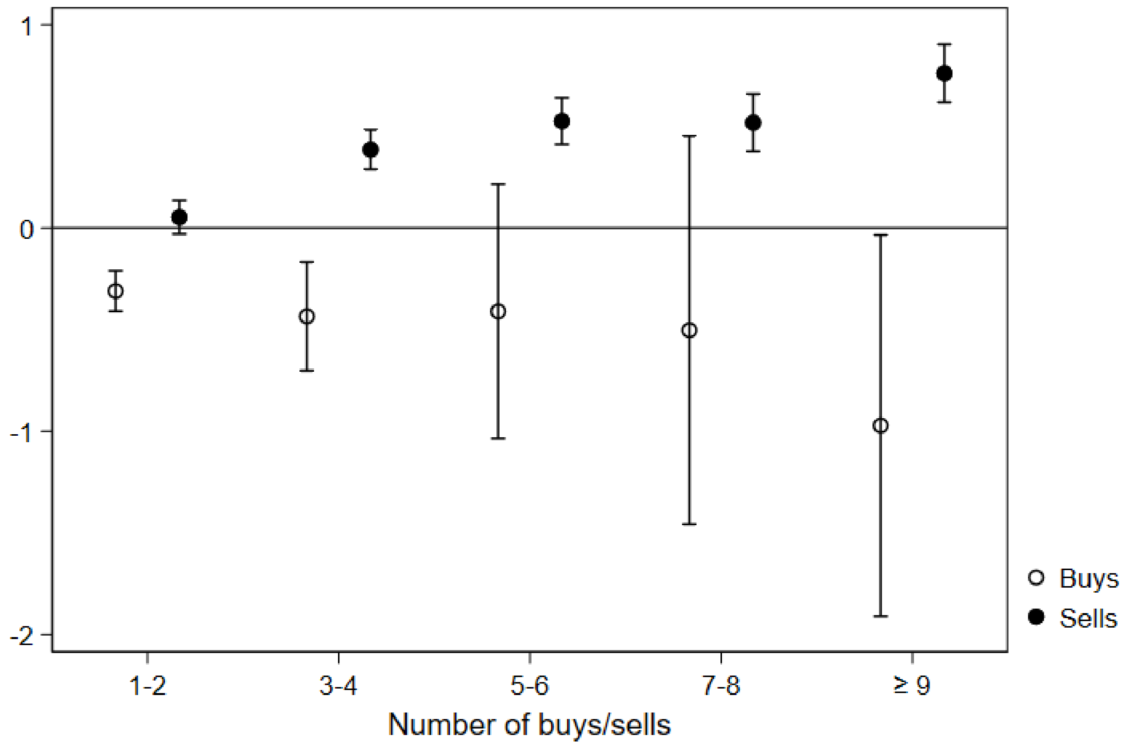
Each quarter, we might observe several buys and sales by insiders of the same firm. In the paper, we take two different approaches, the first one consists of using a counting process leading to the implicit assumption that every sale or buy has the same effect. If this assumption is not true, we would recover an average effect. The second one consists of including in the model a dummy that takes value one after the first buy or sale, which corresponds to the total average effect of insider transactions. These are the two extremes. In this section, we divide the transactions depending on their order within a quarter and estimate the same model as in column (3) of Panel B of Table 3 but including several dummies depending if the sale is the first sale, one of the first three sales, one of the first five sales, etc. We use the same procedure with purchases.

In Figure C.1 we examine how the effect evolves with the number of purchases and sales. In line with a signal mechanism, we find an increasing and concave pattern in the effect of sales. It suggests that observing one or two sales represents a weak signal as it is not a rare scenario while observing three or four reveal significant information. Finally, from the fifth to the eight sale, the market extracts very few information and, only if the number of sales keeps increasing, the informativeness of the announcement increases more. The case of buys is similar but, due to their rarity, a single buy is already a strong signal. Several buys convey more information; however, we lose too much statistical power because there are extremely few quarters with numerous insider buys.

Finally, it is worth mentioning that these results indicate a much stronger effect than the baseline estimation. This fact is due to the high number of quarters with few sales, which lower the average effect significantly.

Figure C.1: EA and insider trading: number of purchases and sells

The hollow dots shows the estimate of γ_B and the 95% confidence intervals depending on the number of past transactions since the last earnings announcement, while the solid dots show the estimate of γ_S depending on the number of transactions. Standard errors are clustered at both the day and the firm-quarter level.



D Event study analysis

The analysis in the main text uses the whole time series of each firm to estimate the effect of insiders' sales and buys. The benefits of this approach are twofold. First, we obtain more precise estimates by including more data. Second, the model accommodates sales and buys of the same stock in subsequent days. In an event study jargon, the pre-event period length varies depending on when was the last transaction 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 sales doubles the effect of one (see Section C). Second, we consider that our measure of informativeness remains similar across days and firms. These concerns become really 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 wrongly conclude that sales increase the earnings informativeness.

To take into account the different frequency of transactions 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 insider transaction as $\tau = 0$ and include in the final sample the implied volatility of the firm transacted only for the days such that $|\tau| \leq \overline{\tau}$, where $\overline{\tau} \in \{1, 2, 5, 10\}$ depending on the specification. Then, we estimate by OLS:

$$2log(IV_e, \tau, T) = \delta_{e,\tau} + \frac{\mathbf{1}\{T > t_{R_{i,t}}\}}{T-t}\Big(\gamma + 1\{\tau \geq 0\}(\gamma_B(1 - \mathbf{1}\{Sell_e\}) + \gamma_S \mathbf{1}\{Sell_e\})\Big) \qquad (2)$$
$$+ \sum_{j=1}^{2} \lambda_j (T-t)^{j/2} + \frac{\mathbf{1}\{T > t_{R_{i,t}}\}}{T-t} \sum_{j=1}^{2} \theta_j (t_R - t)^{j/2} + \varepsilon_{e,\tau,T}$$

where e indexes the events and τ is the event time. $\mathbf{1}\{Sell_e\}$ is a dummy variable that takes value one if the event is a sale and zero if it is a buy. 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 D.1 shows that the baseline informativeness and the effect of sales are very similar to the ones resulting from our main analysis. The effect of buys is qualitatively the same but one order of magnitude stronger.

Table D.1: Event study approach

This table compiles the estimate of equation 2, which mimics the method in the main text but restricts the sample to the days around insider trades. 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.

Estimator	(1) $\overline{\tau}=1$	(2) $\overline{\tau}=2$	(3) $\overline{\tau}=5$	(4) $\overline{\tau}=10$
Dep. var: Nonparametric implied volatility (Bakshi et al., 2003)				
$\frac{\mathbf{1}\{T>t_{R_{i,t}}\}}{T-t}$ (γ)	2.357***	2.262***	2.137***	2.382***
	(0.090)	(0.080)	(0.081)	(0.085)
$\frac{\mathbf{1}\{T>t_{R_{i,t}}\}}{T-t} \times \mathbf{1}\{\tau \geq 0\} \times \mathbf{1}\{buy\}$ (γ_B)	-1.222***	-1.198***	-1.380***	-1.168***
	(0.148)	(0.136)	(0.145)	(0.137)
$\frac{\mathbf{1}\{T>t_{R_{i,t}}\}}{T-t} \times \mathbf{1}\{\tau \geq 0\} \times \mathbf{1}\{sell\}$ (γ_S)	0.047**	0.054***	0.064***	0.033*
	(0.018)	(0.017)	(0.018)	(0.019)
Ajusted R2	0.952	0.952	0.951	0.951
Obs.	501,009	832,852	1,805,432	3,436,925
Dep. var: Nonparametric implied volatility (Demeterfi et al., 1999)				
$\frac{\mathbf{1}\{T>t_{R_{i,t}}\}}{T-t}$ (γ)	2.285***	2.157***	2.242***	2.150***
	(0.075)	(0.076)	(0.074)	(0.065)
$\frac{\mathbf{1}\{T>t_{R_{i,t}}\}}{T-t} \times \mathbf{1}\{\tau \geq 0\} \times \mathbf{1}\{buy\}$ (γ_B)	-1.155***	-1.387***	-1.121***	-1.115***
	(0.128)	(0.141)	(0.119)	(0.112)
$\frac{\mathbf{1}\{T>t_{R_{i,t}}\}}{T-t} \times \mathbf{1}\{\tau \geq 0\} \times \mathbf{1}\{sell\}$ (γ_S)	0.039**	0.051***	0.078***	0.077***
	(0.017)	(0.018)	(0.018)	(0.017)
Ajusted R2	0.961	0.961	0.961	0.960
Obs.	501,009	832,852	1,805,432	3,436,925
Dep. var: Parametric implied volatility by OptionMetrics				
$\frac{\mathbf{1}\{T>t_{R_{i,t}}\}}{T-t}$ (γ)	2.006***	1.955***	1.879***	1.720***
	(0.066)	(0.054)	(0.047)	(0.046)
$\frac{\mathbf{1}\{T>t_{R_{i,t}}\}}{T-t} \times \mathbf{1}\{\tau \geq 0\} \times \mathbf{1}\{buy\}$ (γ_B)	-1.331***	-1.071***	-1.075***	-1.270***
	(0.119)	(0.107)	(0.100)	(0.103)
$\frac{\mathbf{1}\{T>t_{R_{i,t}}\}}{T-t} \times \mathbf{1}\{\tau \geq 0\} \times \mathbf{1}\{sell\}$ (γ_S)	0.087***	0.162***	0.152***	0.161***
	(0.018)	(0.020)	(0.018)	(0.018)
Ajusted R2	0.971	0.971	0.971	0.970
Obs.	501,009	832,852	1,805,432	3,436,925

E 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 VIX computation, 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 the same main 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.

(2013). 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, 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, as it is usual in 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:

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

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

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

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

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

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

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

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 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 alternate 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 insider trading. Nonetheless, to avoid extreme noisy observations, we drop those firm-date-maturity triplets 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 compute 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 owns the highest Vega and, therefore, its price is the most affected by the earnings announcement risk. As a consequence, the identification would be cleaner.

The second disadvantage is the parametric assumption. The abovementioned papers assumed the Black-Scholes model holds, at least to some extent. However, if insiders exploit their private information, 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 the wrong conclusions in the presence of informed traders. In particular, we show that the implied volatility computed using Black-Scholes increases after insiders trade, 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 he 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, it is idiosyncratic to the firm.

Due to risk-neutrality, the informed investor always trade. 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). □

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,

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

□

This example illustrates the problem of using Black-Scholes in an extreme setting. The more symmetric is the posterior signal received from the trade, the more reliable is Black-Scholes. There are many missing ingredients that would contribute to relax 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.

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

The first column of this table repeats the fourth column of Table E.1 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	Restricted BKM	Restricted DDKZ	Restricted OptionMetrics	Whole OptionMetrics
$\mathbf{1}(T > t_R)\dfrac{1}{T-t}$ (γ)	2.370***	2.219***	2.206***	1.978***
	(0.024)	(0.022)	(0.021)	(0.018)
Maturity pol.	Yes	Yes	Yes	Yes
Learning pol.	No	No	No	Yes
Fixed Effects	No	Day × firm	Day × firm	Day × firm
Ajusted R2	0.953	0.964	0.971	0.940
Obs.	2,928,937	2,928,937	2,928,937	5,592,397

Table E.2: Insider trading and EA informativeness: Alternative measures of implied volatility

This table shows the results of a regression of implied volatility on corporate insider purchases and sales. Panel A uses a dummy variable for insider buys and sells which is set to 1 for the first insider purchase (sale) after the last quarterly earnings announcement, and to 0 in case there has been no insider buy (sell) since the last earnings announcement. Panel B uses the cumulative number of buys and sells, respectively, since the last quarterly earnings announcement instead of the dummy. Column 1 estimates implied volatility according to Demeterfi et al. (1999), and column 2 uses the implied volatility of the closest to at-the-money option provided by OptionMetrics, while we restrict attention to observations for which we can calculate our standard measure of implied volatility according to Bakshi et al. (2003). Column 3 uses the same measure as column 2 and the whole sample. 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.

Panel A: Number of insider purchases and sales

Dep. var.: implied volatility Sample Measure	(1) Restricted DDKZ	(2) Restricted OptionMetrics	(3) Whole OptionMetrics
$\mathbf{1}(T > t_R)\frac{1}{T-t}(\gamma)$	2.112***	2.082***	1.677***
	(0.025)	(0.025)	(0.023)
$\mathbf{1}(T > t_R)\frac{1}{T-t}CBuys\,(\gamma_B)$	-0.136***	-0.143***	-0.100***
	(0.021)	(0.022)	(0.016)
$\mathbf{1}(T > t_R)\frac{1}{T-t}CSales\,(\gamma_S)$	0.056***	0.066***	0.077***
	(0.004)	(0.004)	(0.004)
Maturity pol.	Yes	Yes	Yes
IT maturity pol.	Yes	Yes	Yes
Learning pol.	Yes	Yes	Yes
Fixed effects	Day × firm	Day × firm	Day × firm
Adjusted R2	0.964	0.971	0.943
Obs	2,928,937	2,928,937	5,592,397

Panel B: Dummy for insider purchases and sales

Dep. var.: implied volatility Sample Measure	(1) Restricted DDKZ	(2) Restricted OptionMetrics	(3) Whole OptionMetrics
$\mathbf{1}\left(T > t_R\right) \frac{1}{T-t} \left(\gamma\right)$	2.101***	2.049***	1.555***
	(0.032)	(0.032)	(0.030)
$\mathbf{1}\left(T > t_R\right) \frac{1}{T-t} Buy \left(d\right)$	-0.345***	-0.348***	-0.274***
	(0.044)	(0.046)	(0.034)
$\mathbf{1}\left(T > t_R\right) \frac{1}{T-t} Sale \left(d\right)$	0.276***	0.340***	0.511***
	(0.033)	(0.034)	(0.030)
Maturity pol.	Yes	Yes	Yes
IT maturity pol.	Yes	Yes	Yes
Learning pol.	Yes	Yes	Yes
Fixed effects	Day × firm	Day × firm	Day × firm
Adjusted R2	0.964	0.971	0.942
Obs	2,928,937	2,928,937	5,592,397

Table E.3: Insider trading and firm characteristics: DDKZ

This table reports the results of the regression shown in the last column of Table 3 for the top 25% and bottom 25% of firms sorted according to certain characteristics at the year end. Panel E is an exception and sorts firms according to the existence of Universal Demand Laws in the state of incorporation. Column 3 tests the equality of the coefficient estimates for the low and high group. 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 Sample	(1) Low	(2) High	(3) Low - High
Panel A: insider filing demand on EDGAR			
$\mathbf{1}\,(T > t_R)\,(^1/_{T-t})\,CBuys\,(\gamma_B)$	-0.082*	-0.167***	0.086
	(0.043)	(0.042)	(0.059)
$\mathbf{1}\,(T > t_R)\,(^1/_{T-t})\,CSales\,(\gamma_S)$	0.050***	0.089***	-0.039**
	(0.007)	(0.015)	(0.016)
Panel B: stock return volatility			
$\mathbf{1}\,(T > t_R)\,(^1/_{T-t})\,CBuys\,(\gamma_B)$	-0.109**	-0.120***	0.011
	(0.047)	(0.031)	(0.056)
$\mathbf{1}\,(T > t_R)\,(^1/_{T-t})\,CSales\,(\gamma_S)$	0.038***	0.059***	-0.022*
	(0.010)	(0.008)	(0.012)
Panel C: share of idiosyncratic volatility			
$\mathbf{1}\,(T > t_R)\,(^1/_{T-t})\,CBuys\,(\gamma_B)$	-0.286***	-0.120***	-0.166***
	(0.037)	(0.036)	(0.052)
$\mathbf{1}\,(T > t_R)\,(^1/_{T-t})\,CSales\,(\gamma_S)$	0.050***	0.062***	-0.012
	(0.009)	(0.012)	(0.015)
Panel D: R&D			
$\mathbf{1}\,(T > t_R)\,(^1/_{T-t})\,CBuys\,(\gamma_B)$	-0.162***	-0.137***	-0.026
	(0.026)	(0.051)	(0.057)
$\mathbf{1}\,(T > t_R)\,(^1/_{T-t})\,CSales\,(\gamma_S)$	0.025***	0.039***	-0.014
	(0.008)	(0.005)	(0.010)
Panel E: litigation risk (states with Universal Demand Laws versus states without)			
$\mathbf{1}\,(T > t_R)\,(^1/_{T-t})\,CBuys\,(\gamma_B)$	-0.209**	-0.134***	-0.071
	(0.103)	(0.022)	(0.106)
$\mathbf{1}\,(T > t_R)\,(^1/_{T-t})\,CSales\,(\gamma_S)$	-0.046***	0.062***	-0.104***
	(0.015)	(0.004)	(0.016)
Day × firm	Yes	Yes	Yes
Maturity pol.	Yes	Yes	Yes
IT maturity pol.	Yes	Yes	Yes
Learning pol.	Yes	Yes	Yes

Table E.4: Insider trading and firm characteristics: OptionMetrics ATM

This table reports the results of the regression shown in the last column of Table 3 for the top 25% and bottom 25% of firms sorted according to certain characteristics at the year end. Panel E is an exception and sorts firms according to the existence of Universal Demand Laws in the state of incorporation. Column 3 tests the equality of the coefficient estimates for the low and high group. 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 Sample	(1) Low	(2) High	(3) Low - High
Panel A: insider filing demand on EDGAR			
$\mathbf{1}(T > t_R)\,(1/T-t)\,CBuys\,(\gamma_B)$	-0.092**	-0.177***	0.085
	(0.043)	(0.042)	(0.060)
$\mathbf{1}(T > t_R)\,(1/T-t)\,CSales\,(\gamma_S)$	0.062***	0.098***	-0.036**
	(0.007)	(0.015)	(0.017)
Panel B: stock return volatility			
$\mathbf{1}(T > t_R)\,(1/T-t)\,CBuys\,(\gamma_B)$	-0.081*	-0.129***	0.048
	(0.045)	(0.032)	(0.056)
$\mathbf{1}(T > t_R)\,(1/T-t)\,CSales\,(\gamma_S)$	0.042***	0.072***	-0.030**
	(0.009)	(0.008)	(0.012)
Panel C: share of idiosyncratic volatility			
$\mathbf{1}(T > t_R)\,(1/T-t)\,CBuys\,(\gamma_B)$	-0.259***	-0.136***	-0.123**
	(0.038)	(0.038)	(0.053)
$\mathbf{1}(T > t_R)\,(1/T-t)\,CSales\,(\gamma_S)$	0.062***	0.076***	-0.014
	(0.009)	(0.012)	(0.015)
Panel D: R&D			
$\mathbf{1}(T > t_R)\,(1/T-t)\,CBuys\,(\gamma_B)$	-0.170***	-0.131**	-0.039
	(0.028)	(0.054)	(0.060)
$\mathbf{1}(T > t_R)\,(1/T-t)\,CSales\,(\gamma_S)$	0.030***	0.048***	-0.018*
	(0.009)	(0.005)	(0.010)
Panel E: litigation risk (states with Universal Demand Laws versus states without)			
$\mathbf{1}(T > t_R)\,(1/T-t)\,CBuys\,(\gamma_B)$	-0.158	-0.144***	-0.008
	(0.100)	(0.022)	(0.103)
$\mathbf{1}(T > t_R)\,(1/T-t)\,CSales\,(\gamma_S)$	-0.040***	0.072***	-0.108***
	(0.015)	(0.005)	(0.016)
Day × firm	Yes	Yes	Yes
Maturity pol.	Yes	Yes	Yes
IT maturity pol.	Yes	Yes	Yes
Learning pol.	Yes	Yes	Yes

Table E.5: Insider trading and firm characteristics: OptionMetrics ATM (whole sample)

This table reports the results of the regression shown in the last column of Table 3 for the top 25% and bottom 25% of firms sorted according to certain characteristics at the year end. Panel E is an exception and sorts firms according to the existence of Universal Demand Laws in the state of incorporation. Column 3 tests the equality of the coefficient estimates for the low and high group. 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 Sample	(1) Low	(2) High	(3) Low - High
Panel A: insider filing demand on EDGAR			
$\mathbf{1}(T > t_R)\,(1/T-t)\,CBuys\,(\gamma_B)$	-0.079**	-0.158***	0.080*
	(0.031)	(0.032)	(0.044)
$\mathbf{1}(T > t_R)\,(1/T-t)\,CSales\,(\gamma_S)$	0.054***	0.102***	-0.049***
	(0.005)	(0.013)	(0.014)
Panel B: stock return volatility			
$\mathbf{1}(T > t_R)\,(1/T-t)\,CBuys\,(\gamma_B)$	-0.097***	-0.086***	-0.010
	(0.033)	(0.025)	(0.041)
$\mathbf{1}(T > t_R)\,(1/T-t)\,CSales\,(\gamma_S)$	0.076***	0.071***	0.005
	(0.008)	(0.006)	(0.010)
Panel C: share of idiosyncratic volatility			
$\mathbf{1}(T > t_R)\,(1/T-t)\,CBuys\,(\gamma_B)$	-0.203***	-0.070**	-0.133***
	(0.026)	(0.029)	(0.039)
$\mathbf{1}(T > t_R)\,(1/T-t)\,CSales\,(\gamma_S)$	0.067***	0.078***	-0.011
	(0.007)	(0.009)	(0.011)
Panel D: R&D			
$\mathbf{1}(T > t_R)\,(1/T-t)\,CBuys\,(\gamma_B)$	-0.153***	-0.124***	-0.028
	(0.022)	(0.046)	(0.051)
$\mathbf{1}(T > t_R)\,(1/T-t)\,CSales\,(\gamma_S)$	0.028***	0.046***	-0.018**
	(0.007)	(0.005)	(0.008)
Panel E: litigation risk (states with Universal Demand Laws versus states without)			
$\mathbf{1}(T > t_R)\,(1/T-t)\,CBuys\,(\gamma_B)$	-0.181***	-0.121***	-0.058
	(0.062)	(0.019)	(0.065)
$\mathbf{1}(T > t_R)\,(1/T-t)\,CSales\,(\gamma_S)$	-0.016	0.067***	-0.081***
	(0.011)	(0.004)	(0.011)
Day × firm	Yes	Yes	Yes
Maturity pol.	Yes	Yes	Yes
IT maturity pol.	Yes	Yes	Yes
Learning pol.	Yes	Yes	Yes

Table E.6: Insider trading characteristics: DDKZ

This table reports the results of the regression shown in the last column of Table 3 for different groups of trade and insider characteristics using implied volatility according to Demeterfi et al. (1999). Panel A distinguishes between filings that are late and on time, respectively. Panel B compares trade occuring in the different periods until the next earnings announcement. Panel C compares insider types, and Panel D considers different periods between the time between the trade and the report. 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.

Panel A: Timeliness of filings

Dep. var.: implied volatility	(1)
$\mathbf{1}(T > t_R)\dfrac{1}{T-t}(\gamma)$	2.113***
	(0.025)
Filed on-time $\times \mathbf{1}(T > t_R)\,(1/T-t)\,CBuys$	-0.121***
	(0.022)
Filed on-time $\times \mathbf{1}(T > t_R)\,(1/T-t)\,CSales$	0.056***
	(0.004)
Filed late $\times \mathbf{1}(T > t_R)\,(1/T-t)\,CBuys$	-0.430***
	(0.111)
Filed late $\times \mathbf{1}(T > t_R)\,(1/T-t)\,CSales$	-0.006
	(0.114)
Maturity pol.	Yes
IT $\times$ type maturity pol.	Yes
Learning pol.	Yes
Fixed effects	Day $\times$ firm
Adjusted R2	0.964
Obs	2,928,937

Panel B: Months to the next earnings announcement

Dep. var.: implied volatility	(1)
$\mathbf{1}(T > t_R) \dfrac{1}{T-t} (\gamma)$	2.079***
	(0.025)
1 month $\times \mathbf{1}(T > t_R)\, (1/T-t)\, CBuys$	-0.253***
	(0.081)
1 month $\times \mathbf{1}(T > t_R)\, (1/T-t)\, CSales$	-0.071***
	(0.016)
2 months $\times \mathbf{1}(T > t_R)\, (1/T-t)\, CBuys$	-0.248***
	(0.042)
2 months $\times \mathbf{1}(T > t_R)\, (1/T-t)\, CSales$	0.047***
	(0.012)
3 months $\times \mathbf{1}(T > t_R)\, (1/T-t)\, CBuys$	-0.061*
	(0.035)
3 months $\times \mathbf{1}(T > t_R)\, (1/T-t)\, CSales$	0.097***
	(0.009)
Maturity pol.	Yes
IT $\times$ type maturity pol.	Yes
Learning pol.	Yes
Fixed effects	Day $\times$ firm
Adjusted R2	0.964
Obs	2,928,937

Panel C: Insider types

Dep. var.: implied volatility	(1)
$\mathbf{1}\left(T>t_R\right)\frac{1}{T-t}\left(\gamma\right)$	2.125***
	(0.025)
Officer $\times\mathbf{1}\left(T>t_R\right)\left({}^1/_{T-t}\right)CBuys$	-0.051
	(0.048)
Officer $\times\mathbf{1}\left(T>t_R\right)\left({}^1/_{T-t}\right)CSales$	0.050***
	(0.005)
Director $\times\mathbf{1}\left(T>t_R\right)\left({}^1/_{T-t}\right)CBuys$	-0.209***
	(0.031)
Director $\times\mathbf{1}\left(T>t_R\right)\left({}^1/_{T-t}\right)CSales$	0.056***
	(0.013)
Beneficial owner $\times\mathbf{1}\left(T>t_R\right)\left({}^1/_{T-t}\right)CBuys$	-0.104***
	(0.025)
Beneficial owner $\times\mathbf{1}\left(T>t_R\right)\left({}^1/_{T-t}\right)CSales$	0.019
	(0.024)
Other $\times\mathbf{1}\left(T>t_R\right)\left({}^1/_{T-t}\right)CBuys$	-0.380
	(0.240)
Other $\times\mathbf{1}\left(T>t_R\right)\left({}^1/_{T-t}\right)CSales$	-0.102**
	(0.052)
Maturity pol.	Yes
IT $\times$ type maturity pol.	Yes
Learning pol.	Yes
Fixed effects	Day $\times$ firm
Adjusted R2	0.964
Obs	2,928,937
Day $\times$ firm	Yes
Maturity pol.	Yes
IT maturity pol.	Yes
Learning pol.	Yes

Table E.7: Insider trading characteristics: OptionMetrics ATM

This table reports the results of the regression shown in the last column of Table 3 for different groups of trade and insider characteristics using implied volatility provided by OptionMetrics. Panel A distinguishes between filings that are late and on time, respectively. Panel B compares trade occuring in the different periods until the next earnings announcement. Panel C compares insider types, and Panel D considers different periods between the time between the trade and the report. 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.

Panel A: Timeliness of filings

Dep. var.: implied volatility	(1)
$\mathbf{1}(T > t_R)\frac{1}{T-t}(\gamma)$	2.084***
	(0.025)
Filed on-time $\times\mathbf{1}(T > t_R)(1/T-t)\,CBuys$	-0.130***
	(0.022)
Filed on-time $\times\mathbf{1}(T > t_R)(1/T-t)\,CSales$	0.067***
	(0.004)
Filed late $\times\mathbf{1}(T > t_R)(1/T-t)\,CBuys$	-0.404***
	(0.114)
Filed late $\times\mathbf{1}(T > t_R)(1/T-t)\,CSales$	-0.042
	(0.115)
Maturity pol.	Yes
IT $\times$ type maturity pol.	Yes
Fixed effects	Day $\times$ firm
Adjusted R2	0.971
Obs	2,928,937

Panel B: Months to the next earnings announcement

Dep. var.: implied volatility	(1)
$\mathbf{1}\left(T > t_R\right)\dfrac{1}{T-t}\left(\gamma\right)$	2.046***
	(0.025)
1 month $\times\mathbf{1}\left(T > t_R\right)\left({}^{1}/{T-t}\right) CBuys$	-0.331***
	(0.093)
1 month $\times\mathbf{1}\left(T > t_R\right)\left({}^{1}/{T-t}\right) CSales$	-0.083***
	(0.016)
2 months $\times\mathbf{1}\left(T > t_R\right)\left({}^{1}/{T-t}\right) CBuys$	-0.263***
	(0.044)
2 months $\times\mathbf{1}\left(T > t_R\right)\left({}^{1}/{T-t}\right) CSales$	0.055***
	(0.012)
3 months $\times\mathbf{1}\left(T > t_R\right)\left({}^{1}/{T-t}\right) CBuys$	-0.054
	(0.035)
3 months $\times\mathbf{1}\left(T > t_R\right)\left({}^{1}/{T-t}\right) CSales$	0.116***
	(0.010)
Maturity pol.	Yes
IT $\times$ type maturity pol.	Yes
Learning pol.	Yes
Fixed effects	Day $\times$ firm
Adjusted R2	0.972
Obs	2,928,937

Panel C: Insider types

Dep. var.: implied volatility	(1)
$\mathbf{1}(T > t_R)\,\frac{1}{T-t}\,(\gamma)$	2.094***
	(0.024)
Officer $\times \mathbf{1}(T > t_R)\,(1/T-t)\,CBuys$	-0.060
	(0.050)
Officer $\times \mathbf{1}(T > t_R)\,(1/T-t)\,CSales$	0.059***
	(0.006)
Director $\times \mathbf{1}(T > t_R)\,(1/T-t)\,CBuys$	-0.194***
	(0.033)
Director $\times \mathbf{1}(T > t_R)\,(1/T-t)\,CSales$	0.066***
	(0.014)
Beneficial owner $\times \mathbf{1}(T > t_R)\,(1/T-t)\,CBuys$	-0.136***
	(0.026)
Beneficial owner $\times \mathbf{1}(T > t_R)\,(1/T-t)\,CSales$	0.035
	(0.025)
Other $\times \mathbf{1}(T > t_R)\,(1/T-t)\,CBuys$	-0.367
	(0.233)
Other $\times \mathbf{1}(T > t_R)\,(1/T-t)\,CSales$	-0.113**
	(0.050)
Maturity pol.	Yes
IT × type maturity pol.	Yes
Learning pol.	Yes
Fixed effects	Day × firm
Adjusted R2	0.971
Obs	2,928,937
Day × firm	Yes
Maturity pol.	Yes
IT maturity pol.	Yes
Learning pol.	Yes

Table E.8: Insider trading characteristics: OptionMetrics ATM (whole sample)

This table reports the results of the regression shown in the last column of Table 3 for different groups of trade and insider characteristics using the implied volatility provided by OptionMetrics for the whole sample. Panel A distinguishes between filings that are late and on time, respectively. Panel B compares trade occuring in the different periods until the next earnings announcement. Panel C compares insider types, and Panel D considers different periods between the time between the trade and the report. 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.

Panel A: Timeliness of filings

Dep. var.: implied volatility	(1)
$\mathbf{1}(T > t_R)\dfrac{1}{T-t}(\gamma)$	1.679***
	(0.023)
Filed on-time $\times \mathbf{1}(T > t_R)\,(1/T-t)\,CBuys$	-0.089***
	(0.016)
Filed on-time $\times \mathbf{1}(T > t_R)\,(1/T-t)\,CSales$	0.078***
	(0.004)
Filed late $\times \mathbf{1}(T > t_R)\,(1/T-t)\,CBuys$	-0.343***
	(0.078)
Filed late $\times \mathbf{1}(T > t_R)\,(1/T-t)\,CSales$	-0.200***
	(0.068)
Maturity pol.	Yes
IT $\times$ type maturity pol.	Yes
Learning pol.	Yes
Fixed effects	Day $\times$ firm
Adjusted R2	0.943
Obs	5,592,397

Panel B: Months to the next earnings announcement

Dep. var.: implied volatility	(1)
$\mathbf{1}\left(T > t_R\right) \dfrac{1}{T-t} \left(\gamma\right)$	1.639***
	(0.023)
1 month $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CBuys$	-0.256***
	(0.070)
1 month $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CSales$	-0.084***
	(0.013)
2 months $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CBuys$	-0.216***
	(0.032)
2 months $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CSales$	0.077***
	(0.010)
3 months $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CBuys$	-0.010
	(0.025)
3 months $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CSales$	0.122***
	(0.008)
Maturity pol.	Yes
IT $\times$ type maturity pol.	Yes
Learning pol.	Yes
Fixed effects	Day $\times$ firm
Adjusted R2	0.943
Obs	5,592,397

Panel C: Insider types

Dep. var.: implied volatility	(1)
$\mathbf{1}\left(T > t_R\right) \dfrac{1}{T-t} \left(\gamma\right)$	1.688***
	(0.023)
Officer $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CBuys$	-0.058*
	(0.033)
Officer $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CSales$	0.073***
	(0.004)
Director $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CBuys$	-0.143***
	(0.023)
Director $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CSales$	0.074***
	(0.010)
Beneficial owner $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CBuys$	-0.058***
	(0.021)
Beneficial owner $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CSales$	0.021
	(0.015)
Other $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CBuys$	-0.274**
	(0.116)
Other $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CSales$	-0.178***
	(0.019)
Maturity pol.	Yes
IT $\times$ type maturity pol.	Yes
Learning pol.	Yes
Fixed effects	Day $\times$ firm
Adjusted R2	0.943
Obs	5,592,397
Day $\times$ firm	Yes
Maturity pol.	Yes
IT maturity pol.	Yes
Learning pol.	Yes

F Filtering EDGAR log files

We retrieve the EDGAR log files from the https://www.sec.gov/dera/data/edgar-log-file-data-set.html. This website hosts internet search traffic for EDGAR filings for the period from February 2003 to June 2017. For the purposes of our analysis, we construct a measure of relative attention to insider trading, i.e., we compute the ratio of the number of logs in a given year for insider filings scaled by the number of insider filings, and the number of logs for 10K and 10Q filings scaled by the number of these filings in a given year. We apply the following filter to the log files (Ryans, 2017):

1. We restrict attention to observations with non-missing values for CIK, date, accession, and IP address.
2. We keep records where *code* is equal to 200, as this indicates that the requested document has been successfully delivered by the server.
3. We limit attention to filings, and remove access to index pages by removing records where *idx* is equal to 1.
4. We remove records by web crawlers, i.e., observations where *crawler* is equal to 1.
5. We remove records of IP addresses with more than 500 requests on a given day that satisfy the above criteria, as these are likely generated by a crawler.

G Analysts, Schedule 13D filers and insiders

In the paper, we show that information from analysts and the information from 13D filings and their amendments reduce the informativeness of earnings announcements. Likewise, we show that insider buys reduce and sales increase the informativeness of these announcements. Nonetheless, we have shown those results independently. Since analysts might react to insider trading or corporate executives might react to analyst forecasts, these effects could be related. Table G.1 presents the results of including in the regression analyst revisions and insider trades at the same time. Hence, if one drives the other, one of them will become insignificant. Instead, we observe that the sign, significance, and even magnitude are very close to the baseline specification.

In Table G.2, we split 13D filers into institutional and non-institutional investors. Institutional investors include investment companies, investment advisors, insurance companies, and banks, while non-institutional investors are individuals, corporations or parent companies. We find that transactions of both groups substitute the information content of the next earnings announcement, while the effect appears to be more pronounced for institutional investors. We find that the magnitude of the effect of stake increases is approximately halved when we control for the impact of insider buys, which suggests that stake increases and some insider buys may carry similar pieces of information.

Table G.1: Insider trading, analyst and earnings informativeness

The first column of this table repeats the first column of Table 4 which includes the effect of upward and downward analyst revisions relative to the mean forecast. Columns (2) to (5) repeat the same estimation including the effect of insider trading as well. Each column uses a different benchmark to sign the analyst forecast. Finally, each panel considers one of the implied volatility measures considered before. Standard errors are clustered both at the day and firm-quarter level and presented within parenthesis. *, † and ‡ indicates statistical significance at the 10%, 5%, and 1% level respectively.

	(1)	(2)	(3)	(4)	(5)
Benchmark:	Mean	Mean	Median	Own	Recom.
Dep. var: Nonparametric implied volatility (Bakshi et al., 2003)					
$\mathbf{1}(T > t_R)\frac{1}{T-t}$	2.916‡	2.786‡	2.757‡	2.536‡	2.345‡
	(0.029)	(0.032)	(0.032)	(0.029)	(0.031)
$\mathbf{1}(T > t_R)\frac{1}{T-t} \times CBuys$		-0.097‡	-0.108‡	-0.108‡	-0.138‡
		(0.022)	(0.022)	(0.021)	(0.023)
$\mathbf{1}(T > t_R)\frac{1}{T-t} \times CSales$		0.048‡	0.046‡	0.048‡	0.059‡
		(0.004)	(0.005)	(0.004)	(0.005)
$\mathbf{1}(T > t_R)\frac{1}{T-t} \times CUpward$	-0.084‡	-0.087‡	-0.098‡	-0.120‡	-0.057‡
	(0.007)	(0.007)	(0.008)	(0.008)	(0.011)
$\mathbf{1}(T > t_R)\frac{1}{T-t} \times CDownward$	-0.086‡	-0.075‡	-0.091‡	-0.122‡	-0.068‡
	(0.007)	(0.007)	(0.008)	(0.006)	(0.012)
Dep. var: Nonparametric implied volatility (Demeterfi et al., 1999)					
$\mathbf{1}(T > t_R)\frac{1}{T-t}$	2.761‡	2.650‡	2.619‡	2.401‡	2.210‡
	(0.026)	(0.029)	(0.029)	(0.026)	(0.029)
$\mathbf{1}(T > t_R)\frac{1}{T-t} \times CBuys$		-0.093‡	-0.104‡	-0.102‡	-0.132‡
		(0.020)	(0.020)	(0.020)	(0.021)
$\mathbf{1}(T > t_R)\frac{1}{T-t} \times CSales$		0.047‡	0.045‡	0.047‡	0.058‡
		(0.004)	(0.004)	(0.004)	(0.004)
$\mathbf{1}(T > t_R)\frac{1}{T-t} \times CUpward$	-0.078‡	-0.081‡	-0.090‡	-0.115‡	-0.059‡
	(0.007)	(0.007)	(0.008)	(0.008)	(0.010)
$\mathbf{1}(T > t_R)\frac{1}{T-t} \times CDownward$	-0.083‡	-0.073‡	-0.089‡	-0.117‡	-0.067‡
	(0.006)	(0.006)	(0.007)	(0.006)	(0.011)
Dep. var: Parametric implied volatility by OptionMetrics					
$\mathbf{1}(T > t_R)\frac{1}{T-t}$	2.761‡	2.631‡	2.604‡	2.379‡	2.176‡
	(0.025)	(0.028)	(0.029)	(0.026)	(0.028)
$\mathbf{1}(T > t_R)\frac{1}{T-t} \times CBuys$		-0.099‡	-0.110‡	-0.108‡	-0.139‡
		(0.021)	(0.021)	(0.021)	(0.022)
$\mathbf{1}(T > t_R)\frac{1}{T-t} \times CSales$		0.057‡	0.055‡	0.057‡	0.069‡
		(0.004)	(0.004)	(0.004)	(0.005)
$\mathbf{1}(T > t_R)\frac{1}{T-t} \times CUpward$	-0.079‡	-0.083‡	-0.092‡	-0.123‡	-0.059‡
	(0.007)	(0.007)	(0.008)	(0.008)	(0.011)
$\mathbf{1}(T > t_R)\frac{1}{T-t} \times CDownward$	-0.085‡	-0.073‡	-0.091‡	-0.119‡	-0.063‡
	(0.007)	(0.007)	(0.008)	(0.006)	(0.012)
Maturity pol.	Yes	Yes	Yes	Yes	Yes
Revision maturity pol.	Yes	Yes	Yes	Yes	Yes
Learning pol.	Yes	Yes	Yes	Yes	Yes
IT maturity pol.	Yes	Yes	Yes	Yes	Yes
Fixed effects	Day × firm	Day × firm	Day × firm	Day × firm	Day × firm
Obs.	2,928,937	2,928,937	2,928,937	2,928,937	2,928,937

Table G.2: Insider trading, 13D filings and earnings informativeness

The first column of this table repeats the fourth column of Table 4 which includes the effect of increases and decreases of stakes by Schdedule 13D filers relative to the mean forecast. Columns 2 distinguishes between 13D filers that are either classified as an institutional investor if they are an investment company, an investment adviser, bank, or insurance company as specified in item 12, and as a non-institutional investor otherwise. Column 3 and 4 repeat the same estimation while including the effect of insider trading as well. 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)
Dep. var: Nonparametric implied volatility (Bakshi et al., 2003)				
$\mathbf{1}(T > t_R)\left(\frac{1}{T-t}\right)$	2.382***	2.382***	2.258***	2.258***
	(0.024)	(0.024)	(0.028)	(0.028)
$\mathbf{1}(T > t_R)\,(1/T-t)\,CBuys\,13D$	-0.316***		-0.137	
	(0.083)		(0.084)	
$\mathbf{1}(T > t_R)\,(1/T-t)\,CSales\,13D$	-0.203**		-0.209**	
	(0.083)		(0.083)	
$\mathbf{1}(T > t_R)\,(1/T-t)\,CBuys\,13D\,inst$		-0.390*		-0.148
		(0.201)		(0.189)
$\mathbf{1}(T > t_R)\,(1/T-t)\,CSales\,13D\,inst$		-0.359**		-0.309*
		(0.166)		(0.160)
$\mathbf{1}(T > t_R)\,(1/T-t)\,CBuys\,13D\,noninst$		-0.296***		-0.138
		(0.095)		(0.098)
$\mathbf{1}(T > t_R)\,(1/T-t)\,CSales\,13D\,noninst$		-0.163*		-0.183*
		(0.095)		(0.096)
$\mathbf{1}(T > t_R)\,(1/T-t)\,Insider\,CBuys$			-0.137***	-0.137***
			(0.024)	(0.024)
$\mathbf{1}(T > t_R)\,(1/T-t)\,Insider\,CSales$			0.056***	0.056***
			(0.005)	(0.005)
Maturity pol.	Yes	Yes	Yes	Yes
IT maturity pol.	Yes	Yes	Yes	Yes
Learning pol	Yes	Yes	Yes	Yes
Fixed effects	Day × firm	Day × firm	Day × firm	Day × firm
Adjusted R2	0.953	0.953	0.954	0.954
Obs	2,901,294	2,901,294	2,901,294	2,901,294

Table G.2: Insider trading, 13D filings and earnings informativeness (continued)

Dep. var.: implied volatility	(1)	(2)	(3)	(4)
Dep. var: Nonparametric implied volatility (Demeterfi et al., 1999)				
$\mathbf{1}(T > t_R)\left(\frac{1}{T-t}\right)$	2.230***	2.230***	2.120***	2.121***
	(0.022)	(0.022)	(0.025)	(0.025)
$\mathbf{1}(T > t_R)(^1/_{T-t})\,CBuys\,13D$	-0.282***		-0.111	
	(0.079)		(0.078)	
$\mathbf{1}(T > t_R)(^1/_{T-t})\,CSales\,13D$	-0.202***		-0.210***	
	(0.077)		(0.076)	
$\mathbf{1}(T > t_R)(^1/_{T-t})\,CBuys\,13D\,inst$		-0.416**		-0.185
		(0.194)		(0.183)
$\mathbf{1}(T > t_R)(^1/_{T-t})\,CSales\,13D\,inst$		-0.341**		-0.294*
		(0.157)		(0.151)
$\mathbf{1}(T > t_R)(^1/_{T-t})\,CBuys\,13D\,noninst$		-0.250***		-0.099
		(0.089)		(0.091)
$\mathbf{1}(T > t_R)(^1/_{T-t})\,CSales\,13D\,noninst$		-0.162*		-0.184**
		(0.087)		(0.087)
$\mathbf{1}(T > t_R)(^1/_{T-t})\,Insider\,CBuys$			-0.132***	-0.133***
			(0.022)	(0.022)
$\mathbf{1}(T > t_R)(^1/_{T-t})\,Insider\,CSales$			0.055***	0.055***
			(0.004)	(0.004)
Maturity pol.	Yes	Yes	Yes	Yes
IT maturity pol.	Yes	Yes	Yes	Yes
Learning pol	Yes	Yes	Yes	Yes
Fixed effects	Day × firm	Day × firm	Day × firm	Day × firm
Adjusted R2	0.964	0.964	0.964	0.964
Obs	2,901,294	2,901,294	2,901,294	2,901,294

Table G.2: Insider trading, 13D filings and earnings informativeness (continued)

Dep. var.: implied volatility	(1)	(2)	(3)	(4)
Dep. var: Parametric implied volatility by OptionMetrics				
$\mathbf{1}(T > t_R)\left(\frac{1}{T-t}\right)$	2.218***	2.218***	2.092***	2.092***
	(0.021)	(0.021)	(0.025)	(0.025)
$\mathbf{1}(T > t_R)\,(1/T-t)\,CBuys\,13D$	-0.336***		-0.155*	
	(0.080)		(0.080)	
$\mathbf{1}(T > t_R)\,(1/T-t)\,CSales\,13D$	-0.222***		-0.233***	
	(0.078)		(0.078)	
$\mathbf{1}(T > t_R)\,(1/T-t)\,CBuys\,13D\,inst$		-0.493**		-0.242
		(0.193)		(0.188)
$\mathbf{1}(T > t_R)\,(1/T-t)\,CSales\,13D\,inst$		-0.314*		-0.257*
		(0.162)		(0.153)
$\mathbf{1}(T > t_R)\,(1/T-t)\,CBuys\,13D\,noninst$		-0.295***		-0.137
		(0.090)		(0.092)
$\mathbf{1}(T > t_R)\,(1/T-t)\,CSales\,13D\,noninst$		-0.197**		-0.225**
		(0.089)		(0.090)
$\mathbf{1}(T > t_R)\,(1/T-t)\,Insider\,CBuys$			-0.138***	-0.138***
			(0.023)	(0.023)
$\mathbf{1}(T > t_R)\,(1/T-t)\,Insider\,CSales$			0.066***	0.066***
			(0.004)	(0.004)
Maturity pol.	Yes	Yes	Yes	Yes
IT maturity pol.	Yes	Yes	Yes	Yes
Learning pol	Yes	Yes	Yes	Yes
Fixed effects	Day × firm	Day × firm	Day × firm	Day × firm
Adjusted R2	0.971	0.971	0.971	0.971
Obs	2,901,294	2,901,294	2,901,294	2,901,294

H Negative corporate news

Next, we analyze how EA informativeness changes with the arrival of negative corporate news other than corporate insider sales. Two such signals that are typically associated with negative information about firm value are already considered in our paper: analyst forecast revisions (or revisions of analyst recommendations), and sales by activist shareholders filing 13D. One way to expand the analysis of negative corporate news would be to create an exhaustive sample of negative corporate events. Examples of such events may include natural disasters affecting the firm's operations, dividend decreases or omissions, profit warnings, FDA warnings, SEC enforcement actions, personnel changes, M&A transactions, announcement of seasoned equity offerings, or business disruptions. Unfortunately, it is difficult to gather an exhaustive set of information relevant to the firm, as this would not only include ad-hoc diclosures made by the firm, but also industry information, events affecting suppliers or customers, macro-economic news (which are likely to affect firms differently). Moreover, merely conditioning on the type of event, it maybe difficult to infer whether or not this signal carries information, and whether this information is positive or negative news. Even if we conduct textual analysis to interpret the tone of the message, the market response also depends on the novelty of the information content because some of the information content could have already arrived at the market before through an information leakage or alternative means of communication. To circumvent the issues raised above, we take an agnostic approach to which type of news generates negative corporate events by considering days with extreme negative returns.

This approach gives us a sample of firm-days where negative signals about firm value are likely to arrive in the market. We proceed as follows to classify days with negative corporate news: we create the dummy variable *NegRet*, which indicates the bottom 2.5th, 5th and 10th percentile, respectively, of daily raw returns in a given firm-year, additionally requiring that the daily return is negative. To account for heterogeneity in exposure to risk factors, we repeat the classification based on excess daily returns using the Fama-French three-factor model as a benchmark. The correlation between the dummy variables classified as "negative corporate events" under both variants is 0.52. Analogously to our measure of insider purchases and sales, we calculate the cumulative number of negative return days since the last earnings announcement for each quarter.

We estimate the following model, similar to Equation (4) of the main text:

$$ln(IV_{i,t,T}^2) = \mu_{i,t} + \sum_{j=1}^{2} \lambda_j (T-t)^{j/2} + \sum_{j=1}^{2} \delta_j (t_{R_{i,t}} - t)^{j/2} + \mathbf{1}\left(T > t_{R_{i,t}}\right) \left(\gamma_0 \frac{1}{T-t}\right) \quad (3)$$
$$+ \mathbf{1}\left(T > t_{R_{i,t}}\right) \left(\gamma_N \frac{1}{T-t} CNegRet_{i,t}\right) + CNegRet_{i,t} \sum_{j=1}^{2} \lambda_j^B (T-t)^{j/2} + \varepsilon_{i,t,T}$$

where $IV_{i,t,T}$ is the implied volatility of firm i on day t of options expiring at T; t_R denotes the day at which the earnings announcement takes place; and $CNegRet_{i,t}$ is the cumulative number of days with negative corporate news that have occured since since the last earnings announcement. γ_N provides us with an estimate of how EA informativeness changes with the arrival of negative corporate events.

Table H.1 shows that EA informativeness decreases with the arrival of negative news. The results for raw as opposed to excess returns are slightly larger. We also note that the economic magnitude of $\widehat{\gamma_N}$ increases for a stricter definition of negative return days, which is likely to capture negative news with greater information content, leading to larger market responses.

This analysis shows that corporate sales as an example of a signal that might carry negative information about firm value leads to remarkably different set of results as compared to other negative news events. It also rules out the leverage effect as the driving force behind our results.

Table H.1: Negative (abnormal) returns

Columns (1) to (6) report the estimate of γ in Equation (3). Column 1 classifies the negative returns in the bottom 10th percentile as a "negative news event", while columns 2 and 3 use the bottom 5th percentile and the bottom 2.5th percentile as the cutoff. Columns 4. 5, and 6 present the same findings, but the "negative news event" is classified based on the excell returns relative to the Fama-French three-factor model. 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.

	(1)	(2)	(3)	(4)	(5)	(6)
Return	raw	raw	raw	excess	excess	excess
Threshold	p10	p5	p2.5	p10	p5	p2.5
γ_N	-0.107***	-0.161***	-0.226***	-0.068***	-0.113***	-0.158***
	(0.007)	(0.010)	(0.015)	(0.007)	(0.010)	(0.015)
Mat. pol.	Yes	Yes	Yes	Yes	Yes	Yes
IT mat. pol.	Yes	Yes	Yes	Yes	Yes	Yes
Learn. pol.	Yes	Yes	Yes	Yes	Yes	Yes
Day × firm	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.954	0.954	0.954	0.954	0.954	0.954
Obs	2,928,937	2,928,937	2,928,937	2,928,937	2,928,937	2,928,937

I Opportunistic versus routine trading

One may argue that trading patterns by insiders help reveal their information content. Cohen et al. (2012) observe that there are insiders which tend to trade during the same months in several consecutive years, suggesting that these insiders trade according to a routine scheme. Based on this observation, the authors distinguish between these 'routine' trades on the one hand and opportunistic trades on the other, which are not following such routine and find that the opportunistic trades elicit a larger abnormal return. This finding indicates that the classification, which is easy to implement, helps to filter out trades that predict future returns. We now re-examine our results using the split into opportunistic and routine traders. To be able to classify the insiders, Cohen et al. (2012) use the past three-year trading history, requiring that the first trade of the insider observable in the database dates back at least three years, such that at least a three-year trading history is known. Ignoring these insiders would require the assumption that their trades do not carry any information, which is why we decide to keep them as a separate category, labelled 'unclassifiable'.[2]

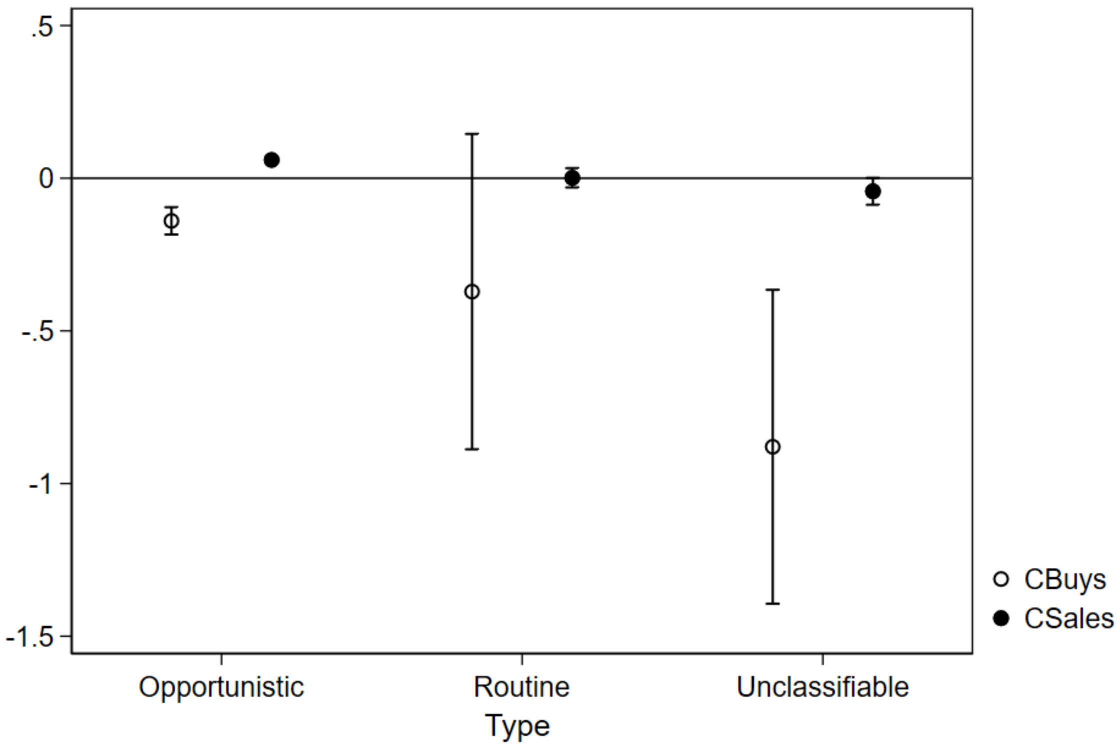
For traders with a three-year trading history, we classify a trade as 'routine' if the insider has traded in a time window of plus or minus four days around the date in each of the three prior years. All other trades by insiders with a sufficient trading history that are not 'routine', are classified as 'opportunistic'.

As Figure I.1 shows, both purchases and sales by insiders that do not have any three-year trading history appear to be more informative and decrease earnings announcement informativeness, suggesting that these trades are more likely based on foreknowledge about the earnings announcement. Figure I.1 also compares trades by opportunistic and routine traders. The positive effect of sales is unique to opportunistic trades, while the coefficient for routine sales is close to zero. However, the estimate for opportunistic purchases is negative, with the confidence interval being much larger, given that there less purchases that qualify as 'routine'. This evidence does not contradict Cohen et al. (2012); instead, it provides the intuitive result that insiders, who trade on foreknowledge systematically, may become routine traders.

[2]Note that in order to classify a transaction as either routine or opportunistic, we do not require that the insider trades *in each* of the three consecutive prior years. We only require one trade that dates back at least three years.

Figure I.1: Trading history and opportunistic vs. routine trades

This figure shows the estimates of γ_B (hollow dots) and γ_S (solid dots) and the 95% confidence intervals for different insider characteristics. The Figure compares opportunistic trades, routine trades and unclassifiable trades, i.e., trades by insiders that do not any transactions in a period of three years prior to the transaction. A trade is defined to have a three-year history if the first trade of the insider in the sample has occured at least three years prior to the trading date of the respective transactions. Trades that meet this condition are classified as 'routine' if the trader has traded on the same day plus or minus the transaction day in the past three years consecutively. Non-routine trades that meet the trading-history requirement are classified as 'opportunistic'. Standard errors are clustered at both the day and the firm-quarter level.



J By reporting lag

We investigate the market reaction by different lengths of periods between the trade and the disclosure of the trades. According to a causal interpretation of our results, the market primarily responds to the disclosure of the trade, not mainly to the occurrence of the trade. Conversely, according to the alternative interpretation that both the insider and the market participants respond to a signal that is observable to those two groups, but missed by the researcher, we would expect a stronger effect for the shortest delay between the trade and the disclosure of the trade. We do not find that the information content of trades reported with a longer delay differs much from the information content of trades with a short delay, consistent with the notion that the market in fact appears to respond to the *disclosure*.

Table J.1: Insider trading and EA informativeness: by reporting lag

This table shows the results of a regression of implied volatility on corporate insider purchases and sales. 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)
$\mathbf{1}\left(T > t_R\right) \dfrac{1}{T-t} \left(\gamma\right)$	2.244***
	(0.027)
High lag $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CBuys$	-0.141**
	(0.069)
High lag $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CSales$	0.057***
	(0.019)
Medium lag $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CBuys$	-0.090**
	(0.043)
Medium lag $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CSales$	0.073***
	(0.012)
Low lag $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CBuys$	-0.169***
	(0.045)
Low lag $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CSales$	0.037***
	(0.007)
Maturity pol.	Yes
IT $\times$ type maturity pol.	Yes
Learning pol.	Yes
Fixed effects	Day $\times$ firm
Adjusted R2	0.954
Obs	2,928,937
Difference in coefficients	
Buys: high - medium	-0.051
F-value	(3.44)
Buys: high - low	0.028
F-value	(1.39)
Buys: medium - low	0.079
F-value	(14.70)
Sales: high - medium	-0.016
F-value	(4.81)
Sales: high - low	0.020
F-value	(12.86)
Sales: medium - low	0.036
F-value	(69.82)

K 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. 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.

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 K.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

[3]The number of observations decreases because we do not observe the deviation for the first year in the sample,

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 K.2 the majority of option days, 97%, that are classified as treated under expected earnings dates would also be classified as treated under the actual earnings dates. Similarly, 98% 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 K.3 shows the results using the expected earnings announcement dates. We confirm a negative estimate for γ_B and a positive estimate for γ_S, though we note that the economic magnitude of γ_S is smaller.

Next, we investigate whether the precision of our estimates are affected by the deviation between expected and actual earnings announcement dates. To do so, we sort our observations into 3 groups (bottom 25%, medium 50% and top 25%) based on the quarter-specific absolute deviation between the expected and the actual earnings announcement date. The results in Table K.4 show that the estimates for γ_B are very comparable for all three groups. The estimate for γ_S only slightly differs between the low deviation and the medium deviation group, however, the difference is economically small.

Table K.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	4,104	0	3	-2	0	4
Deviation Q2	3,876	0	3	-2	-1	4
Deviation Q3	4,171	0	4	-2	-1	4
Deviation Q4	4,118	-0	5	-2	0	4
Mean firm-year deviation	3,113	0	2	-2	-0	2
Mean absolute firm-year deviation	3,113	2	1	1	2	4

and because some earnings announcements could be missing.

Table K.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)	1,586,435	99%	21,373	1%	1,608,172
Treated (actual)	25,555	3%	942,000	97%	967,555

Table K.3: Insider trading and EA informativeness: expected earnings 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 volatility	(1)	(2)	(3)
$\mathbf{1}(T > t_R)\frac{1}{T-t}(\gamma)$	2.378***	2.387***	2.030***
	(0.030)	(0.030)	(0.032)
$\mathbf{1}(T > t_R)\frac{1}{T-t}CBuys\,(\gamma_B)$	-0.165***	-0.172***	-0.150***
	(0.025)	(0.025)	(0.025)
$\mathbf{1}(T > t_R)\frac{1}{T-t}CSales\,(\gamma_S)$	0.045***	0.040***	0.050***
	(0.006)	(0.006)	(0.006)
Maturity pol.	Yes	Yes	Yes
IT maturity pol.	No	Yes	Yes
Learning pol.	No	No	Yes
Fixed effects	Day × firm	Day × firm	Day × firm
Adjusted R2	0.947	0.948	0.948
Obs	2,659,372	2,659,372	2,659,372

Table K.4: Insider trading and deviation from expected announcement date

This table reports the results of the regression shown in column 3 of Table K.3 for three different groups based on the absolute deviation between the expected and the actual earnings announcement date in business days. Firm-quarters are sorted in the low group, consisting of the bottom 25%, the medium group consisting of the middle 50%, and the high group consisting of the top 25%. Column 3 tests the equality of the coefficient estimates for the low and high group. Standard errors, shown in parentheses in columns 1 and 2, are clustered at both the firm and the day level. Table 6 describes the variables. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level respectively.

Dep. var.: implied volatility Sample	(1) Low	(2) High	(3) (1)-(2)
$\mathbf{1}\,(T > t_R)\,(1/T-t)\,CBuys\,(\gamma_B)$	-0.140***	-0.126**	-0.014
	(0.029)	(0.057)	(0.064)
$\mathbf{1}\,(T > t_R)\,(1/T-t)\,CSales\,(\gamma_S)$	0.059***	0.043***	0.016
	(0.006)	(0.010)	(0.012)

L Unobserved heterogeneity in earnings announcement informativeness

In the main text, 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 implemented to support our finding was to estimate the model using an event study (Section D). 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 decided to exclude the heterogeneity from the main model because it adds another layer of complexity, which seems unnecessary. Moreover, there is not an 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 text.

L.1 Firm Heterogeneity

The first heterogeneity we consider is across firms. To implement this estimation, we estimate equation (4) of the main text 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. The main conclusions remain unchanged but the estimates halve. 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 L.1: Insider trading and EA informativeness: controlling for firm-specific informativeness

This table shows the results of a regression of implied volatility on corporate insider purchases and sales. 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. Column 2 includes the control for an interaction term of each firm dummy and the expression $\mathbf{1}\left(T > t_{R_{i,t}}\right)\left(\frac{1}{T-t}\right)$. 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)	(2)	(3)
Relevance × CBuys (γ_B)	-0.044***	-0.050***	-0.041***
	(0.007)	(0.007)	(0.007)
Relevance × CSales (γ_S)	0.017***	0.016***	0.023***
	(0.002)	(0.002)	(0.002)
Maturity pol.	Yes	Yes	Yes
IT maturity pol.	No	Yes	Yes
Learning pol.	No	No	Yes
Fixed effects	Day × firm	Day × firm	Day × firm
Relevance × firm FE	Yes	Yes	Yes
Adjusted R2	0.957	0.958	0.958
Obs	2,928,937	2,928,937	2,928,937

L.2 Fiscal quarter heterogeneity

The second dimension of heterogeneity we consider is across fiscal quarters. If one of the quarters, for instance the fourth, when annual results are communicated, carries more information and it is also associated wit a higher (or lower) likelihood of insider trades; then, our findings would be spurious. Table L.2 splits the analysis by fiscal quarter and indicates that the main effects persist within each of the four quarters.

Table L.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 by fiscal 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.

Fiscal quarter	(1) Q1	(2) Q2	(3) Q3	(4) Q4
$\mathbf{1}\left(T>t_R\right)\frac{1}{T-t}\left(\gamma\right)$	2.174***	2.222***	2.258***	2.331***
	(0.014)	(0.014)	(0.015)	(0.013)
$\mathbf{1}\left(T>t_R\right)\frac{1}{T-t}CBuys\left(\gamma_B\right)$	-0.139***	-0.111***	-0.153***	-0.172***
	(0.015)	(0.012)	(0.014)	(0.016)
$\mathbf{1}\left(T>t_R\right)\frac{1}{T-t}CSales\left(\gamma_S\right)$	0.046***	0.058***	0.068***	0.052***
	(0.002)	(0.003)	(0.003)	(0.003)
Maturity pol.	Yes	Yes	Yes	Yes
IT maturity pol.	Yes	Yes	Yes	Yes
Learning pol.	Yes	Yes	Yes	Yes
Fixed effects	Day × firm	Day × firm	Day × firm	Day × firm
Adjusted R2	0.951	0.955	0.957	0.951
Obs	713,855	696,989	750,409	767,684

M Option liquidity

In this section we investigate how our results vary with option liquididy. To that end 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.

Figure M.1 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.

Table M.1 examines the effects of insider buys and sells in samples of high (top 25%) and low (bottom 25%) open interest respectively. The findings indicate that the effect of insider purchases is negative for both groups, but more pronounced in the sample of low open interest. Conversely, we only find the positive effect of insider sales in the sample of high open interest. When open interest is in the bottom 25%, we even find a negative effect of insider sales. These findings could be consistent with the notion that a lower monitoring of low-liquidity firms leads to more opportunities to profit from foreknowledge.

Figure M.1: 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.

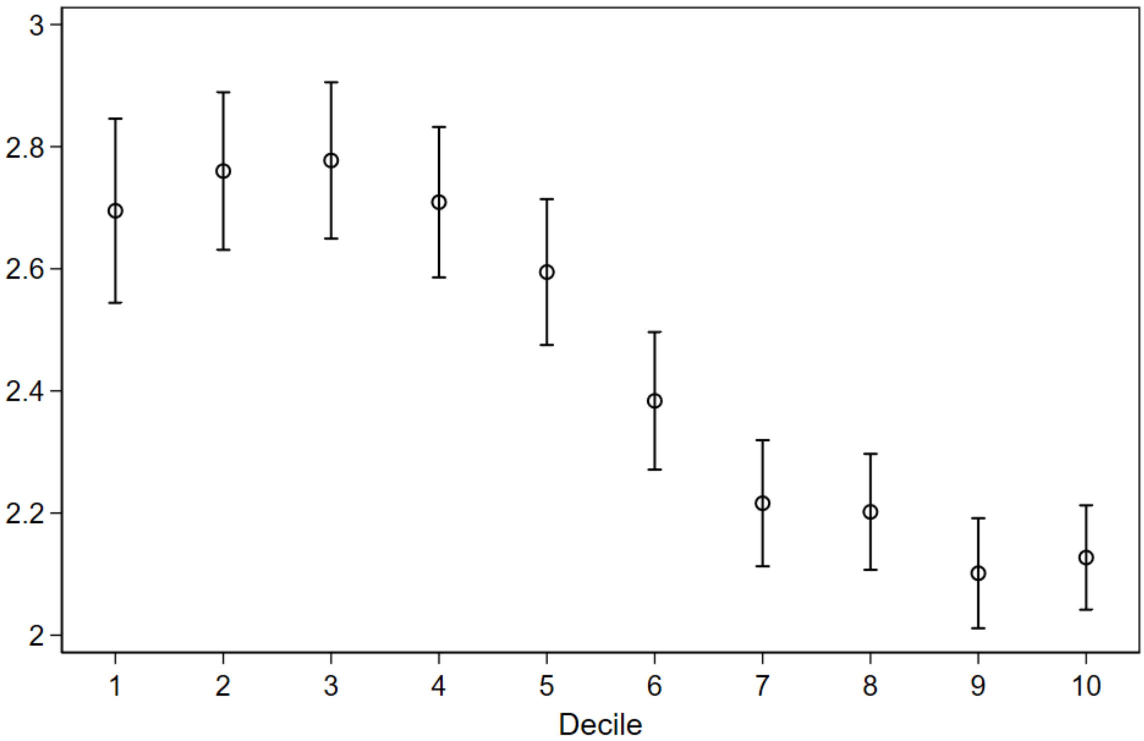


Table M.1: Insider trading, earnings informativeness and option liquidity

This table reports the results of the regression shown in the last column of Table 3 for the top 25% and bottom 25% of firms sorted according to open interest each 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.

Sample	(1) Low	(2) High	(3) Low - High
Dep. var: Nonparametric implied volatility (Bakshi et al., 2003)			
$\mathbf{1}(T > t_R)\,(1/T-t)\,CBuys\,(\gamma_B)$	-0.198***	-0.159***	-0.039
	(0.039)	(0.036)	(0.052)
$\mathbf{1}(T > t_R)\,(1/T-t)\,CSales\,(\gamma_S)$	-0.004	0.085***	-0.089***
	(0.015)	(0.007)	(0.016)
Dep. var: Nonparametric implied volatility (Demeterfi et al., 1999)			
$\mathbf{1}(T > t_R)\,(1/T-t)\,CBuys\,(\gamma_B)$	-0.185***	-0.155***	-0.030
	(0.036)	(0.033)	(0.049)
$\mathbf{1}(T > t_R)\,(1/T-t)\,CSales\,(\gamma_S)$	-0.006	0.083***	-0.089***
	(0.014)	(0.007)	(0.015)
Dep. var: Parametric implied volatility by OptionMetrics			
$\mathbf{1}(T > t_R)\,(1/T-t)\,CBuys\,(\gamma_B)$	-0.190***	-0.171***	-0.019
	(0.039)	(0.034)	(0.052)
$\mathbf{1}(T > t_R)\,(1/T-t)\,CSales\,(\gamma_S)$	0.002	0.093***	-0.092***
	(0.014)	(0.007)	(0.015)
Day × firm	Yes	Yes	Yes
Maturity Pol.	Yes	Yes	Yes
IT maturity Pol.	Yes	Yes	Yes

N Tables underlying figures

Table N.1: Insider trading characteristics

This table reports the results of the regression shown in the last column for different groups of trade and insider characteristics. Panel A distinguishes between filings that are late and on time, respectively. Panel B compares trade occuring in the different periods until the next earnings announcement. Panel C compares insider types, and Panel D considers different periods between the time between the trade and the report. 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.

Panel A: Timeliness of filings

Dep. var.: implied volatility	(1)
$\mathbf{1}\left(T > t_R\right)\dfrac{1}{T-t}\,(\gamma)$	2.250***
	(0.028)
Filed on-time $\times \mathbf{1}\left(T > t_R\right)\left(1/T-t\right) CBuys$	-0.126***
	(0.023)
Filed on-time $\times \mathbf{1}\left(T > t_R\right)\left(1/T-t\right) CSales$	0.057***
	(0.005)
Filed late $\times \mathbf{1}\left(T > t_R\right)\left(1/T-t\right) CBuys$	-0.461***
	(0.119)
Filed late $\times \mathbf{1}\left(T > t_R\right)\left(1/T-t\right) CSales$	-0.015
	(0.122)
Maturity pol.	Yes
IT $\times$ type maturity pol.	Yes
Learning pol.	Yes
Fixed effects	Day $\times$ firm
Adjusted R2	0.954
Obs	2,928,937
Difference in coefficients	
Buys: Filed on time - filed late	0.335
F-value	(7.60)
Sales: Filed on time - filed late	0.072
F-value	(0.35)

Panel B: Months to the next earnings announcement

Dep. var.: implied volatility	(1)
$\mathbf{1}\left(T > t_R\right) \dfrac{1}{T-t} \left(\gamma\right)$	2.208***
	(0.028)
1 month $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CBuys$	-0.251***
	(0.085)
1 month $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CSales$	-0.075***
	(0.017)
2 months $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CBuys$	-0.257***
	(0.045)
2 months $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CSales$	0.053***
	(0.013)
3 months $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CBuys$	-0.063*
	(0.037)
3 months $\times \mathbf{1}\left(T > t_R\right) \left(1/T-t\right) CSales$	0.101***
	(0.010)
Maturity pol.	Yes
IT × type maturity pol.	Yes
Learning pol.	Yes
Fixed effects	Day × firm
Adjusted R2	0.954
Obs	2,928,937
Difference in coefficients	
Buys: 1 month - 2 months	0.006
F-value	(0.00)
Buys: 1 month - 3 months	-0.188
F-value	(3.97)
Sales: 1 month - 2 months	-0.128
F-value	(26.16)
Sales: 1 month - 3 months	-0.176
F-value	(68.06)

Panel C: Insider types

Dep. var.: implied volatility	(1)
$\mathbf{1}\left(T > t_R\right) \dfrac{1}{T-t}\left(\gamma\right)$	2.263***
	(0.027)
Officer $\times \mathbf{1}\left(T > t_R\right) \left({}^{1}/_{T-t}\right) CBuys$	-0.044
	(0.052)
Officer $\times \mathbf{1}\left(T > t_R\right) \left({}^{1}/_{T-t}\right) CSales$	0.050***
	(0.006)
Director $\times \mathbf{1}\left(T > t_R\right) \left({}^{1}/_{T-t}\right) CBuys$	-0.221***
	(0.034)
Director $\times \mathbf{1}\left(T > t_R\right) \left({}^{1}/_{T-t}\right) CSales$	0.059***
	(0.014)
Beneficial owner $\times \mathbf{1}\left(T > t_R\right) \left({}^{1}/_{T-t}\right) CBuys$	-0.115***
	(0.025)
Beneficial owner $\times \mathbf{1}\left(T > t_R\right) \left({}^{1}/_{T-t}\right) CSales$	0.014
	(0.025)
Other $\times \mathbf{1}\left(T > t_R\right) \left({}^{1}/_{T-t}\right) CBuys$	-0.432*
	(0.246)
Other $\times \mathbf{1}\left(T > t_R\right) \left({}^{1}/_{T-t}\right) CSales$	-0.105*
	(0.058)
Maturity pol.	Yes
IT $\times$ type maturity pol.	Yes
Learning pol.	Yes
Fixed effects	Day $\times$ firm
Adjusted R2	0.954
Obs	2,928,937
Difference in coefficients	
Buys: officer - director	0.177
F-value	(7.40)
Buys: officer - beneficial owner	0.071
F-value	(1.28)
Buys: director - beneficial owner	-0.106
F-value	(6.48)
Sales: officer - director	-0.009
F-value	(0.27)
Sales: officer - beneficial owner	0.036
F-value	(1.90)
Sales: director - beneficial owner	0.045
F-value	(2.39)

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