

Augustin, Patrick; Brenner, Menachem; Grass, Gunnar; Orłowski, Piotr;
Subrahmanyam, Marti G.

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Informed Options Strategies Before Corporate Events

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Piotr Orłowski | Marti G. Subrahmanyam

Informed options strategies before corporate events*

Patrick Augustin,[†] Menachem Brenner,[‡] Gunnar Grass,[§] Piotr Orłowski,[¶] and Marti G. Subrahmanyam,^{||}

Abstract

We analyze how informed investors trade in the options market ahead of corporate news when they receive private, but noisy, information about the timing and impact of these announcements on stock prices. We propose a framework that ranks options trading strategies (option type, maturity, and strike price) based on their maximum attainable leverage when price-taking investors face market frictions. We exploit the heterogeneity in announcement characteristics across twelve categories of corporate events to support that event-specific information signals are informative for announcement returns and that they impact the optimal choice of option moneyness and tenor.

JEL Classification: G12, G13, G14, K42

Keywords: corporate announcements, derivatives, event studies, insider trading, market microstructure

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[†]Desautels Faculty of Management at McGill University, 1001 Sherbrooke St. W, Montreal QC H3A 1G5 Canada & Canadian Derivatives Institute; patrick.augustin@mcgill.ca.

[‡]New York University, Leonard N. Stern School of Business; mbrenner@stern.nyu.edu.

[§]HEC Montréal; gunnar.grass@hec.ca.

[¶]HEC Montréal; piotr.orlowski@hec.ca.

^{||}New York University, Leonard N. Stern School of Business & NYU Shanghai; msubrahm@stern.nyu.edu.

1 Introduction

There is extensive evidence of informed trading in the options market ahead of corporate news events.¹ The literature is, however, less informative about how private information affects investors' options trading strategies. Our objective is, therefore, to understand the relation between private information signals and investors' choice of option strikes and tenors.

When informed investors trade on private information, they react to a tip or a signal about future news or corporate announcements. These signals can include information about the timing of the news announcement and its potential impact on stock prices and returns. Across different categories of corporate events, both dimensions of the private signal vary in terms of expected value, as well as uncertainty.² For example, an investor with private information about a scheduled earnings announcement knows precisely when the news will be published, yet may find it difficult to estimate the (typically moderate) impact of the earnings news on stock prices. By contrast, an investor with private information about the deal premium paid in a merger and acquisition (M&A) transaction may predict the (typically large) price impact precisely, but may not know the exact timing of the deal announcement.

Heterogeneity across corporate announcements in terms of type and precision of signals is likely to affect an informed investor's trading strategy, and, therefore, the nature of informed trading. By contrast to the existing research, we explicitly incorporate this heterogeneity about the price impact and timing of the announcement to study the differences in trading strategies of informed investors, ahead of numerous categories of corporate announcements.

We propose a framework for identifying the optimal option trading strategies of privately informed investors, i.e., the "first best" strategy. In other words, we identify the combination of option type, strike price, and maturity that maximizes the expected returns from informed trading on a noisy signal in the presence of illiquid option markets. The maximization of

¹Augustin and Subrahmanyam (2020) review the evidence on options trading before corporate events.

²We also refer to the expected value of a signal as "magnitude," and its certainty as "precision."

expected returns is equivalent to the maximization of leverage, which is a primary motivation for privately informed investors to trade in the options market (Black, 1975).

We assume that the private information received by an investor consists of two signals: information about the timing of a news announcement and information about the announcement's return on the underlying stock.³ In addition to their expected values, we also consider the precisions of the two signals, characterized by the uncertainty in the timing of the future announcement, and the uncertainty in the future stock price's reaction to the announcement.

A central feature of our framework is that it accounts for two important frictions that price-taking investors face in options markets. First, most options trade with wide bid-ask spreads, which typically depend on their moneyness. This implies much higher percentage bid-ask spreads for options that are further away from the money, due to their lower prices. Second, most options do not trade below a minimum price of ten cents. Both these frictions can make trading out-of-the money (OTM) and deep-out-of-the money (DOTM) options prohibitively expensive, and limit the maximum attainable leverage/returns. Run-ups in implied volatilities before scheduled news announcements further increase trading costs.

We illustrate numerically that this minimal set of frictions (bid-ask spreads, minimum prices, volatility run-ups) drastically reduces the benefits to informed trading. Maximum attainable returns drop from unrealistically high levels (multi-million percent returns) to more realistic magnitudes observed for trades that, according to the U.S. Securities and Exchange Commission (SEC), are based on private information.⁴ More importantly, we show that these frictions introduce an important non-linear trade-off between leverage and transaction costs that significantly affects informed investors' choice of option strikes and tenors.

Our analysis reveals three main insights about the strategic trading behavior of informed

³We focus on a two-dimensional signal, for reasons of tractability, and leave an extension to private, but noisy, signals about changes in the volatility of the underlying stock price distribution for future research.

⁴Trading profits for insider trading violations are available at <https://www.sec.gov/litigation/litreleases.shtml>.

investors in options markets. First, market frictions, including lower bounds for prices and bid-ask spreads, typically lead informed investors to trade options that are only slightly OTM rather than DOTM, as one would intuitively expect. Thus, our framework may help rationalize the puzzling heterogeneity of stock return predictability by option order imbalances computed for different degrees of moneyness (Hu, 2014). Second, the expected announcement return is the primary determinant of the option choice. Uncertainty about the announcement return is quantitatively less meaningful for strategic trading. Third, the precision of the timing signal significantly affects the choice of option maturity. All else equal, a greater event date uncertainty leads informed investors to trade in longer maturity options. With precise timing signals, investors can maximize leverage by trading short maturity options shortly before the announcement. These choices may partially be offset by implied volatility run-ups and increases in bid-ask spreads before scheduled events.

We provide empirical support for our framework using a sample of 30,975 “significant corporate news” (SCN) events between 2000 and 2014. The sample consists of significant stock price movements that can be associated with firm-specific news using the millisecond timestamped data from RavenPack News Analytics. We classify all SCNs into twelve categories that exhibit a substantial amount of heterogeneity with respect to their announcement characteristics. Thus, they exhibit rich variation with respect to the magnitude and the precision of private signals that impact informed options strategies according to our framework.

Our analysis suggests that the event-specific characteristics, which represent the signals to informed investors, are useful for explaining variation in the announcement returns of SCNs. Thus, expected jump size and its uncertainty, as well as the expected time to announcement and its uncertainty, are significant predictors of stock price jumps, after controlling for firm and industry characteristics, and macroeconomic variables.

We next use the event-specific information signals to quantify, using our framework, the maximum expected option returns attainable to informed investors before SCNs. Thus, we

use the expected announcement return and its standard deviation for each news category to identify the option moneyness and tenor that would yield the highest expected return, accounting for observed market frictions. Our analysis suggests that, consistent with our framework, investors would trade less OTM or even ITM options when they expect smaller stock price reactions, while they would trade further OTM when they expect larger stock price jumps. Moreover, the optimal option maturity is increasing in the event uncertainty. Since the magnitude of frictions depends on firm-specific characteristics, we find rich heterogeneity in the return maximizing moneyness and tenor within each news category.

The calibration of expected option returns to noisy signals about a future price jump and news announcement date allows us to rank the informed options strategies in terms of expected returns. In a final step, we construct a novel measure of informed trading based on the trading volume of those options that yield the highest expected returns (i.e., options that maximize leverage). We define the relative call volume (RCV) as the ratio of the call volume of high expected return options to total options trading volume. Similarly, relative put volume (RPV) is defined as the ratio of the put volume of high expected return options relative to total options volume. We show that RCV and RPV predict positive and negative announcement returns of SCNs, respectively, after controlling for measures of informed options trading. We also show that our measures of informed trading are both theoretically and empirically different from measures of option elasticity, and that similar measures computed using OTM options are not informative for SCNs.

Our main contribution is that we formally show how the characteristics of private signals that relate to the stock price reaction and uncertainty around future news announcements impact the options trading strategy of informed investors. We explicitly show that the optimal choice of option moneyness and tenor endogenously arises as a trade-off between the benefits of leverage and the liquidity-related trading costs. Thus, we formalize a trade-off that has been suggested in earlier work. For example, Chakravarty et al. (2004) argue

that informed trading is driven towards ATM options when they are cheap to trade relative to OTM options. Similarly, Ge et al. (2016, p.603) suggest that “higher transaction costs for out-of-the money (OTM) options might lead some traders to capitalize on their private information by trading at-the-money (ATM) or in-the-money (ITM) options, depending on the content of the private information.” Hu (2014) argues that high trading costs drive informed traders away from OTM options, and reports that order imbalances of ATM and ITM options have more predictive power than those of OTM options.

A second key departure from prior work is that we account for heterogeneity in event characteristics, allowing us to examine how informed investors trade differentially as a function of corporate announcement characteristics. To the best of our knowledge, other studies on informed options trading focus on one individual event category, such as M&A transactions, corporate divestitures, or earnings announcements. One exception is contemporaneous work by Cremers et al. (2021), who distinguish how informed investors differentially trade around scheduled earnings announcements and unscheduled news items in their empirical analysis of informed trading activity. By contrast, we provide theoretical guidance for ranking options strategies in terms of expected returns when investors obtain information signals with different degrees of precision regarding the timing and announcement effect of corporate news.

Previous Studies emphasize how market frictions affect the choice of trading in the options market. Instead, we focus on how frictions and the characteristics of private information affect investors’ choice of option strategy, conditional on trading in the options market. Anand and Chakravarty (2007) take another perspective and show that informed investors may split up their trades and engage in stealth trading to minimize the price impact. According to extant theory, informed investors may migrate towards the options markets, as they provide more “bang for the buck,” i.e., leverage, especially in the presence of superior information (Boyer and Vorkink, 2014; Ge et al., 2016) capital constraints and asymmetric information

(Easley et al., 1998), differences in opinion (Cao and Ou-Yang, 2009), short-sale constraints (Johnson and So, 2012), or margin requirements and wealth constraints (John et al., 2003).

There is also substantial empirical support for the presence of informed investors in the options market. Various studies pinpoint informed options trading ahead corporate events, including analyst recommendations (Kadan et al., 2018), macroeconomic news (Bernile et al., 2016), the announcement of earnings (Roll et al., 2010; Goyenko et al., 2014), M&As (Cao et al., 2005; Chan et al., 2015; Kedia and Zhou, 2014; Augustin et al., 2019; Lowry et al., 2019), spin-offs (Augustin et al., 2020), leveraged buyouts (Acharya and Johnson, 2010), and the announcements of strategic trades by activist investors (Collin-Dufresne et al., 2015).

Our work more generally relates to the vast literature that examines the predictive power of information-based measures derived from option markets for stock returns, namely option volume (Easley et al., 1998; Ge et al., 2016), put-call ratios (Pan and Poteshman, 2006), the implied volatility (Bali and Hovakimian, 2009; Xing et al., 2010; Lin and Lu, 2015; Jin et al., 2012), put-call parity deviations (Cremers and Weinbaum, 2010), option-to-stock volume ratio (Johnson and So, 2012; Lin and Lu, 2015), and hedging activity by market makers (Hu, 2014). Our focus on informed trading relates this study also to the literature on insider trading, for which we refer to Bhattacharya (2014) and Augustin and Subrahmanyam (2020) for reviews.

The remainder of the paper is organized as follows. In Section 2, we present a novel framework for identifying option trades that maximize expected returns to informed traders with private, but noisy signals. In Section 3, we provide empirical support for our framework. We discuss extensions in Section 4 and conclude in Section 5.

2 Trading strategies of informed investors

In 2007, the SEC charged Thomas Flanagan, a former vice president at Deloitte and Touche LLP with material private information on client firms, on multiple accounts of illegal insider trading. In one instance, he bought 485 put options on the stock of Walgreen's ahead of a negative earnings surprise. The options were bought at strike prices of \$45 and \$47.5, were set to expire in October 2007, and cost a total of \$46,619. Upon the firm's first negative earnings surprise in almost a decade, share prices dropped 15% and the insiders realized an illicit profit of \$268,107 corresponding to 575% of their option investment. By contrast, a short stock position would have yielded profits of merely 15% before transaction costs.

The previous example begs the question of why the insiders chose the \$45 and \$47.5 strike options with a short time to expiration. As we formally show in this section, expected returns to informed trading vary substantially across a wide spectrum of trading strategies, in terms of both strike price and maturity. Specifically, the optimal choice of option moneyness and tenor depends on the level and the precision of private information signals about the timing and stock price reaction of future news announcements. To better understand informed trading strategies, we propose a framework for calculating the expected returns to informed option trading when informed investors receive noisy private signals about the expected timing and stock price reactions of upcoming news.

2.1 Theoretical framework

We derive the optimal option strategy of an atomistic investor, facing a menu of equilibrium option prices and transaction costs, in response to a private signal about future news. We assume that the informed agent's primary objective is to maximize her expected return by leveraging her private information.⁵ Thus, the optimal option contract depends only on

⁵The assumption of leverage-maximizing investors is consistent with previous studies on informed options trading (e.g., Acharya and Johnson, 2010). Analyzing expected returns delivers all our insights. Accounting

the expected return net of transaction costs.⁶ We calculate the expected return, $\mathbb{E}[R]$ from buying an option today (at t_0) and selling it after a news-induced jump (at $t_1 = t_0 + \Delta t$) as:

$$\mathbb{E}[R] = \frac{\mathbb{E}[P_{bid, t_1}]}{P_{ask, t_0}} - 1, \quad (1)$$

where $[P_{bid, t_1}]$ denotes the bid price at which the investor expects to sell the option, and $[P_{ask, t_0}]$ is today's option ask price as observed in the market. Analogously, we compute the expected returns of trading strategies involving multiple securities by summing up the expected future bid and the current observed ask prices of all securities in the numerator and denominator, respectively. In the Black-Scholes-Merton (BSM) framework (Merton, 1973; Black and Scholes, 1973) without dividend payments, the expected return to option trading around a news event is given by:

$$\mathbb{E}[R] = \frac{\mathbb{E}[\theta(S_0 e^\kappa, T_0 - \Delta t, K, \sigma, r)]}{\theta(S_0, T_0, K, \sigma_0, r)} - 1 = \frac{\mathbb{E}[\theta_1]}{\theta_0} - 1, \quad (2)$$

where $\theta(\cdot)$ denotes the BSM value of a European call or put option as a function of the underlying stock price S_0 , the option's strike price K , the option's time to maturity T_0 , and the risk-free rate r . The parameter κ is a random variable describing the anticipated change in the stock price between time t_0 and t_1 , expressed as a continuous return.⁷ Similar to Cremers et al. (2021), we incorporate the run-up in implied volatility ahead of scheduled events as in Dubinsky et al. (2019) by defining $\sigma_0 = \sqrt{\sigma^2 + \frac{\sigma_j^2}{T_0}}$. For unscheduled events, $\sigma_0 = \sigma$. The parameter σ is the unconditional implied volatility excluding any run-up, and

for higher moments of the return distribution and risk aversion would possibly strengthen our conclusions at the expense of making the framework less tractable. We leave such extensions for future research.

⁶Informed investors may strategically deviate from the "first best" to mitigate the price impact and/or to avoid detection by other traders or regulators. Our empirical analysis accounts for such strategic trades since we focus on traded options that rank in the top tercile of the options that maximize expected returns.

⁷Incorporating informed trading based on anticipated changes in σ would only marginally impact predicted trading behavior but distract from our focus. In unreported results, we show that "vega" or implied volatility strategies (e.g., straddles) may be rational with extremely noisy information signals, even though trading on changes in the implied volatility does not offer high expected returns to informed investors.

σ_j is the volatility of the jump anticipated by (uninformed) investors ahead of a scheduled event.

We only consider long options positions that do not face margin requirements.⁸ In Appendix B, we show that accounting for margins dramatically lowers the realized returns of short options positions. This is consistent with studies which document that margin requirements substantially increase the cost of equity options (Santa-Clara and Saretto, 2009; Hitzemann et al., 2016; Noel, 2017). It also agrees with Ge et al. (2016, p.602), who “find no evidence that trades related to synthetic short positions in the underlying stocks contain more information than trades related to synthetic long positions.”

Writing options generally provides less leverage than purchasing options due to the significant margin requirements for short option positions. For example, the initial margin for short put options is determined by the minimum of 10% of the strike price or 20% of the underlying stock price reduced by any OTM amount. In practice, brokers charge additional margins on top of the exchange-required minima. Adding uncertainty in the magnitude of the price jumps and/or the timing of the announcement, the run-up in implied volatility ahead of scheduled news, and the uncertainty of its evolution after the announcement would further lower expected returns.

We next account for market frictions by introducing a bid-ask spread, α , and a minimum option price, P_{min} , consistent with institutional trading frictions. When the BSM option value adjusted for half the bid-ask spread is below the minimum price, as can be expected for DOTM options, the market price equals this minimum price. The most important friction is the bid-ask spread, which is determined by economic considerations. By contrast, the minimum price, typically related to the tick size, is determined by the exchange and has become a negligible number over time. At time t_1 , the informed investor will sell her position

⁸Since we consider investors with private information signals, we differ from Cremers et al. (2021) who suggest that publicly informed investors sell put options ahead of scheduled news.

whenever doing so yields more than the position's intrinsic value I_1 , and exercise the option(s) otherwise. We can, thus, rewrite the previous expression as:

$$\mathbb{E}[R] = \frac{\mathbb{E}[\max(\theta_1 - 0.5\alpha_1, I_1)]}{\max(\theta_0 + 0.5\alpha_0, P_{min})} - 1. \quad (3)$$

Finally, we incorporate the perspective of an informed investor who receives two private signals about future news. The first is information about the timing of the news event. Since we assume that the informed investor unwinds her position instantly after the news-induced jump, the notation for the timing of the jump corresponds to that for the time between the opening and the closing of the option position, Δt . The second signal relates to information about the announcement's return induced by the news, κ . As both of these signals may be noisy, both Δt and κ are random variables. Denoting their joint probability density function by $\phi(\kappa, \Delta t)$,⁹ the expected return to the option strategy is the probability-weighted average:

$$\mathbb{E}[R] = \frac{\int_{\kappa} \int_{\Delta t} \phi(\kappa, \Delta t) \max(\theta_1(\kappa, \Delta t) - 0.5\alpha_1, I_1) d\kappa d\Delta t}{\max(\theta_0 + 0.5\alpha_0, P_{min})} - 1. \quad (4)$$

Equation (4) allows us to pinpoint the strike price, maturity, and type of the option contract(s) an informed investor would trade to maximize expected returns.

Previous studies examine how strategic interactions between informed and uninformed investors endogenously determines option prices and transaction costs (e.g., Kyle, 1985). By contrast, we consider the optimal option strategy of a price-taking investor faced with equilibrium prices and transaction costs. General equilibrium considerations, whereby market makers learn and widen bid-ask spreads for contracts with informed trading, are likely to have only a moderate impact on our results, because informed trading is only a small fraction of the aggregate order flow. This is especially true for the “moderately” OTM options with

⁹We assume that κ follows a normal distribution and that Δt follows a truncated normal distribution.

high volumes and narrow bid-ask spreads, which are favored by liquidity traders.

2.2 Evidence on frictions

In Figure 1, we provide information on the magnitude of the frictions of equity options in the OptionMetrics database. Panel (a) of Figure 1 shows the evolution of bid-ask spreads. The median (average) spread reduced over time, from 25% (23%) in 1996 to 5% (10%) in 2010. Bid-ask spreads for the OTM options remain nevertheless important. In Panel A of Table 1, we show the distribution of bid-ask spreads for OTM call and put options. The median firm has an absolute spread that is 19 (15) cents for put (call) options, corresponding to 67% of the mid price. for the median firm. The fact that bid-ask spreads for OTM options can range up to 143% of mid prices undercores the important tradeoff between between leverage and the frictions faced by investors with private information.

In Panel (b) of Figure 1, we illustrate the historical evolution of minimum option prices. We plot the minimum (dotted line) and the first percentile (dashed line) of option prices below three dollars, using all contract days with a trading volume of at least 100 options. Besides market liquidity, minimum prices are driven by the minimum tick size dictated by the Chicago Board Options Exchange (CBOE), and other major options exchanges. Since 2000, the minimum tick size for most options equals five cents, if the option traded below three dollars, and ten cents otherwise. Exceptions were introduced in the CBOE's experimental Penny Pilot Program that started in January 2007, decreasing the minimum tick of liquid options to one and five cents for options priced below or above three dollars, respectively.

The observed minimum prices are mostly equal to or above 10 cents, which is significantly larger than the minimum tick size. Thus, the regulatory minimum prices do not seem to be a binding constraint. This is reinforced by the evidence for OTM options reported in Panel A of Table 1, which shows that the distribution of absolute spreads is comparable to

that of ask prices if we restrict the sample to zero-bid options. Thus, the minimum prices of tradeable options are often 2-4 times as large as the exchange-mandated minimums of 5 and 10 cents.

That DOTM options are rarely offered at the minimum price of 5 cents, even if their “fair” (i.e., BSM) value is lower, may be explained by fat tails, downside risk, risk aversion, informed trading, adverse selection, or other factors such as inventory costs and illiquidity. Indeed, Goyenko et al. (2014) show, using intraday transactions data, that the bid-ask spreads of OTM options are driven by information asymmetry and demand pressures that increase ahead of earnings announcements. Boyer and Vorkink (2014, p.1485) suggest that high premia for writing OTM options “compensate intermediaries for bearing unhedgeable risk when accommodating investor demand for lottery-like options.”¹⁰

High minimum prices render the trading of DOTM options expensive, and, therefore, lower expected returns, which is also reflected in the high implied volatilities of DOTM options. As a result, in anticipation of a significant stock price jump, informed traders may not trade DOTM (or OTM) options even if these are the options that are intuitively expected to provide the greatest leverage based on their intrinsic value. By contrast, it may be optimal to trade in options that are slightly OTM, or, potentially even ITM. The tradeoff between option moneyness and frictions is reinforced if investors face uncertainty about the magnitude of the future price jump and its timing.

Panels B, C, and D in Table 1 support the view that, in light of the expensiveness of DOTM options, these options hardly trade. The results in Panel B suggests that the median firm only has three quoted OTM puts and calls and the menu of available options is even smaller if we exclude all options with zero bid prices. In that case, the median firm only has one OTM put and call option quoted on it, and only six puts and four calls, respectively,

¹⁰This argument relates to work on the inelasticity of the option supply curve (e.g., Bollen and Whaley, 2004; Garleanu et al., 2009; Deuskar et al., 2011; Bates, 2013).

at the 95th percentile of the distribution. Panel C of Table 1 highlights that options with zero bid price literally do not trade. The median firm also has no trading volume for options with non-zero bid prices.

The view that DOTM options are not always the securities that maximize expected returns is suggested by the indictment of Thomas Flanagan, who purchased put options with a strike price of USD 47.50 when the underlying stock was trading between USD 47 and USD 48. That view is also suggested by Chakravarty et al. (2004), Hu (2014), and Ge et al. (2016), who argue that informed trading is driven towards ATM or ITM options, when these are cheap to trade relative to OTM options, even though OTM options appear to offer an informed trader the highest leverage. Our contribution is to explicitly formalize the strategic behavior of informed investors, which is implicit in the choice of option strike price and maturity. The choice of option strategy depends on market frictions and the noise associated with the private signal. In our simple framework, we can generate a trade-off without appealing to the higher moments of the return distribution, investor risk aversion or the price impact of informed trades.

2.3 Impact of market frictions on expected option returns

In Figure 2, we illustrate the effect of market frictions (i.e., minimum option prices and bid-ask spreads) on expected returns to informed trading in call options using equation (4). Without loss of generality, we consider an expected future price jump signal of $E[\kappa] = 20\%$ in $E[\Delta_t] = 3$ days, without uncertainty about the magnitude of the jump or about the timing of the news announcement, i.e., $\sigma_\kappa = 0$, and $\sigma_{\Delta t} = 0$. We calibrate the remaining parameters to the values $S_0 = 10$, $r = 0.03$, and $\sigma = 0.4$.

Panels (a) and (b) in Figure 2 report the benchmark expected returns without market frictions, when the bid-ask spread and the minimum price are equal to zero. Under these

assumptions, the BSM value of an OTM option close to expiration is a small fraction of a cent. Buying the OTM option at such a low price, and selling it once it becomes ITM after the news-induced jump, yields the unrealistic return of more than 1.8 million percent.

Panels (c) and (d) in Figure 2 report the expected returns using a more realistic parameterization of the bid-ask spread α of \$0.05 and a minimum price of \$0.10, all other parameters remaining unchanged. In addition to market frictions, we also consider a run-up in implied volatility ahead of scheduled announcements following Dubinsky et al. (2019). Even without a run-up in option prices in the case of unscheduled announcements, market frictions reduce maximum expected returns to more realistic values that are less than 2,000%. That number is much closer to the average 1,300% option return earned by investors with private information that are reported in the SEC's public record of insider trading litigations (Augustin et al., 2019). The stylized example underscores that non-zero minimum prices, bid-ask spreads, and run-ups in implied volatility significantly impact the expected option returns to informed traders. This is because such frictions significantly reduce investors' leverage in option markets.

2.4 Impact of information signals on expected option returns

In Figure 3, Panels (a) to (d), we illustrate the impact of information signals on expected returns using comparative statics. We calibrate all parameters to sample estimates obtained in Section 3 and illustrate the impact for different types of firms by varying the price of the underlying stock from the 25th to the 75th percentile of the underlying stock price distribution of all options in our sample. We refer to the figure caption for details.

Panels (a) and (b) show that an increase in both the expected stock price jump and its uncertainty positively impacts expected option returns (and, hence, leverage). All else equal, these effects are larger for firms with larger stock prices, primarily due to the fixed

bid-ask spreads and minimum prices that are less binding for larger stock price jumps in this comparative statics exercise. Although important, noise/uncertainty in the information signal about the future stock price jump has a less significant quantitative impact on expected returns than the level of the signal and market frictions.

Panel (c) of Figure 3 shows that an increase in the expected timing of an announcement decreases the maximum expected returns. According to Panel (d), uncertainty in the timing information signal amplifies these effects, but the second order effect is lower in its economic magnitude. In the cross-section, the expected returns are larger for stocks with higher stock prices, since the fixed frictions are less binding in that case.

2.5 Impact of information signals on options strategies

We next explore how the expected value and the noise relating to an informed investor's private signal affect the strike price (moneyness) and maturity of the return-maximizing option contract. We report comparative statics using the same parameter values as before, calibrated to the empirical sample estimates that we discuss in Section 3 and illustrate the impact for a cross-section of firms with stock prices corresponding to the interquartile range of the underlying stock price distribution.

The expected price jump of the stock following a news announcement, $E[\kappa]$, is a key determinant of the expected option returns, as long as minimum prices are not binding. In Panels (e) and (i) of Figure 3, we show that a greater jump in the expected announcement returns incentivizes informed investors to increase leverage by trading further OTM (i.e., higher strikes) and reducing the option's etnor. The kink in the black solid line indicates the point at which minimum prices become binding, preventing informed investors from trading further OTM. In that case, the only way to increase leverage is to increase the option maturity, which leads to a non-monotonic relation between optimal maturity and

expected stock price jump. In the cross-section, frictions are more binding for firms with smaller stock prices. Expected return maximizing investors may, therefore, choose to trade ATM or even ITM, as illustrated by the range of option moneyness from below to above one. The effects of price jump uncertainty are similar to those of the expected price jumps, due to the convexity of option payoffs, as shown in Panels (f) and (j) of Figure 3.

A natural intuition in light of the binding minimum prices is that investors should prefer DOTM options that are just above the minimum price levels. However, DOTM options are rarely available and do not exist with prices just above the exchange mandated minimums. As mentioned above, Panel B in Table 1 shows that the menu of OTM options available to investors ranges on average from 1 to 12 for puts, and from 1 to 11 for calls. For the median firm, there are only 3 OTM puts and calls, respectively. Moreover, according to Panel A of Table 1, minimum prices for these options are, in most cases, a multiple fold of exchange mandated minimums, and bid-ask spreads for OTM options can range up to 143% of mid prices, with the median relative bid-ask spread being equal to 67%.

In Panel E of Table 1, we report for the same options sample moneyness, standardized by each option's spot volatility and time to maturity. Adjusted moneyness approximately captures the distance of the option's strike from the underlying stock price, measured in the number of standard deviations of the log-return. For the median firm, the moneyness is 1.27 (1.73) for calls (puts). These are the same options that have minimum prices of 15-19 cents with relative bid-ask spreads of 67%. Moving to the 75th percentile of the distribution, the moneyness distance for calls is 1.82, while minimum prices jump up to 25 cents with relative bid-ask spreads of 100%. It is only at the 95th percentile of the distribution that we reach a moneyness of 3.14, which is considered to be DOTM in the options index literature (e.g., Andersen et al., 2017), while minimum prices of 45 cents correspond to relative bid-ask spreads of 143%. In the terms of moneyness distance, the gap between the OTM options just above and below the minimum prices are significant. Moreover, call options "just above"

the minimum price are in almost all cases considered OTM or even ATM, while this is true in at least 50% of all cases for put options.

These statistics highlight the sharp and non-linear trade-off that arises between leverage and transaction costs that is considered in our framework. A slight increase in leverage significantly increases transaction costs. This trade-off is especially pronounced in the limit when we approach minimum prices. For that reason, investors may choose to trade options that are ATM, or even ITM, providing support for the frequently observed trading activity that is taking place in ATM and ITM options.

In Panels (g) and (k) of Figure 3, we illustrate the impact of the timing signal on the expected return-maximizing option strategy. In response to an announcement that is expected to occur in a more distant future, investors optimally choose longer option maturities that are further OTM. However, the effect on option moneyness is non-linear since very distant information events incentive trades that are ATM or even ITM. In Panels (h) and (l), we show that greater timing uncertainty leads to optimal option trades that are further OTM with longer tenors. In other words, greater timing uncertainty incentivizes informed traders to choose longer-dated options to reduce the likelihood that the trades expire worthless, prior to the announcement of news. In the absence of timing uncertainty, leverage can be maximized by choosing an option maturity that corresponds exactly to the timing signal (i.e., 11 days in our benchmark calibration).¹¹

2.6 Impact of market frictions on options strategies

In Figure 4, we examine the impact of variation in frictions (minimum prices and bid-ask spreads) on the option moneyness and maturity. In Panels (a) and (b), we vary minimum prices holding bid-ask spreads at their median sample estimate of \$0.15. An increase in

¹¹Informed investors may have more precise information to estimate expected returns compared to an econometrician. The comparative statics for signal uncertainties help assess how differences in information precision may impact the choice of option strike and tenor, and, therefore, expected returns.

spreads does not impact the optimal option strategy in terms of option strike and maturity unless frictions become binding, which arises at the kink in both graphs. Beyond that point, an increase in frictions leads informed investors to trade less aggressively in terms of moneyness (lower strike) and longer maturity options. The binding constraints depend both on the level of the friction and on the aggressiveness of the optimal option strategy. Since, all else equal, informed investors choose to trade further OTM, an increase in the minimum price starts binding more quickly compared to strategies that are ATM or even ITM.

In Panels (c) and (d) of Figure 4, we vary the bid-ask spreads holding minimum prices constant at their median sample estimate of \$0.19. Both figures show that informed investors compensate for an increase in the bid-ask spread by trading more aggressively, that is, they choose higher strikes relative to the current stock price and lower option maturities. If spreads increase to the point where the optimal option strategy is constrained by the existence of minimum prices, then wider spreads constrain the return-maximizing option strategy to lower strikes and higher tenors.

2.7 Scheduled events and trading in synthetic calls and puts

Figure A-1 in Appendix A illustrates that expected returns to informed trading in call options are lower for scheduled events. This is due to the fact that the run-up in implied volatilities ahead of scheduled events temporarily inflates the option prices at which investors can enter a position. In our graphs, we assume a jump size volatility of $\sigma_j = 0.1$. In Figure A-2 in Appendix A, we show that synthetic calls enable investors to reduce the impact of market frictions and substantially increase expected returns. This is because OTM, or even DOTM call options, can be created by trading the underlying together with ITM or DITM put options, which are substantially less affected by market frictions, due to

their higher values.¹² However, trading synthetic call options requires an investor to partly finance her positions by borrowing at (or higher than) the risk-free rate, which is thus likely to be restricted to sophisticated investors.¹³ Finally, in Figure A-3 in Appendix A, we show that the patterns observed for informed trading in call options are similar for put options, suggesting that the above insights extend to the latter.

3 Informed trading before significant corporate news

An important implication of our framework is that event-specific information signals are important for the choice of the optimal option strategy. These information signals are useful to informed investors only to the extent that they help predict returns.

Thus, to validate our framework, we exploit a heterogeneous sample of news categories and explain variation in their announcement returns using announcement characteristics. Using different categories of corporate events allows us to exploit the cross-sectional differences in announcement effects and their timing uncertainty to better understand heterogeneity in informed options strategies.

3.1 Constructing significant corporate news

We construct a sample of significant corporate news (SCNs) by identifying significant stock price movements that can be associated with firm-specific news. Consistent with the

¹²Even though DITM options can, in absolute terms, have higher absolute bid-ask spreads than DOTM options, the percentage spread of DITM options relative to their price tends to be substantially lower, given that prices include a high intrinsic value. For the same reason, minimum prices are less relevant to the pricing of ITM options.

¹³We do not examine synthetic put options, which can be created by combining a long call position with a short position in the underlying, as these imply significant margin requirements. Margin requirements will substantially reduce an investor's leverage and reduce returns to informed trading, and, hence, synthetic puts are dominated by the strategies considered here. See also Appendix B for an analysis of margins on returns from writing put options. Note that almost no (publicly reported) civil litigation initiated by the SEC refers to insider trading implemented through the use of synthetic options positions.

literature emphasizing the importance of news for stock prices (Roll, 1988; Lee and Mykland, 2008; Boudoukh et al., 2013; Bradley et al., 2014), we use news information with millisecond time stamps to correctly associate them with stock price jumps. This is crucial to our analysis because the news category characteristics impact the informed option strategy that maximizes expected returns.

To construct our sample of SCNs, we start with information from the Center for Research in Security Prices database (CRSP). To identify news, we use RavenPack News Analytics, which employs textual analysis to identify companies, news categories, and news relevance with millisecond time stamps in Dow Jones news articles and press releases published since 2000. We complement the RavenPack database with information on earnings news from Compustat's Capital IQ Key Development (CIQKD) database, and quarterly earnings announcement dates from the Compustat Quarterly files. See Appendix C for details.

Our starting sample includes all stock-days in the CRSP database between 2000 and 2014 with a stock price of at least five dollars, a market capitalization of at least ten million dollars and is restricted to stocks for which we observe news in the RavenPack database at least once. We first identify extreme price movements (EPMs) through the identification scheme of stock price jumps following Lee and Mykland (2008, 2012); Brogaard et al. (2018), which is described in Appendix D. We also require the availability of stock market data for at least 189 of the past 252 trading days, exclude the EPMs of stocks without information on options price and volume, require a minimum of one option trade during the 63 trading days prior to the EPM, and delete observations that we cannot match to the Compustat database. These filters lead to a sample of 83,653 EPMs – 50.9% of which are negative – observed for 4,131 securities on 3,761 different dates between 2000 and 2014.

Second, we define a SCN as an EPM associated with a news headline. To associate the EPMs with firm-specific news from RavenPack, we follow Bradley et al. (2014) and estimate logistic regressions to identify which news categories are relevant determinants of EPMs.

Specifically, we regress an indicator variable that is one for either positive or negative EPMS, and zero otherwise, on variables indicating the RavenPack news categories. A news indicator is set equal to one if a news story in that category was reported for the stock between 4 p.m. on the previous trading day and 4 p.m. on the given day. Among the 527 news categories in the RavenPack database, 80 (81) are associated with positive (negative) EPMS. This represents a broad set of corporate events with rich heterogeneity in terms of event characteristics.

In Tables A-1 and A-2 in Appendix A, we report statistics for those news categories that are statistically related to EPMS. If more than one news category is a significant determinant of EPMS, we associate the stock price jump with the category that has the highest odds ratio. Out of 41,092 (42,561) positive (negative) EPMS, 15,211 (15,764) are associated with SCNs.

In a final step, we use information on earnings news from Compustat's Capital IQ Key Development (CIQKD) database and quarterly earnings announcement dates from the Compustat Quarterly files to distinguish between scheduled SCNs (e.g., earnings announcements) and unscheduled SCNs that do not occur with earnings. We consider all news released on earnings announcement dates as scheduled. We then assign all news categories to a less granular classification of twelve categories that we use in the subsequent analysis.

Table 2 reports descriptive statistics for the sample of positive and negative SCNs for each news category. A news story about a firm being acquired is associated with the highest announcement return, and almost always induces a significant amount of trading activity. Negative news about drug developments are comparable, even though the sub-sample is substantially smaller, i.e., 103 SCNs relative to 780 for targets in merger/takeover deals. EPMS that cannot be associated with news using the above approach (and which we thus do not classify as SCNs) often do not occur on days with high trading volumes, indicating that they may partly be due to the impact of trading on the prices of illiquid stocks, rather than fundamental news. We ignore this category of EPMS in our subsequent analysis, as

such events may likely be noise that does not permit informed trading.

3.2 Informativeness of event characteristics

We next explain variation in stock returns to SCNs using the characteristics of the news categories. This illustrates that the heterogeneity in event characteristics is informative for the choice of options strategy.

Specifically, we project returns to SCNs on the event characteristics that reflect the information signals in our theoretical framework. That is, we use the expected announcement returns $E[\kappa]$ and their uncertainty σ_κ (i.e., standard deviation) for each news category reported in Table 2. We also add an indicator variable that is one for scheduled events (i.e., earnings announcements) and zero otherwise, to capture the expected announcement time and its uncertainty, $\mathcal{I}(Scheduled)$, as well as their interaction effects.

The different regression specifications reported in Table 3 account for time fixed effects (year-month) to absorb the sources of common variation, such as macroeconomic fluctuations, and two-digit SIC industry or firm fixed effects to account for unobserved time-invariant industry and firm characteristics. We also control for time-varying firm characteristics including size, book leverage, the number of stock analysts, and stock return volatility. Heteroskedasticity-robust standard errors are reported in parentheses.

Our findings in Table 3 show that the average and standard deviation of the announcement return are significant predictors of the announcement returns measured around SCNs. Similarly, an indicator that is equal to one for scheduled news and zero otherwise is a statistically significant determinant of SCNs. This finding supports our model's prediction that the expected announcement return of a particular event category, its standard deviation, and announcement time uncertainty also provide useful information for the optimal choice of option maturity and moneyness.

3.3 Characteristics of informed options strategies

We next quantify the expected option returns to informed trading before SCNs. Thus, we exploit the heterogeneity in event characteristics to understand how informed investors differentially leverage their private information (i.e., the magnitude and precision regarding timing and impact of a particular SCN). By contrast to the numerical analysis, our analysis in this section depends explicitly on the liquidity and availability of options on each stock.

We compute the expected option returns after calibrating the information signals to the anticipated stock price reaction $E[\kappa]$ and the standard deviation of stock returns σ_κ in each news category reported in Table 2. For the timing of the trades, we take guidance from the evidence of illegal insider trades reported in Augustin et al. (2019) and assume that investors trade on their information signals 11 days ahead of unscheduled announcements, and one day ahead of scheduled announcements. We further assume a four-day uncertainty for the timing of unscheduled announcements, and no uncertainty for scheduled announcements.

Table 4 reports the expected returns to call (put) option trading around positive (negative) SCNs for each news category in our sample. We split the distribution of expected option returns into terciles and report the average within each group. The average expected returns to informed trading are substantially higher for events with stronger stock price reactions, such as M&As, for example. In most instances, trading ahead of scheduled news provides higher leverage (i.e., higher expected returns), which is due to the trading of short-dated options briefly ahead of an announcement.

The expected returns from trading short-term options are lower than those in the numerical analysis due to limited options liquidity. In theory, a precise timing signal enables investors to leverage their private information by trading options expiring right after an event. In practice, this effect is constrained by the limited number of option contracts expiring shortly after the event, pre-event run-ups in implied volatility, and poor liquidity in

many of these contracts (see Table 1).

Table 5 reports the average moneyness across terciles of expected option returns. We report option moneyness as the natural logarithm of the strike price relative to the spot price. For positive (negative) events, the expected returns for call (put) options and positive moneyness thus correspond to OTM (ITM) options. Consistent with our framework in Figure 3, we find that the return-maximizing options are not necessarily deep OTM, suggesting that the benefits of trading deeper OTM can be limited. For example, ahead of events with moderate stock price reactions, such as positive dividend or financing announcements, the optimal leverage options are closer to being ATM than for events with a high anticipated stock return, such as business contracts. Even when investors expect high stock price reactions, such as for target stocks in acquisitions, they would not necessarily trade deep OTM options.

Table 6 reports the average time to maturity by tercile of expected option returns. Across all sub-samples, option days with high expected returns have a short time to maturity relative to those with lower expected returns. Furthermore, the average time to maturity of high leverage options tends to be lower for scheduled events than for unscheduled events.

3.4 Evidence of heterogeneity in informed options strategies

Our framework implies that informed investors consider the trade-off between option leverage and frictions to determine their optimal options strategies. As a result, they may not always choose the most short-dated and DOTM options. In addition, the choice of option moneyness and tenor also depends on the type and precision of information signals.

We provide supporting evidence for such heterogeneity in informed options strategies using illicit insider option trades registered in civil and criminal litigations initiated by the U.S. Securities and Exchange Commission (SEC) and the U.S. Department of Justice (DoJ).

We obtain information on the characteristics of illicit option trades from Augustin et al. (2019) follow their process to collect the data.

We focus on the subset of SEC litigation cases related to insider trading in options prior to the announcements of M&As and earnings because these cases represent a particularly interesting benchmark for our analysis. M&A announcements are unscheduled, exhibit timing uncertainty, and are typically associated with large upward price movements for target stocks. Earnings announcements are scheduled, have no timing uncertainty, and come frequently with positive and negative earnings surprises.

Table 7 reports the evidence for the sample of 151 litigations, among which 109 are related to M&As. These cases cover illicit option trades across 358 different days. Call options are used in 83.90% of all cases and put options appear to be used exclusively when informed investors have information about negative earnings surprises.

The characteristics of insider trades, which are allegedly informed, offer empirical support for our framework. Option moneyness decreases in the magnitude of expected stock price jumps. Ahead of M&A announcements, insiders purchase call options that are slightly OTM with a spot to strike price ratio that is 97.65, on average. By contrast, ahead of earnings announcements, insiders purchase ITM calls and puts, with strike to spot ratios that are on average 104.72 and 90.67 for positive and negative earnings announcements, respectively. The precise information signal may also influence the moneyness choice, as demonstrated by the heterogeneity across percentiles of the reported distribution. Consistent with our framework, the timing uncertainty of M&A announcements is associated with option trades that have longer tenors – 48.79 days on average – than those for earnings announcements

In our framework, frictions are important drivers of informed options strategies. We, therefore, provide information on option prices and bid-ask spreads of prosecuted trades. Consistent with our earlier analysis, this evidence suggests that minimum prices are rarely binding. While implied bid-ask spreads account for an important fraction of mid prices,

insiders appear to choose options with lower proportional costs than those implied by DOTM options (see Table 1). We note that option returns are significantly higher than those of stock returns, especially for M&As announcements that have higher expected stock price jumps.

3.5 Informed options trading volume

After having calibrated the expected option returns to news-specific event characteristics, we now propose a new volume-based measure of informed trading implied by our framework. Accounting for bid-ask spreads and minimum option prices, we rank the options strategies that maximize returns subject to (potentially noisy) signals about future price jumps $E[\kappa]$ and the arrival date of news $E[\Delta t]$. Our measure is based on the volume of options that yield high expected returns, where expected returns are computed using equation (4). We define “high” expected returns as those that are in a top quantile of achievable returns. To make the measures stationary and comparable across firms, we scale the high-returns volume by the aggregate options volume for each company.

Computing the measure separately for calls and puts, we define the relative call volume (relative put volume), i.e., RCV (RPV), as the volume of call (put) options with high expected returns to informed trading scaled by total call (put) volume. More precisely, for firm i having N traded options on day t , we have that:

$$RCV_{i,t} = \frac{\sum_{j=1}^N C_{j,i,t} \mathbb{I}(E[R](\kappa, \Delta t) \geq \bar{R})}{\sum_{j=1}^N C_{j,i,t}} \quad RPV_{i,t} = \frac{\sum_{j=1}^N P_{j,i,t} \mathbb{I}(E[R](\kappa, \Delta t) \geq \bar{R})}{\sum_{j=1}^N P_{j,i,t}}, \quad (5)$$

where C and P denote the call and put volumes, respectively, and \bar{R} denote the cut-off level for high expected returns. Intuitively, large values for RCV and RPV suggest the presence of significant trading activity in options that provide significant “bang for the buck.” In other

words, these options with high values for RCV and RPV are the ones that allow investors to benefit the most, especially when they receive tips about upcoming news. We provide summary statistics for these two variables and other predictors in Table A-3 in Appendix A.

In Table 8, we report results from a regression of our sample of SCNs on the new informed trading measures. These are based on the volume of options that ought to be informative for announcement returns, since they incorporate event-specific information signals.

Indeed, RCV is consistently positive and statistically significant, implying that greater volume in the informed call options positively predicts announcement returns. Similarly, the statistically significant and negatively estimated coefficients for RPV suggest that greater volume in the informed put options is associated with more negative announcement returns. These results hold regardless of the inclusion of year-month fixed effects to account for unobserved common variation at the year-month level, or fixed effects for scheduled events and or two-digit SIC industries. Only in column (4), when we include firm fixed effects, does RCV lose its significance, which is to be expected since the firm fixed effects absorb much of the variation that is specific to firm-specific announcement returns.

We next add OTM call and put volumes (OCV and OPV), two relative volume measures that are constructed similarly to RCV and RPV , but where options are ranked according to moneyness depth. In column (5), both measures are borderline significant at the 10% level, do not add to the explanatory power of the regression, and their economic magnitude is a fraction of that found for RCV and RPV . Furthermore, OCV has the wrong economic sign, implying that higher OTM call volume predicts more negative returns. In unreported regressions, we also find that the significance of OPV is driven out by the price-based option measures. The fact that the OTM volume measures are less informative suggests that our measure is not purely capturing a leverage effect.

In the regressions for columns (6) to (11), we benchmark our measures against the existing return predictors implied from option volume or price information, including the put-call ra-

tio of Pan and Poteshman (2006), the option to stock volume ratio of Johnson and So (2012), the implied volatility spread of Cremers and Weinbaum (2010), and the implied volatility smirk of Xing et al. (2010). None of the measures drives out the statistical significance of our measure of informed options trading.

Note that our measure has a different purpose than existing option-based measures of informed trading. One advantage of our measure is that it explicitly pinpoints those options that provide the greatest leverage to informed investors who receive noisy tips about future news. Thus, it provides a pecking order of informed options strategies and is informative about the likelihood that a particular trade is informed.

4 Discussion and extensions

We show how our framework differs from option elasticity and examine simpler, although less precise, procedures to identify the option that maximizes expected returns. We then discuss an extension to cross-sectional predictions of excess stock returns and news sentiment.

4.1 Option elasticity

The optimal informed trading strategy is driven by the combinations of strike price and maturity that maximize expected returns. Thus, it is plausible to believe that our framework simply captures a monotonic transformation of option elasticity Ω , defined as the product of the option delta Δ and the ratio of the value of the underlying asset to the option price (i.e., $\Omega = \Delta \frac{S}{C}$ in the case of a call option). However, we show in Appendix E that elasticity can be both negatively and positively correlated with maximum expected returns from informed trading, depending on the parameter calibration. This is because our calculations account for noisy signals about both the stock price jump and the timing of the news announcement, in addition to realistic trading frictions.

4.2 A simple procedure for identifying “best” options

The optimal choice of options strategy depends non-linearly on market frictions (minimum prices, bid-ask spreads) and the level and precision of information signals (announcement return and timing). There is no simple procedure that closely approximates the complexity of our framework along both dimensions of option moneyness and maturity. However, we discuss three simplified procedures to partially approximate the optimal options strategy.

The first rule-based procedure simply chooses the most OTM option that has a non-zero bid price. The second procedure picks the option with the highest cost-adjusted measure of options elasticity, where the adjusted option elasticity accounts for trading frictions by adding the option bid-ask spread to the option mid price. The third procedure is a naïve implementation of our framework that shuts down the uncertainty of both information signals and computes option returns assuming immediate exercise after the news announcement.

In Appendix A, we compare in Figure A-4 the option characteristics of those options chosen by our framework (x-axis) to those chosen by the other procedures (y-axis) using scatter plots of quintile averages and medians. We add the 45 degree line to facilitate the comparison across methods.

The results in Panels (a), (d), and (g) suggest that all procedures lead to suboptimal choices in terms of expected option returns. The rule-based measure predicts vastly different choices in terms of moneyness and maturity compared to our framework, as shown by the large distances to the 45 degree line in Panels (b) and (c). While the cost-adjusted elasticity measure does a reasonable job in identifying the optimal moneyness (Panel (e)), it predicts option maturities that are too short (Panel (f)). By contrast, a naïve implementation of our framework better approximates the choice of option maturity predicted by our framework (Panel (i)), but leads to moneyness choices that are consistently less OTM (Panel (h)).

4.3 Predictions of excess returns & news sentiment

In the exercise in subsection 3.5, we examine whether a volume-based measure derived from option returns that are calibrated to event-specific characteristics is useful for explaining variation in the announcement returns to SCNs. While this accurately captures our idea of informed trading signals, it implicitly puts the alternative informed trading measures at a disadvantage, since these measures are not calibrated to any upcoming news characteristics.

Thus, we extend our framework to explain returns and news sentiment scores in the broader cross-section of stocks in Appendix F. While in that exercise we reduce the look-ahead bias associated with the information signals, we have to make assumptions about the magnitude and uncertainty about anticipated stock price jumps. See Appendix F for details.

Our findings in Tables F-7 and F-8 in Appendix F.2 suggest that *RCV* has primarily predictive power for the cross-section of stock returns and that *RPV* has primarily predictive power for the cross-section of news. Importantly, the incremental explanatory power of our informed trading measures relative to a benchmark model with common risk factors is larger than that of other well known option-implied stock predictors. Moreover, the statistical significance of our informed trading measures is not driven out by these alternative measures.

In Table A-4 in Appendix A, we further show that our informed trading measures do not simply capture high leverage. As alternative measures of informed trading, we compute *RCV* and *RPV* based on the volume of options that are in the top tercile of moneyness depth, as opposed to the top tercile of expected option returns implied by our framework. Our findings show that these alternative predictors are insignificant.

5 Conclusion

We propose a framework for describing *how* investors can best leverage their private information in the options market. Informed investors receive private and possibly noisy

signals about the timing of future news events and their impact on stock prices. The parameters of these signals determine investor's choice of option strategy as well as the returns to informed trading in the options market. We identify the optimal combination of option type, strike price, and maturity, as the ones enabling informed investors to maximize their expected returns, accounting for bid-ask spreads and minimum option prices. These minimal market frictions can substantially affect the strategic trading behavior of informed investors, and introduce a trade-off between moneyness and expected return, without the need for modeling higher order effects, such as risk aversion, or more complex price impact frictions.

Overall, we provide a pecking order for informed options trading strategies. Since our framework identifies the option strategy that enables informed investors to maximize the leverage of their private signal under market frictions, it may be useful to regulators for the identification of informed trading activity. In particular, the characterization of informed strategies may help regulators identify informed option trades around corporate news events and differentiate them from thousands of uninformed trades. Thus, our results indicate that not all options should be treated alike and that some do merit closer regulatory scrutiny.

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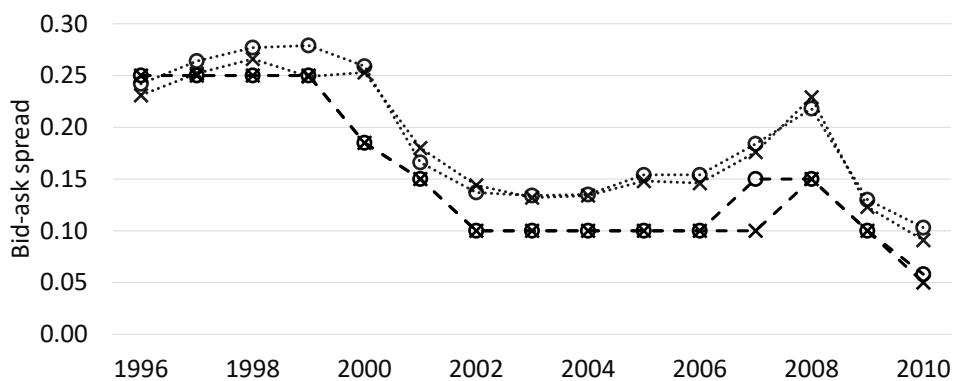
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Figure 1: Time Series of Bid-Ask Spreads & Minimum Prices of Equity Options.

Panel (a) plots the evolution of the average (dotted line) and median (dashed line) of bid-ask spreads of equity options reported in the OptionMetrics database. Circles mark call options, crosses mark put options. Averages and medians are computed over all contract-days with a trading volume of at least 100 options and non-negative bid-ask spreads. Panel (b) displays the evolution of the minimum (dotted line) and the first percentile (dashed line) of option prices below three dollars. Minima and percentiles are computed over all contract-days with a trading volume of at least 100 options.

(a) Bid-Ask Spreads



(b) Minimum Prices

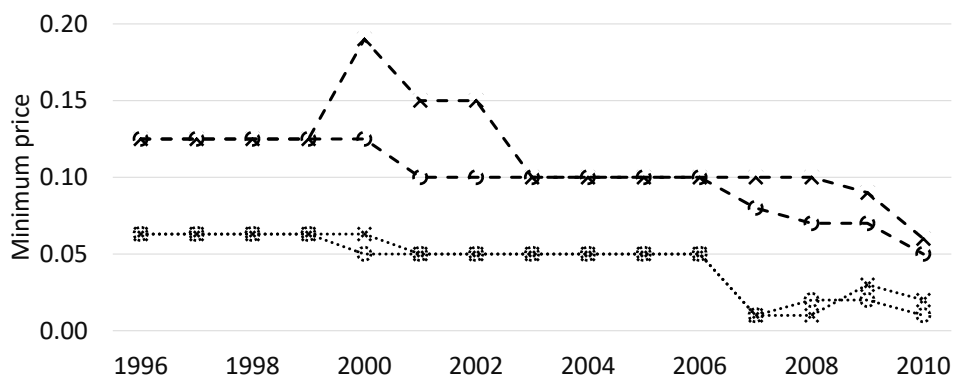
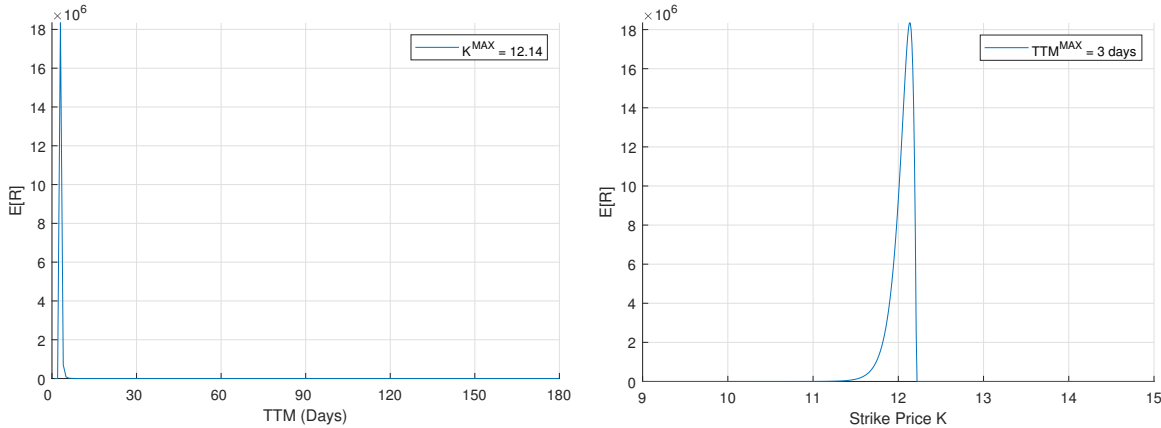


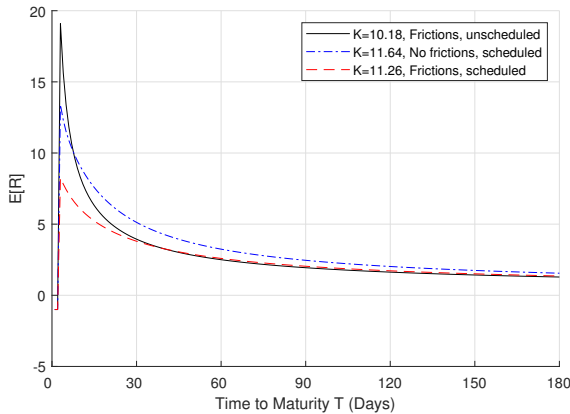
Figure 2: Effect of Market Frictions & Volatility Run-Ups on Expected Returns.

The graphs in this figure plot expected returns to informed trading in call options computed using the BSM framework. Panels (a) and (b) are based on the assumption that there are neither market frictions (zero bid-ask spread and minimum price) nor a run-up in implied volatility. Panels (c) and (d) introduce market frictions and a run-up in implied volatility. The lines labeled “frictions” assume a bid-ask spread α of \$0.05 and a minimum price of \$0.10, all other parameters remaining equal. The lines labeled “scheduled” assume a run-up in implied volatility ahead of the event as in Dubinsky et al. (2019). Strike prices (maturity) are chosen such that the graph shows the global maximum of the expected return function. This explains why the maxima in both graphs of each panel are identical. The timing and the magnitude of the news-induced jump are known with certainty. Parameters are chosen such that $E[\kappa] = 0.2$, $E[\Delta_t] = 3/360$, $\sigma_\kappa = 0$, $\sigma_{\Delta t} = 0$, $S_0 = 10$, $r = 0.03$, and $\sigma = 0.4$.

(a) Zero bid-ask spread & no min. price, no IV run-up (b) Zero bid-ask spread & no min. price, no IV run-up



(c) Market frictions and IV run-up



(d) Market frictions and IV run-up

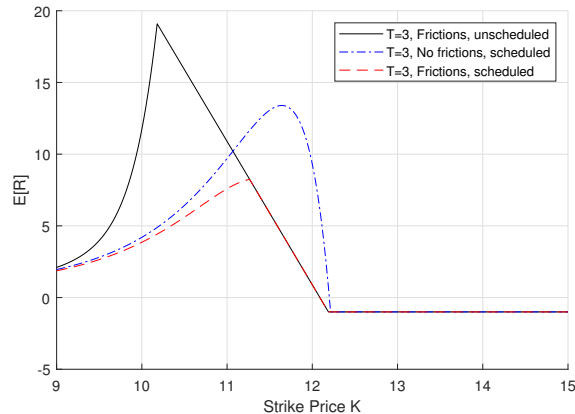


Figure 3: Impact of Information Signals on Option Choice.

In this figure, we characterize the impact of the information signals on the moneyness K^*/S and the time to maturity T^{max} that maximize expected returns $E[R]^{max}$ to informed trading in call options ahead of a positive event. We consider changes in the expected jump in stock prices $E[\kappa]$, the jump size uncertainty σ_κ , the expected time to announcement $E[\Delta t]$, and the expected announcement time uncertainty $\sigma_{\Delta t}$. We report comparative statics, keeping everything else constant. The expected jump size and the uncertainty in the jump size are calibrated to $E[\kappa] = 11.73\%$ and $\sigma_\kappa = 7.47\%$, corresponding to average stock price jump and its standard deviation in our sample of significant corporate news (see Table 2). Following the illegal insider trading litigation statistics of Augustin et al. (2019), we calibrate the expected time to announcement to $E[\Delta t] = 11$ days and the associated uncertainty to $\sigma_{\Delta t} = 4$ days. We use an interest rate of $r = 0.03$. We calibrate the option-implied volatility to the sample median value $IV = 0.35$, the minimum price to $\$0.19$ and the bid-ask spread to $\$0.15$, corresponding to the median estimates in our sample. We vary the price of the underlying stock around its median sample estimate of $S_0 = \$25$ from the 25th ($S_0 = \$14$) to the 75th ($S_0 = \42) percentiles of the underlying stock price distribution.

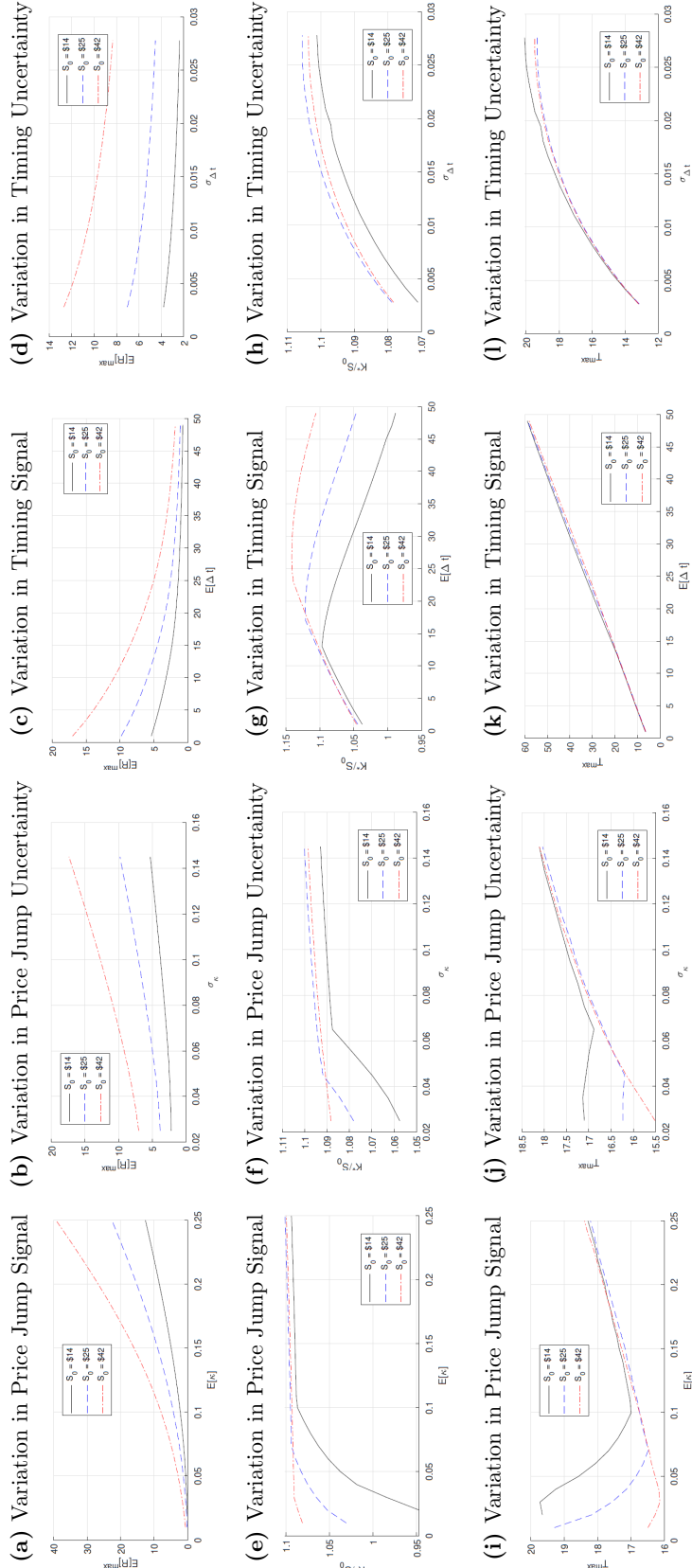


Figure 4: Impact of Frictions on Option Choice.

In this figure, we characterize the impact of frictions (minimum prices, bid-ask spreads) on the moneyness K^*/S and the time to maturity T^{max} that maximize expected returns $E[R]^{max}$ to informed trading in call options ahead of a positive event. In Panels (a) and (b), we consider changes in minimum option price; in panels (c) and (d), we consider changes in the option bid-ask spread. We vary the price of the underlying stock around its median sample estimate of $S_0 = \$25$ from the 25th ($S_0 = \$14$) to the 75th ($S_0 = \42) percentiles of the underlying stock price distribution. The expected jump size and the uncertainty in the jump size are calibrated to $E[\kappa] = 11.73\%$ and $\sigma_\kappa = 7.47\%$, corresponding to the average stock price jump and its standard deviation in our sample of significant corporate news (see Table 2). Following the illegal insider trading litigation statistics of Augustin et al. (2019), we calibrate the expected time to announcement to $E[\Delta t] = 11$ days and the associated uncertainty to $\sigma_{\Delta t} = 4$ days. We use an interest rate of $r = 0.03$. We calibrate the option-implied volatility to the sample median value $IV = 0.35$, the minimum price to $\$0.19$ and the the bid-ask spread to $\$0.15$, corresponding to the median estimates in our sample.

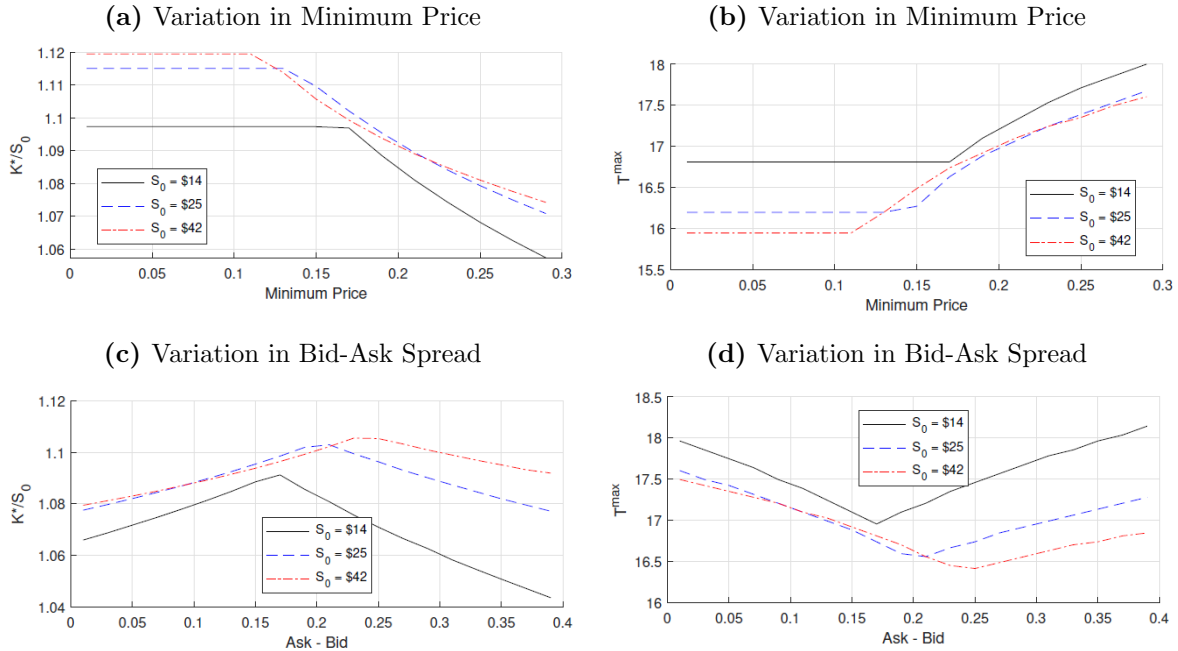


Table 1: Characteristics of OTM Equity Options

This table presents a summary of the frictions encountered by an investor trading out of the money (OTM), short-maturity equity options. In each panel, we characterize the distribution of the measure of interest for OTM put and call options, respectively, using the 5th, 25th, 50th, 75th and 95th percentiles of the distribution. In Panel A, we report the distribution of bid-ask spreads in absolute dollar terms (“Bid–Ask”), in percentage terms (“(Bid – Ask) / Mid”), and the asking price for options that have a bid price of zero (Ask (Bid= 0)). In Panel B, we report the number of quoted OTM option strikes at the firm-day level for all OTM options (“All OTM”) and for all OTM options with non-zero quoted bid prices (“OTM Bid≠ 0”). In Panel C, we report option trading volume, measured as the daily number of option contracts traded for a firm, separately for all OTM options (“OTM”), all OTM options with non-zero (“OTM (Bid≠ 0)”) and zero bid prices (“OTM (Bid= 0)”). In Panel D we report the same statistics after restricting the sample to those firms that have a minimum of one option of each type (Call/Put) being traded on a given day. In Panel E, we report the adjusted option moneyness, defined as $\frac{\log(K/S)}{\sigma_{ATM}\sqrt{\tau}}$, where σ_{ATM} defines the ATM implied volatility and τ the time to maturity. We focus on the moneyness of the most OTM option with a non-zero bid price (“DOTM (Bid≠ 0)”), the least OTM option with a zero bid price (“DOTM (Bid= 0)”), and the OTM option closest to the ATM-forward price of the stock (“CATM”). The starting sample contains all equity options in the OptionMetrics dataset between 1996 and 2014 that have between 7 and 93 days to maturity, excluding options on penny stocks. For options with more than 15 days to maturity, we only consider the first two nearest contract maturities. The complete sample consists of 313,395,467 observations.

	OTM Put Options					OTM Call Options				
	$q_{0.05}$	$q_{0.25}$	$q_{0.50}$	$q_{0.75}$	$q_{0.95}$	$q_{0.05}$	$q_{0.25}$	$q_{0.50}$	$q_{0.75}$	$q_{0.95}$
Panel A: Spreads of OTM Options										
Bid–Ask	0.05	0.10	0.19	0.25	0.50	0.05	0.10	0.15	0.25	0.45
Ask (Bid= 0)	0.05	0.10	0.19	0.25	0.50	0.05	0.10	0.15	0.25	0.50
(Bid – Ask) / Mid	0.20	0.40	0.67	1.00	1.43	0.17	0.40	0.67	1.00	1.43
Panel B: Number of OTM Quoted Option Strikes										
All OTM	1	2	3	5	12	1	2	3	5	11
OTM Bid≠ 0	0	0	1	2	6	0	0	1	2	4
Panel C: OTM Option Trading Volumes, Unconditional										
OTM	0	0	0	12	521	0	0	0	32	777
OTM (Bid≠ 0)	0	0	0	10	507	0	0	0	30	751
OTM (Bid= 0)	0	0	0	0	0	0	0	0	0	5
Panel D: OTM Option Trading Volumes, Conditional on at Least One Trade										
OTM	2	11	47	215	2047	2	11	50	225	2109
OTM (Bid≠ 0)	1	10	44	207	2012	1	10	45	214	2061
OTM (Bid= 0)	0	0	0	0	20	0	0	0	0	30
Panel E: Adjusted Moneyness of OTM Option										
DOTM (Bid≠ 0)	-5.75	-2.73	-1.73	-0.98	-0.23	0.19	0.75	1.27	1.82	3.14
DOTM (Bid= 0)	-6.24	-3.76	-2.82	-2.13	-1.27	1.06	1.68	2.12	2.68	3.93
CATM	-1.33	-0.67	-0.34	-0.14	-0.02	0.03	0.14	0.32	0.61	1.15

Table 2: Significant Corporate News - Descriptive Statistics

This table reports descriptive statistics for the sample of positive (Panel A) and negative (Panel B) news events for each of the categories to which we assign news in our sample. Displayed are the number of observations N, the percentage of observations that fall on an earnings announcement day and are thus classified as scheduled (%EAD), the average, median, and standard deviation of returns, as well as the percentage of observations for which the relative trading volume (defined as the number of shares traded on a given day scaled by the number of shares outstanding) is above the 90th percentile of a stock's distribution of this measure (%High Vlm.).

Panel A: Positive News	N	% EAD	Return			%High Vlm.
			Avg.	Median	Std. Dev.	
Acquisition (Acquirer)	552	27.90	11.42	9.88	6.99	87.14
Acquisition (Target)	780	13.59	24.98	21.61	16.63	99.36
Analyst	3,606	43.93	12.44	10.27	8.74	89.24
Business Contract	653	11.94	13.47	10.69	9.78	79.02
Credit Rating	124	19.35	12.79	9.66	9.11	95.97
Drug & Product Development	103	13.59	13.62	10.42	12.85	83.50
Dividends	165	13.33	8.25	6.97	4.56	76.36
Earnings	7,412	100.00	11.33	9.92	6.28	90.21
Financing	338	55.92	8.96	7.73	5.09	84.32
Guidance	901	59.82	11.20	9.74	7.19	91.45
Management Change	305	7.21	10.58	8.13	12.10	69.18
Merger	71	19.72	12.42	11.06	8.08	92.96
Others	201	24.88	14.31	11.71	10.32	88.06
ALL	15,211	69.30	11.73	9.98	7.47	89.59
No Associated News	25,881	12.24	10.57	8.71	7.75	63.12

Panel B: Negative News	N	% EAD	Return			%High Vlm.
			Avg.	Median	Std. Dev.	
Acquisition (Acquirer)	161	8.07	-10.03	-8.73	6.47	84.47
Analyst	5,732	53.02	-15.74	-12.54	11.17	94.78
Credit Rating	189	33.86	-15.08	-11.40	13.33	91.53
Drug & Product Development	54	16.67	-22.62	-18.90	14.70	94.44
Earnings	6,918	100.00	-11.15	-9.30	6.78	91.15
Financing	265	18.49	-10.30	-9.23	5.87	87.92
Guidance	1,970	61.37	-13.73	-11.43	8.79	94.87
Management Change	240	35.83	-13.33	-9.69	11.48	87.92
Merger	64	18.75	-10.78	-8.20	7.95	95.31
Others	171	14.04	-13.73	-11.18	9.66	87.72
ALL	15,764	72.46	-13.26	-10.82	8.83	92.76
No Associated News	26,797	11.05	-9.56	-7.93	6.41	61.35

Table 3: Importance of Information Signals for Significant Corporate News

This table presents the results from the projection of significant corporate news (SCNs) on the information signals to informed investors. Panel A (B) reports results for positive (negative) SCNs. The information signals are the expected announcement return $E[\kappa]$, the uncertainty of the announcement return σ_κ , and an indicator variable that is one for scheduled events (i.e., earnings announcements) and zero otherwise, to capture the expected announcement time and its uncertainty, $\mathcal{I}(Scheduled)$. We also consider their interaction effects. The different regression specifications account for time fixed effects (year-month), industry fixed effects (2-digit SIC industry code) or firm fixed effects. Firm-specific control variables include size (measured as the natural logarithm of total firm assets from Compustat), book leverage (sum of long-term debt and current liabilities scaled by total assets), the number of analysts (IBES), and stock return volatility (measured using daily stock returns during the three months preceding the announcement). Heteroskedasticity-robust standard errors are reported in parentheses. ***,**,* indicate statistical significance at the one, five, or ten percent level, respectively based on heteroskedasticity-robust standard errors (reported in parentheses).

(A) Positive News	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$E[\kappa]$	0.010*** (0.0004)					0.011*** (0.0009)	0.011*** (0.0009)	0.011*** (0.0008)
σ_κ		0.011*** (0.0004)				-0.001 (0.001)	-0.002** (0.001)	-0.002** (0.001)
$\mathcal{I}(Scheduled)$			-0.019*** (0.001)			-0.002 (0.002)	-0.003 (0.002)	-0.003 (0.002)
$E[\kappa] \cdot \mathcal{I}(Scheduled)$				-0.002*** (0.0001)				
$\sigma_\kappa \cdot \mathcal{I}(Scheduled)$					-0.003*** (0.0002)			
Constant	-0.000 (0.004)	0.033*** (0.003)	0.134*** (0.001)	0.134*** (0.001)	0.134*** (0.001)	-0.001 (0.005)	0.004 (0.007)	-0.001 (0.008)
Time FE	x	x	x	x	x	x	x	x
Industry FE	x	x	x	x	x	x		x
Firm FE							x	
Firm Controls								x
Obs.	15,211	15,211	15,211	15,211	15,211	15,211	15,211	15,128
R2	0.25	0.22	0.14	0.14	0.14	0.25	0.32	0.41
(B) Negative News	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$E[\kappa]$	0.008*** (0.0003)					0.008*** (0.002)	0.007*** (0.002)	0.005*** (0.002)
σ_κ		-0.008*** (0.0003)				-0.001 (0.002)	-0.002 (0.002)	-0.002 (0.001)
$\mathcal{I}(Scheduled)$			0.027*** (0.001)			-0.007*** (0.002)	-0.007*** (0.002)	-0.005** (0.002)
$E[\kappa] \cdot \mathcal{I}(Scheduled)$				-0.002*** (0.0001)				
$\sigma_\kappa \cdot \mathcal{I}(Scheduled)$					0.004*** (0.0002)			
Constant	-0.028*** (0.004)	-0.063*** (0.002)	-0.144*** (0.001)	-0.144*** (0.001)	-0.144*** (0.001)	-0.011 (0.010)	-0.031*** (0.011)	-0.022** (0.011)
Time FE	x	x	x	x	x	x	x	x
Industry FE	x	x	x	x	x	x		x
Firm FE							x	
Firm Controls								x
Obs.	15,748	15,748	15,748	15,748	15,748	15,748	15,748	15,636
R2	0.25	0.25	0.24	0.24	0.24	0.25	0.32	0.43

Table 4: Expected Returns to Informed Trading Ahead of News

This table reports the average expected returns to informed trading in call (put) options ahead of positive (negative) SCNs for each news category covered in our sample. We classify acquisitions as scheduled if the announcement falls on the same day as another scheduled announcement. The mean of expected returns is shown for each tercile T1 through T3 of the distribution of expected returns for a given subsample. Expected returns are computed using the BSM framework (Equation (4)), assuming that informed investors trade eleven days ahead of unscheduled news and one day ahead of scheduled news. The anticipated stock price reaction and its uncertainty are equal to the average and standard deviation of the return in each category, as reported in Table 2.

Panel A: Positive News	<i>Scheduled</i>			<i>Unscheduled</i>		
	T1	T2	T3	T1	T2	T3
Acquisition (Acquirer)	47.62	118.14	617.70	32.36	95.26	444.96
Acquisition (Target)	120.21	311.23	1,329.54	121.64	331.72	1,727.97
Analyst	51.88	124.66	609.44	37.44	107.48	519.38
Business Contract	49.00	116.15	800.12	35.27	102.40	591.20
Credit Rating	52.37	112.30	562.86	45.29	148.10	689.02
Drug & Product Development	69.08	177.15	1,225.00	31.86	128.26	859.62
Dividends	37.96	86.21	314.58	22.35	70.23	282.65
Earnings	47.86	114.45	467.49			
Financing	49.03	117.33	497.93	28.98	80.59	377.20
Guidance	60.11	143.67	591.00	30.78	96.78	472.58
Management Change	37.37	110.21	603.44	31.76	95.13	614.28
Merger	77.15	159.09	543.04	26.13	102.01	825.93
Others	64.04	164.73	705.62	34.99	118.74	835.71

Panel B: Negative News	<i>Scheduled</i>			<i>Unscheduled</i>		
	T1	T2	T3	T1	T2	T3
Acquisition (Acquirer)	36.99	103.39	297.16	6.00	63.74	264.08
Analyst	44.71	123.26	532.14	27.33	99.19	506.53
Credit Rating	20.85	88.06	592.77	16.97	67.98	403.11
Drug & Product Development	38.95	72.07	298.50	28.64	92.05	398.49
Earnings	40.73	104.61	371.51			
Financing	10.93	38.41	150.23	1.22	47.74	194.58
Guidance	55.88	155.48	722.52	21.91	87.09	421.13
Management Change	45.02	130.44	488.25	26.60	92.98	468.01
Merger	22.44	52.00	346.56	28.50	105.69	439.52
Others	27.73	131.57	834.70	16.50	77.56	426.63

Table 5: Moneyiness by Expected Return Tercile

This table reports the average option moneyiness as a function of expected returns to informed trading in call (put) options ahead of positive (negative) SCNs for each news category covered in our sample. We classify acquisitions as scheduled if the announcement falls on the same day as another scheduled announcement. Moneyiness is defined as the log of the ratio of the strike price over the spot price. The average moneyiness is shown for each tercile T1 through T3 of the distribution of expected returns for a given subsample. Expected returns are computed using the BSM framework (Equation (4)), assuming that informed investors trade eleven days ahead of unscheduled news and one day ahead of scheduled news. The anticipated stock price reaction and its uncertainty are equal to the average and standard deviation of the return in each category, as reported in Table 2.

Panel A: Positive News	<i>Scheduled</i>			<i>Unscheduled</i>		
	T1	T2	T3	T1	T2	T3
Acquisition (Acquirer)	-0.09	0.07	0.11	0.01	0.08	0.12
Acquisition (Target)	0.07	0.07	0.12	-0.04	0.08	0.11
Analyst	-0.05	0.07	0.13	-0.01	0.07	0.09
Business Contract	-0.01	0.09	0.14	0.01	0.09	0.11
Credit Rating	-0.06	0.13	0.10	0.00	0.05	0.08
Drug & Product Development	-0.06	0.11	0.16	-0.03	0.08	0.10
Dividends	0.04	0.03	0.06	0.02	0.08	0.08
Earnings	-0.01	0.06	0.09			
Financing	-0.01	0.05	0.08	-0.02	0.08	0.10
Guidance	-0.03	0.05	0.08	0.00	0.05	0.07
Management Change	0.05	0.08	0.11	0.01	0.10	0.10
Merger	0.04	0.10	0.12	0.08	0.03	0.06
Others	0.24	0.06	0.10	0.06	0.08	0.11

Panel B: Negative News	<i>Scheduled</i>			<i>Unscheduled</i>		
	T1	T2	T3	T1	T2	T3
Acquisition (Acquirer)	-0.04	-0.07	-0.09	-0.14	-0.09	-0.08
Analyst	0.03	-0.09	-0.12	0.03	-0.07	-0.10
Credit Rating	0.05	-0.12	-0.10	0.10	-0.08	-0.09
Drug & Product Development	-0.23	-0.15	-0.15	-0.08	-0.19	-0.17
Earnings	-0.03	-0.08	-0.09			
Financing	0.20	-0.08	-0.08	-0.06	-0.04	-0.08
Guidance	-0.02	-0.08	-0.10	0.04	-0.07	-0.08
Management Change	-0.08	-0.11	-0.13	0.04	-0.08	-0.09
Merger	-0.21	-0.12	-0.08	-0.06	-0.08	-0.09
Others	0.03	-0.10	-0.08	0.08	-0.08	-0.11

Table 6: Time to Maturity by Expected Return Tercile

This table reports the average of the days to maturity as a function of expected returns to informed trading in call (put) options ahead of positive (negative) SCNs for each news category covered in our sample. We classify acquisitions as scheduled if the announcement falls on the same day as another scheduled announcement. The average time to maturity is shown for each tercile T1 through T3 of the distribution of expected returns for a given subsample. Expected returns are computed using the BSM framework (Equation (4), assuming that informed investors trade eleven days ahead of unscheduled news and one day ahead of scheduled news. The anticipated stock price reaction and its uncertainty are equal to the average and standard deviation of the return in each category, as reported in Table 2.

Panel A: Positive News	<i>Scheduled</i>			<i>Unscheduled</i>		
	T1	T2	T3	T1	T2	T3
Acquisition (Acquirer)	252.1	121.6	54.6	203.5	133.1	74.8
Acquisition (Target)	193.3	109.6	63.0	166.8	118.3	69.5
Analyst	205.6	116.0	60.3	204.3	148.5	74.9
Business Contract	203.5	145.6	75.8	214.9	155.1	82.6
Credit Rating	244.1	185.6	83.8	206.5	118.4	59.7
Drug & Product Development	227.4	182.9	92.5	164.7	156.6	81.1
Dividends	176.8	92.5	52.6	266.9	155.4	66.2
Earnings	192.5	106.9	52.2			
Financing	200.3	94.6	44.8	223.5	153.7	64.9
Guidance	196.2	100.1	50.5	189.5	126.3	66.9
Management Change	200.3	141.9	60.9	233.3	159.0	87.0
Merger	224.3	142.7	69.5	210.8	195.9	93.8
Others	195.8	103.7	55.6	185.0	161.0	79.0

Panel B: Negative News	<i>Scheduled</i>			<i>Unscheduled</i>		
	T1	T2	T3	T1	T2	T3
Acquisition (Acquirer)	230.3	124.7	63.5	187.3	165.8	54.8
Analyst	178.0	109.2	52.4	168.1	136.0	63.8
Credit Rating	170.3	182.4	73.3	186.2	173.6	79.7
Drug & Product Development	179.8	131.5	45.0	102.6	126.5	92.4
Earnings	169.6	92.2	41.4			
Financing	141.3	104.5	42.9	139.6	143.3	76.0
Guidance	184.9	94.9	41.5	171.3	135.6	65.6
Management Change	170.3	88.6	39.1	178.7	144.4	73.6
Merger	218.2	120.3	68.4	151.9	120.8	54.0
Others	192.7	156.9	35.4	189.0	179.7	74.7

Table 7: Informed Options Strategies Before SEC Litigations

In this table, we report the characteristics of option trades listed in civil litigations of illegal insider trading cases pursued by the US Securities and Exchange Commission. The illegal insider trading litigations are from Augustin et al. (2019) and we focus on earnings and M&A announcements that present the majority of all litigations. The sample is restricted to trades that could be matched to specific option contracts in the OptionMetrics database. We report the number of events, the number of option trade days, the fraction of trades that are calls vs. puts, the option moneyness in terms of the ratio of the stock to the strike price multiplied by 100 ($S/K \cdot 100$), time to maturity in days, the option price in USD, the bid-ask spread in USD, as well as the option and corresponding stock return (in %). Option prices are end-of-day mid prices. Option returns are the ratio of the option's first available end-of-day bid price after the announcement date and the end-of-day best ask on the purchase date minus one. If an option was not traded within the month following the announcement, we use its intrinsic value the day following the announcement as a numerator instead of the bid price. We report the average, standard deviation, and the 5th, 50th and 95th percentiles of the distribution.

		ALL	Earnings (Calls)	Earnings (Puts)	M&A (Calls)
Number of events		151.00	13.00	29.00	109.00
Number of option days		358.00	16.00	58.00	284.00
Fraction Calls (%)		83.80	100.00	0.00	100.00
Fraction Puts (%)		16.20	0.00	100.00	0.00
Moneyness ($S/K \cdot 100$)	Avg.	96.84	104.72	90.67	97.65
	Std.	14.67	13.84	16.65	13.91
	5th	76.77	77.04	53.36	79.12
	50th	94.60	104.21	96.33	93.90
	95th	123.88	123.18	107.99	125.31
Time to Mat. (Days)	Avg.	46.40	33.31	38.28	48.79
	Std.	37.82	18.61	39.96	37.89
	5th	8.00	6.50	3.00	9.00
	50th	36.00	29.00	24.50	38.00
	95th	130.00	68.10	116.20	135.30
Option Price (\$)	Avg.	1.49	3.05	2.77	1.14
	Std.	1.79	2.84	2.94	1.13
	5th	0.20	0.61	0.36	0.20
	50th	0.95	1.90	1.45	0.80
	95th	4.46	9.78	9.84	3.03
Bid-Ask (\$)	Avg.	0.20	0.21	0.23	0.19
	Std.	0.21	0.15	0.20	0.21
	5th	0.05	0.07	0.05	0.05
	50th	0.15	0.18	0.15	0.15
	95th	0.50	0.50	0.75	0.46
Option Ret [%]	Avg.	1,135.58	109.89	473.05	1,328.68
Stock Ret [%]	Avg.	19.10	4.65	-22.60	28.43

Table 8: Informed Options Volume and Significant Corporate News

This table presents panel regression results from the projection of significant corporate news (SCNs) on measures of informed trading and a set of control variables. Relative call volume RCV (relative put volume, RPV) is the weekly volume traded in call (put) options with high expected returns to informed trading scaled by total call (put) volume. OTM call volume OCV (OTM put volume OPV) are constructed similarly to RCV and RPV but using moneyness depth as a criterion to rank options. PP is the Pan Poteshman (2006) measure of put volume scaled by total volume, O/S the Johnson and So (2012) ratio of option to stock volume, IVS the Cremers and Weinbaum (2010) call minus put implied volatility spread, and SKEW the Xing et al. (2010) measure of the volatility smirk. Following Ge et al. (2016), our set of control variables includes the weekly market adjusted return CAR, logged market capitalization SIZE, the Amihud illiquidity ratio ILLIQ, the stock's market adjusted return over the past six months MOM, and the market to book ratio MB. All variables except the dependent one are normalized. Further details on the construction of our informed trading measures are included in Section 3.5. ***, **, * indicate statistical significance at the one, five, or ten percent level, respectively based on heteroskedasticity-robust standard errors (reported in parentheses). The constant is omitted for brevity.

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
RCV	0.003** (0.001)	0.0005 (0.001)	0.004*** (0.0008)	-0.002 (0.002)	0.004*** (0.0008)	0.004*** (0.0008)	0.004*** (0.0008)	0.004*** (0.001)	0.004*** (0.001)	0.004*** (0.0008)	0.004*** (0.001)	0.004*** (0.001)
RPV	-0.008*** (0.001)	-0.011*** (0.001)	-0.006*** (0.0008)	-0.010*** (0.002)	-0.006*** (0.0008)	-0.006*** (0.0008)	-0.006*** (0.0008)	-0.006*** (0.001)	-0.006*** (0.001)	-0.006*** (0.0008)	-0.006*** (0.001)	-0.006*** (0.001)
OCV					-0.001* (0.0006)							
OPV					-0.001* (0.0006)							
PP						0.0004 (0.0005)				0.0004 (0.0005)	0.0007 (0.001)	0.0007 (0.001)
O/S							-0.0003 (0.0005)			-0.0003 (0.0005)	-0.0002 (0.0005)	-0.0002 (0.0005)
IVS								0.0003 (0.0009)			0.0006 (0.0009)	0.0008 (0.0009)
SKEW									0.001 (0.0010)		0.001 (0.001)	0.002* (0.001)
Time FE	x	x	x	x	x	x	x	x	x	x	x	x
Scheduled FE		x	x	x	x	x	x	x	x	x	x	x
Industry FE			x		x	x	x	x	x	x	x	x
Firm FE				x								
Controls												x
Observations	26,860	26,860	26,860	26,860	25,356	26,835	26,835	12,433	12,433	26,835	12,433	12,433
R²	0.04	0.05	0.69	0.22	0.69	0.69	0.69	0.68	0.68	0.69	0.68	0.68

A Supplementary results

Figure A-1: Impact of Information Signals on Option Choice – Scheduled Events

In this figure, we characterize the impact of the information signals on the moneyness K^*/S and the time to maturity T^{max} that maximize expected returns $E[R]^{max}$ to informed trading in call options ahead of a positive event, assuming that events are scheduled (i.e., we account for a run-up in implied volatility preceding the event). We consider changes in the expected jump in stock prices $E[\kappa]$, the jump size uncertainty σ_κ , the expected time to announcement $E[\Delta t]$, and the expected announcement time uncertainty $\sigma_{\Delta t}$. We report comparative statics, keeping everything else constant. The expected jump size and the uncertainty in the jump size are calibrated to $E[\kappa] = 11.73\%$ and $\sigma_\kappa = 7.47\%$, corresponding to average stock price jump and its standard deviation in our sample of significant corporate news (see Table 2). Following the illegal insider trading litigation statistics of Augustin et al. (2019), we calibrate the expected time to announcement to $E[\Delta t] = 11$ days and the associated uncertainty to $\sigma_{\Delta t} = 4$ days. We use an interest rate of $r = 0.03$. We calibrate the option-implied volatility to the sample median value $IV = 0.35$, the minimum price to \$0.19 and the bid-ask spread to \$0.15, corresponding to the median estimates in our sample. We vary the price of the underlying stock around its median sample estimate of $S_0 = \$25$ from the 25th ($S_0 = \$14$) to the 75th ($S_0 = \42) percentiles of the underlying stock price distribution.

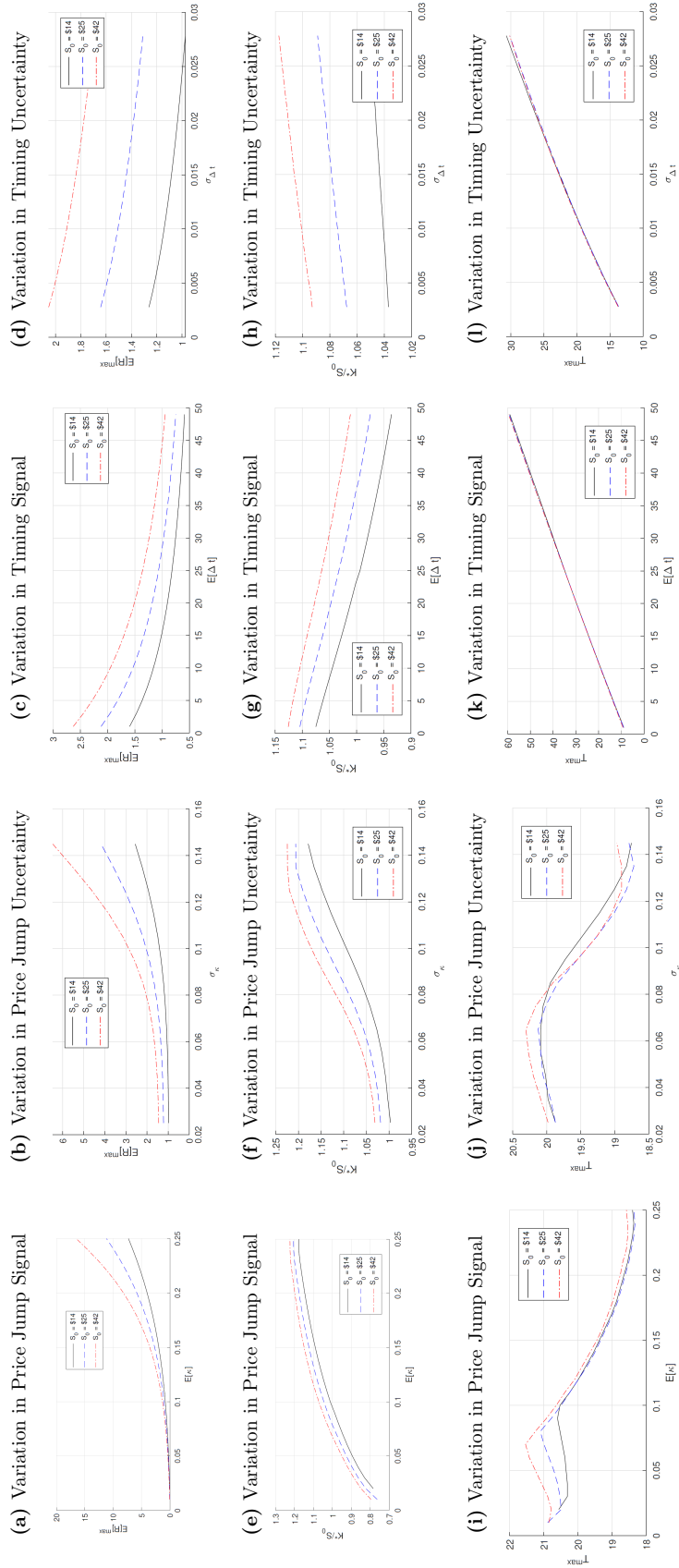


Figure A-2: Impact of Information Signals on Option Choice – Synthetic Call Options

In this figure, we characterize the impact of the information signals on the moneyness K^*/S and the time to maturity T^{max} that maximize expected returns $E[R]^{max}$ to informed trading in synthetic call options (combined position in stock and put option) ahead of a positive event. We consider changes in the expected jump in stock prices $E[\kappa]$, the jump size uncertainty σ_κ , the expected time to announcement $E[\Delta t]$, and the expected announcement time uncertainty $\sigma_{\Delta t}$. We report comparative statics, keeping everything else constant. The expected jump size and the uncertainty in the jump size are calibrated to $E[\kappa] = 11.73\%$ and $\sigma_\kappa = 7.47\%$, corresponding to average stock price jump and its standard deviation in our sample of significant corporate news (see Table 2). Following the illegal insider trading litigation statistics of Augustin et al. (2019), we calibrate the expected time to announcement to $E[\Delta t] = 11$ days and the associated uncertainty to $\sigma_{\Delta t} = 4$ days. We use an interest rate of $r = 0.03$. We calibrate the option-implied volatility to the sample median value $IV = 0.35$, the minimum price to $\$0.19$ and the bid-ask spread to $\$0.15$, corresponding to the median estimates in our sample. We vary the price of the underlying stock around its median sample estimate of $S_0 = \$25$ from the 25th ($S_0 = \$14$) to the 75th ($S_0 = \42) percentiles of the underlying stock price distribution.

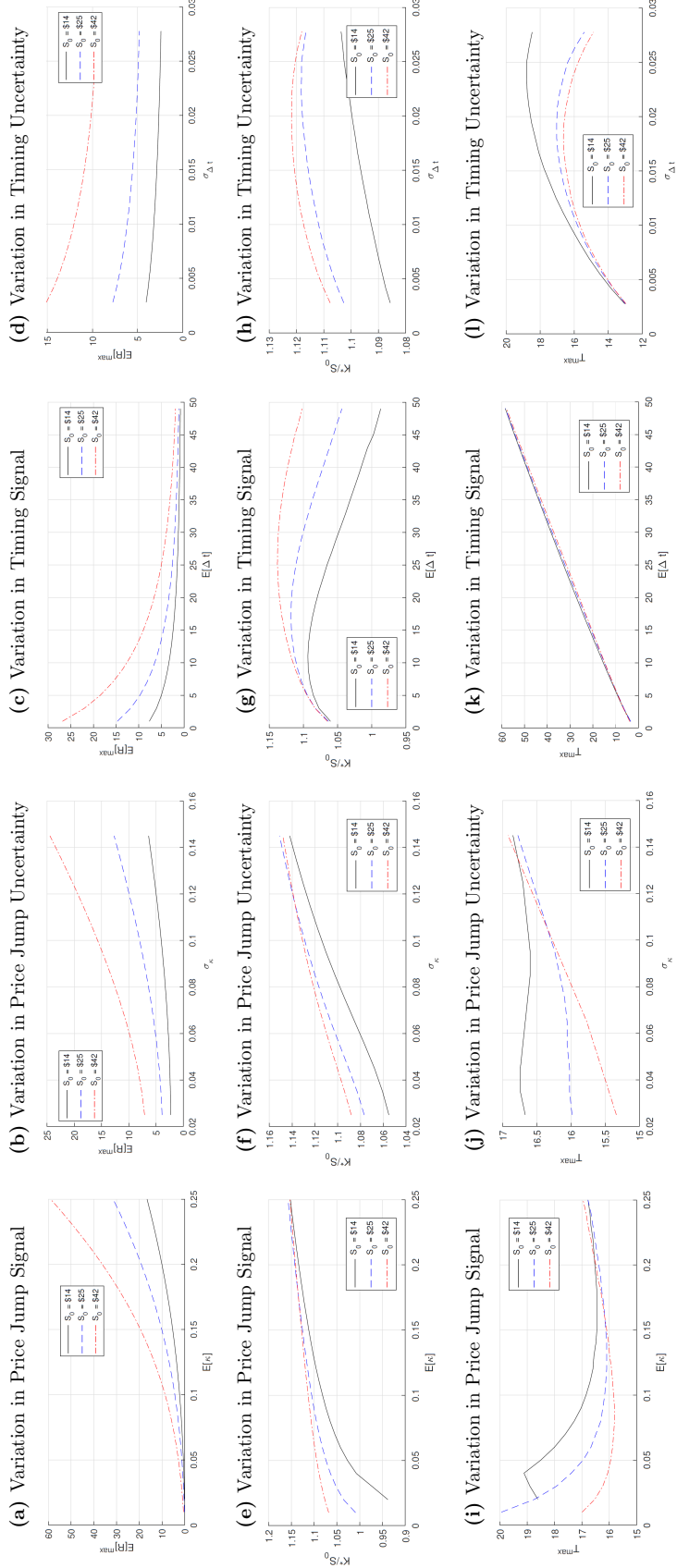


Figure A-3: Impact of Information Signals on Option Choice – Put Options

In this figure, we characterize the impact of the information signals on the moneyness K^*/S and the time to maturity T^{max} that maximize expected returns $E[R]^{max}$ to informed trading in put options ahead of a positive event. We consider changes in the expected jump in stock prices $E[\kappa]$, the jump size uncertainty σ_κ , the expected time to announcement $E[\Delta t]$, and the expected announcement time uncertainty $\sigma_{\Delta t}$. We report comparative statics, keeping everything else constant. The expected jump size and the uncertainty in the jump size are calibrated to $E[\kappa] = 11.73\%$ and $\sigma_\kappa = 7.47\%$, corresponding to average stock price jump and its standard deviation in our sample of significant corporate news (see Table 2). Following the illegal insider trading litigation statistics of Augustin et al. (2019), we calibrate the expected time to announcement to $E[\Delta t] = 11$ days and the associated uncertainty to $\sigma_{\Delta t} = 4$ days. We use an interest rate of $r = 0.03$. We calibrate the option-implied volatility to the sample median value $IV = 0.35$, the minimum price to $\$0.19$ and the bid-ask spread to $\$0.15$, corresponding to the median estimates in our sample. We vary the price of the underlying stock around its median sample estimate of $S_0 = \$25$ from the 25th ($S_0 = \$14$) to the 75th ($S_0 = \42) percentiles of the underlying stock price distribution.

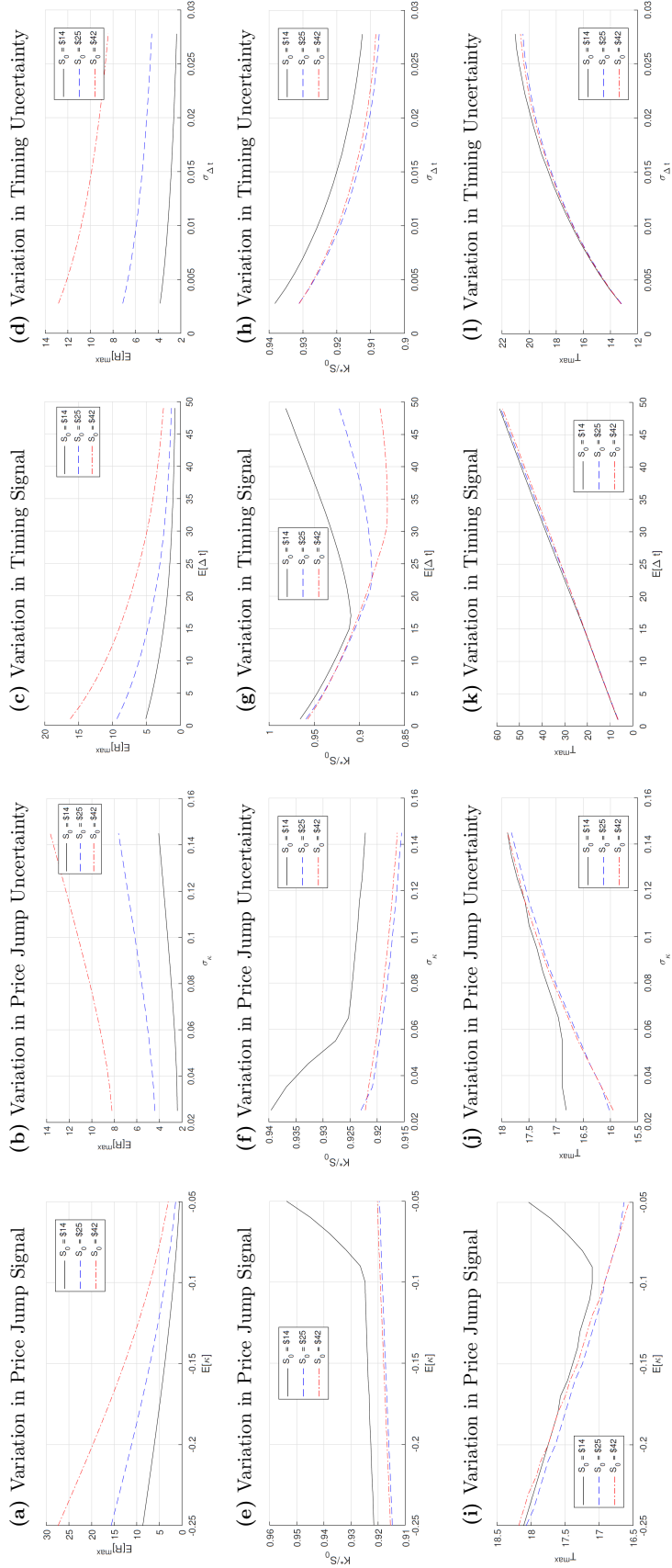


Figure A-4: A Simple Procedure for Identifying Informed Options strategies

In this figure, we report the characteristics (expected returns, strike, maturity) of optimal options strategies identified using alternative procedures to our framework. The first procedure (panels a, b, c) is rule-based and simply chooses the most OTM option that has a non-zero bid price. The second procedure (panels d, e, f) picks the option with the highest cost-adjusted measure of options elasticity Ω^* , where the adjusted option elasticity accounts for trading frictions by adding the option bid-ask spread to the option mid price, i.e., $\Omega^* = \Delta \frac{S}{C+BA}$, where Δ is the option delta, S the underlying stock price, C the call option mid price, and BA the corresponding bid-ask price. The third procedure (panels g, h, i) follows a naive implementation of our framework that shuts down the uncertainty of both information signals ($\sigma_\kappa = 0, \sigma_{\Delta t} = 0$) and computes option returns using their intrinsic value immediately after the news announcement. For each graph, we report scatter plots of the average and median values within each quintile of the corresponding distribution of expected option returns (panels a, d, g), option moneyness reported as $\ln(S/K)$, where S denotes the underlying stock price and K the strike price (panels b, e, h), and option maturity (panels c, f, i).

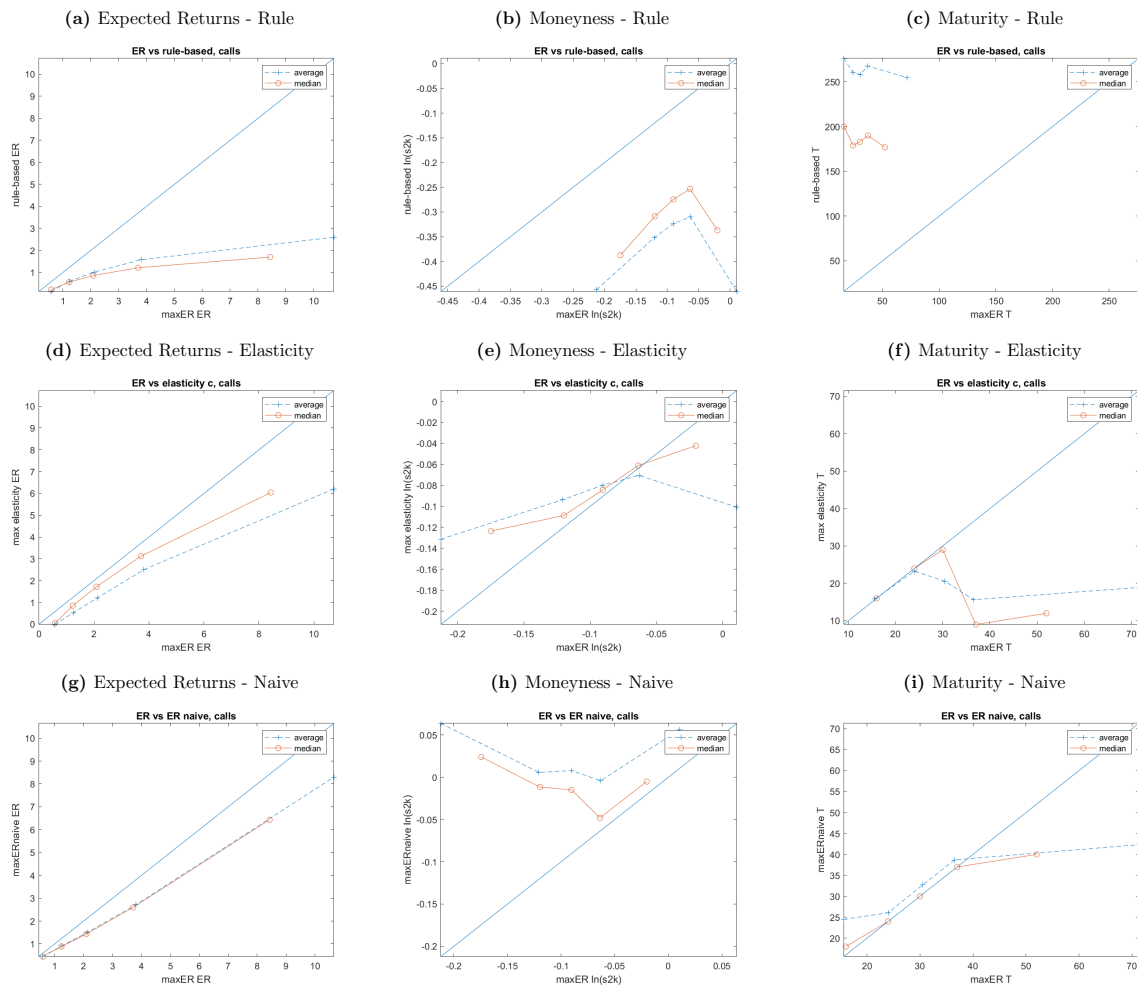


Table A-1: Odds Ratios of News Categories for Positive EPMs

This table reports results from logistic regressions of an indicator of positive EPMs on variables indicating Ravenpack news categories. The sample includes all stock-days in CRSP between 2000 and 2014 with a stock price of at least five dollars, a market capitalization of at least ten million dollars and is restricted to stocks for which we observe news in the Ravenpack database at least once. We observe 62,913 positive EPMs on 11.4 million stock days. For a given stock-day, a news indicator is set equal to one if news in that category were reported for the stock between 4pm on the previous trading day and 4pm of the given trading day. Of the 527 Ravenpack categories for corporate news, we ignore all categories for which not a single news observation is made on a positive EPM day and include indicator variables for all 94 remaining categories. This table only reports statistics for indicator variables that are significant at the one percent level. To account for multiple hypothesis testing we use Bonferroni adjusted p -values, implying a minimum t -value of 4.12. The “Assigned Category” is the less granular definition of news category used in the primary analysis. Odds ratios are computed as the exponential of regression coefficients. N_{reg} is the number of news occurrences in the regression, that is, the sum of the indicator variable. N_{final} equals the number of news events of a given category that are used in the main analysis.

Ravenpack Category	Assigned Category	Beta	Odds Ratio	t -value	N_{reg}	N_{final}
acquisition-acquirer	Acquisition (Acquirer)	1.09	2.98	29.48	1365	552
acquisition-acquiree	Acquisition (Target)	3.39	29.80	74.48	1687	668
acquisition-interest-acquiree	Acquisition (Target)	2.47	11.85	25.28	264	112
analyst-ratings-change-positive	Analyst	2.57	13.13	134.13	4313	3,281
analyst-ratings-history-neutral	Analyst	0.52	1.68	5.56	159	23
analyst-ratings-set-positive	Analyst	0.78	2.19	15.73	435	269
price-target-upgrade	Analyst	0.67	1.96	4.92	106	33
business-contract	Business Contract	0.59	1.80	20.48	2368	653
credit-rating-unchanged	Credit Rating	0.56	1.76	5.11	124	37
credit-rating-watch-negative	Credit Rating	1.49	4.44	14.58	198	87
dividend	Dividends	0.36	1.43	9.03	1199	142
dividend-up	Dividends	0.35	1.42	5.52	414	23
regulatory-prod-approval-granted	Drug & Prod. Develop.	1.06	2.89	12.32	224	103
conference-call	Earnings	0.33	1.39	8.65	1199	210
earnings	Earnings	0.48	1.62	22.29	12532	315
earnings-down	Earnings	0.39	1.48	9.99	1173	105
earnings-per-share-above-expect.	Earnings	1.14	3.14	39.25	3694	2,293
earnings-per-share-below-expect.	Earnings	0.61	1.84	14.41	1082	568
earnings-per-share-positive	Earnings	0.53	1.71	21.11	6394	316
earnings-positive	Earnings	0.63	1.88	22.63	4007	2,222
earnings-up	Earnings	0.53	1.70	19.00	3517	259
revenue-above-expect.	Earnings	0.52	1.69	17.88	3679	93
revenues	Earnings	0.54	1.72	19.62	5093	877
revenue-up	Earnings	0.50	1.64	16.11	2551	134
same-store-sales-up	Earnings	0.35	1.43	6.73	681	20
buybacks	Financing	0.64	1.90	14.09	851	338
earnings-guidance-up	Guidance	0.76	2.15	19.85	1279	643
earnings-per-share-guidance	Guidance	0.36	1.44	13.94	3257	95
ebitda-guidance	Guidance	0.41	1.50	4.19	142	11
revenue-guidance	Guidance	0.27	1.31	10.13	2771	75
revenue-guidance-up	Guidance	0.37	1.45	11.05	1537	77
executive-appointment	Management Change	0.17	1.19	4.86	1649	305
merger	Merger	1.15	3.15	14.17	444	71
regulatory-investigation	Others	1.20	3.32	13.79	254	40
settlement	Others	0.50	1.66	4.39	138	39
stake-acquiree	Others	1.52	4.59	15.07	152	82
stock-splits	Others	1.31	3.69	11.44	144	40

Table A-2: Odds Ratios of News Categories for Negative EPMS

This table reports results from logistic regressions of an indicator of negative EPMS on variables indicating Ravenpack news categories. The sample includes all stock-days in CRSP between 2000 and 2014 with a stock price of at least five dollars, a market capitalization of at least ten million dollars and is restricted to stocks for which we observe news in the Ravenpack database at least once. We observe 63,565 negative EPMS on 11.4 million stock days. For a given stock-day, a news indicator is set equal to one if news in that category were reported for the stock between 4pm on the previous trading day and 4pm of the given trading day. Of the 527 Ravenpack categories for corporate news, we ignore all categories for which not a single news observation is made on a negative EPM day and include indicator variables for all 95 remaining categories. This table only reports statistics for indicator variables that are significant at the one percent level. To account for multiple hypothesis testing we use Bonferroni adjusted p -values, implying a minimum t -value of 4.12. The “Assigned Category” is the less granular definition of news category used in the primary analysis. Odds ratios are computed as the exponential of regression coefficients. N_{reg} is the number of news occurrences in the regression, that is, the sum of the indicator variable. N_{final} equals the number of news events of a given category that are used in the main analysis.

Ravenpack Category	Assigned Category	Beta	Odds Ratio	t -value	N_{reg}	N_{final}
acquisition-acquirer	Acquisition (Acquirer)	0.47	1.60	9.24	720	161
analyst-ratings-change-negative	Analyst	2.94	18.86	186.73	9,181	5,667
analyst-ratings-history-neutral	Analyst	0.53	1.70	4.55	108	18
analyst-ratings-history-positive	Analyst	0.53	1.69	10.45	693	21
price-target-downgrade	Analyst	1.21	3.35	7.99	107	26
credit-rating-downgrade	Credit Rating	0.78	2.18	8.98	230	78
credit-rating-unchanged	Credit Rating	0.70	2.01	6.20	119	48
credit-rating-watch-negative	Credit Rating	1.17	3.23	10.59	152	63
clinical-trials	Drug & Prod. Develop.	1.83	6.22	16.70	161	54
conference-call	Earnings	0.43	1.54	11.83	1,375	252
earnings	Earnings	0.64	1.90	29.45	14,101	2,663
earnings-below-expectations	Earnings	0.34	1.40	7.73	1,108	13
earnings-down	Earnings	0.52	1.69	15.59	1,997	160
earnings-negative	Earnings	0.38	1.46	8.23	1,119	27
earnings-per-share-above-expect.	Earnings	0.68	1.98	21.11	2,463	1,334
earnings-per-share-below-expect.	Earnings	0.87	2.38	23.77	1,892	927
earnings-per-share-meet-expectations	Earnings	0.92	2.52	9.62	147	66
earnings-per-share-negative	Earnings	0.58	1.79	14.80	1,620	112
earnings-per-share-positive	Earnings	0.25	1.28	9.74	5,999	46
earnings-positive	Earnings	0.58	1.79	20.83	3,893	611
earnings-up	Earnings	0.45	1.57	14.40	2,433	171
operating-earnings	Earnings	0.61	1.85	5.13	170	32
revenue-above-expect.	Earnings	0.52	1.68	17.16	3,213	48
revenue-below-expect.	Earnings	0.45	1.57	10.94	1,111	20
revenues	Earnings	0.52	1.69	19.26	5,579	248
revenue-up	Earnings	0.38	1.46	11.38	2,148	67
same-store-sales-down	Earnings	0.53	1.70	8.29	454	113
same-store-sales-up	Earnings	0.25	1.28	4.26	558	8
note-sale	Financing	0.80	2.22	9.78	304	116
public-offering	Financing	1.50	4.49	22.10	409	149
earnings-guidance	Guidance	0.88	2.40	24.13	1,583	544
earnings-guidance-down	Guidance	1.75	5.73	44.09	1,479	845
earnings-guidance-meet-expectations	Guidance	0.24	1.28	4.36	441	19
earnings-per-share-guidance	Guidance	0.50	1.65	19.85	3,858	176
revenue-guidance	Guidance	0.43	1.54	17.12	3,704	136
revenue-guidance-down	Guidance	0.66	1.93	13.19	804	214
revenue-guidance-up	Guidance	0.29	1.34	8.26	1,341	36
executive-resignation	Management Change	0.84	2.32	15.99	789	240
merger	Merger	0.79	2.20	7.14	170	64
layoffs	Others	0.35	1.41	4.29	251	26
legal-issues-defendant	Others	0.58	1.79	6.79	199	76
regulatory-investigation	Others	0.77	2.17	7.12	132	69

Table A-3: Measures of Informed Trading - Descriptive Statistics.

This table presents the average, standard deviation, and the 5th, 25th, 50th, 75th, and 95th percentiles of the distribution of informed trading measures and additional variables used in our empirical analysis together with the number of observations for which data is available. Returns (RET) denote the returns to significant corporate news. Relative call volume RCV (relative put volume, RPV) is the weekly volume traded in call (put) options with high expected returns (top tercile) to informed trading scaled by total call (put) volume. Expected returns are computed using the BSM framework (Equation (4)) and by calibrating our framework to the news specific event characteristics (i.e., information signals). We assume that informed investors trade eleven days ahead of unscheduled news and one day ahead of scheduled news. High expected returns are expected returns in the highest tercile of the pooled distribution. OTM call volume OCV (OTM put volume OPV) are constructed similarly to RCV and RPV but using moneyness depth as a criterion to rank options. All these measures are reported in percentage terms. PP is the Pan and Poteshman (2006) measure of put volume scaled by total volume, O/S is the Johnon and So (2012) ratio of option to stock volume, IVS is the Cremers and Weinbaum (2010) call minus put implied volatility spread, and SKEW is the Xing et al (2010) measure of the volatility smirk. Further details on the construction of our informed trading measure are included in Section 3.5.

	Avg	Std	5th	25th	50th	75th	95th	N
RET	-0.29	15.78	-24.60	-10.55	2.85	10.31	21.95	26,860
RCV	31.41	35.30	0.00	0.00	15.15	60.98	99.30	13,589
RPV	21.84	33.53	0.00	0.00	0.00	37.86	99.10	13,271
OCV	8.16	13.90	0.00	0.00	2.35	10.46	35.96	25,968
OPV	12.23	19.01	0.00	0.00	3.84	16.84	52.08	26,113
PP	38.13	23.07	4.94	20.00	35.86	52.77	82.41	26,835
OS	4.03	9.62	0.01	0.37	1.45	4.44	15.73	26,835
IVS	-0.95	4.11	-6.01	-1.44	-0.44	0.32	2.59	12,433
SKEW	1.17	0.22	1.01	1.07	1.13	1.21	1.43	12,433

Table A-4: Leverage vs. Leverage-Cost Trade-off Hypothesis.

This table presents results from weekly Fama-MacBeth regressions of weekly market adjusted returns (columns 1 to 6) and event sentiment scores ESS (columns 7 to 12) on lagged measures of informed trading and a set of control variables. For each variable, we report coefficient estimates with *t*-statistics based on Newey-West standard errors adjusted for three autocorrelation lags. ESS is a measure of the news tone. Values below, equal to, and above 50 represent negative, neutral, and positive news, respectively. Relative call volume RCV (relative put volume, RPV) is the weekly volume traded in call (put) options with high expected returns to informed trading (top tercile) scaled by total call (put) volume. RVD is the difference between RCV and RPV. We compute similar measures based on the top tercile of moneyness depth to compute informed trading measures based on OTM call volume (OCV), OTM put volume (OPV) and their difference (ROVD). PP is the Pan and Poteshman (2006) measure of put volume scaled by total volume, O/S is the Johnon and So (2012) ratio of option to stock volume, IVS is the Cremers and Weinbaum (2010) call minus put implied volatility spread, and SKEW is the Xing et al. (2010) measure of the volatility smirk. Following Ge et al. (2016), our set of control variables includes the weekly market adjusted return CAR0, the natural logarithm of market capitalization SIZE, the Amihud illiquidity ratio ILLIQ, the stock's market adjusted return over the past six months MOM, and the market to book ratio MB. All variables except the dependent one are normalized. Further details on the construction of our informed trading measures are included in Section 3.5. ***,**,* indicate statistical significance at the one, five, or ten percent level, respectively.

	Returns						News Sentiment					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	0.055 (1.20)	0.053 (1.18)	0.033 (0.84)	0.032 (0.82)	0.043 (0.92)	-0.040 (-0.69)	53.460*** (341.18)	53.465*** (342.47)	53.430*** (336.13)	53.438*** (336.25)	53.440*** (338.20)	53.350*** (215.54)
RCV	0.054** (2.21)	0.054** (2.19)			0.053** (2.15)	0.113*** (3.65)	0.043 (1.47)	0.041 (1.34)			0.053* (1.73)	0.281*** (4.24)
RPV	0.026 (1.27)	0.026 (1.29)			0.024 (1.22)	0.026 (0.95)	-0.108*** (-3.88)	-0.106*** (-3.65)			-0.105*** (-3.57)	-0.199*** (-4.15)
RVD			0.010 (1.30)	0.010 (1.31)					0.073*** (3.62)	0.072*** (3.41)		
OCV		0.008 (1.16)			0.008 (1.09)	-0.006 (-0.70)		-0.011 (-0.67)			-0.014 (-0.90)	-0.020 (-0.86)
OPV		0.001 (0.16)			0.002 (0.24)	-0.004 (-0.45)		-0.017 (-1.05)			-0.018 (-1.14)	-0.044** (-1.97)
ROVD				0.003 (0.38)						0.008 (0.50)		
PP					-0.023** (-2.41)	0.004 (0.29)					-0.173*** (-9.47)	-0.304*** (-3.52)
OS					-0.078** (-2.55)	-0.035 (-1.54)					-0.077 (-1.39)	0.014 (0.32)
IVS						0.107*** (5.30)						0.073 (1.10)
SKEW						-0.037 (-1.27)						-0.074 (-1.10)
CAR0	-0.065*** (-3.24)	-0.067*** (-3.29)	-0.062*** (-2.94)	-0.063*** (-2.97)	-0.069*** (-3.37)	-0.064*** (-2.77)	-0.165*** (-4.97)	-0.163*** (-4.84)	-0.166*** (-5.12)	-0.163*** (-4.94)	-0.183*** (-5.44)	-0.251*** (-6.94)
SIZE	-0.042* (-1.86)	-0.043* (-1.90)	-0.012 (-0.40)	-0.012 (-0.39)	-0.032 (-1.39)	-0.075* (-1.93)	0.748*** (21.21)	0.748*** (20.75)	0.718*** (21.85)	0.719*** (21.41)	0.765*** (20.73)	0.972*** (21.69)
ILLIQ	0.002 (0.13)	0.004 (0.20)	-0.003 (-0.16)	-0.002 (-0.11)	0.005 (0.30)	-0.095 (-0.72)	0.518*** (10.66)	0.516*** (10.39)	0.535*** (10.75)	0.531*** (10.47)	0.519*** (10.52)	2.677*** (8.35)
MOM	0.010 (0.22)	0.015 (0.31)	0.015 (0.28)	0.018 (0.34)	0.013 (0.27)	-0.004 (-0.08)	-0.013 (-0.28)	-0.012 (-0.25)	-0.021 (-0.46)	-0.021 (-0.46)	-0.025 (-0.54)	-0.128*** (-2.36)
MB	-0.055** (-2.05)	-0.057** (-2.14)	-0.064** (-2.25)	-0.067** (-2.34)	-0.052** (-1.99)	-0.043 (-1.23)	0.089** (2.26)	0.090** (2.25)	0.094** (2.39)	0.096** (2.40)	0.096** (2.43)	0.093** (2.03)
Adj. R2	5.38	5.41	4.54	4.57	5.67	7.96	1.36	1.37	1.29	1.31	1.44	1.99
Avg N	1531	1448	1531	1448	1448	674	835	790	835	790	790	416

B The impact of margin requirements

In our application, we only consider long options positions, which do not face margin requirements. Our decision to focus on long only positions is motivated by the fact that margin requirements substantially increase the cost of trading in equity options, thereby lowering realized returns from option trading strategies (Santa-Clara and Saretto, 2009; Hitzemann et al., 2016; Noel, 2017). In our framework, we consider a price-taking investor who faces uncertainty in the timing of a news event and uncertainty in the magnitude of the stock price jump upon the news announcement. This further impacts expected returns from trading in equity options.

We show below that even without this uncertainty, realized option returns from short put options decrease dramatically in the presence of margin requirements, in particular when there is uncertainty about the evolution of volatility following a scheduled news announcement. Moreover, even with a deterministic drop in volatility following a scheduled news event, long call option returns dominate short put option returns for large stock price jumps upon announcement.

In Figure B-5, we provide alterations of Figure 1 in Cremers et al. (2021). In each graph, the solid (dashed) line denotes returns from buying call (selling put) options in an extension of the Black and Scholes (1973) option pricing model augmented with randomly sized but deterministically timed jumps, as in Dubinsky et al. (2019). We also provide the returns from selling put options when we account for margin requirements as described in the CBOE margin manual. The options are considered to be at the money and have one month to expiration, diffusive volatility of 30%, and jump size volatility of 10%. All option positions are held for one day.

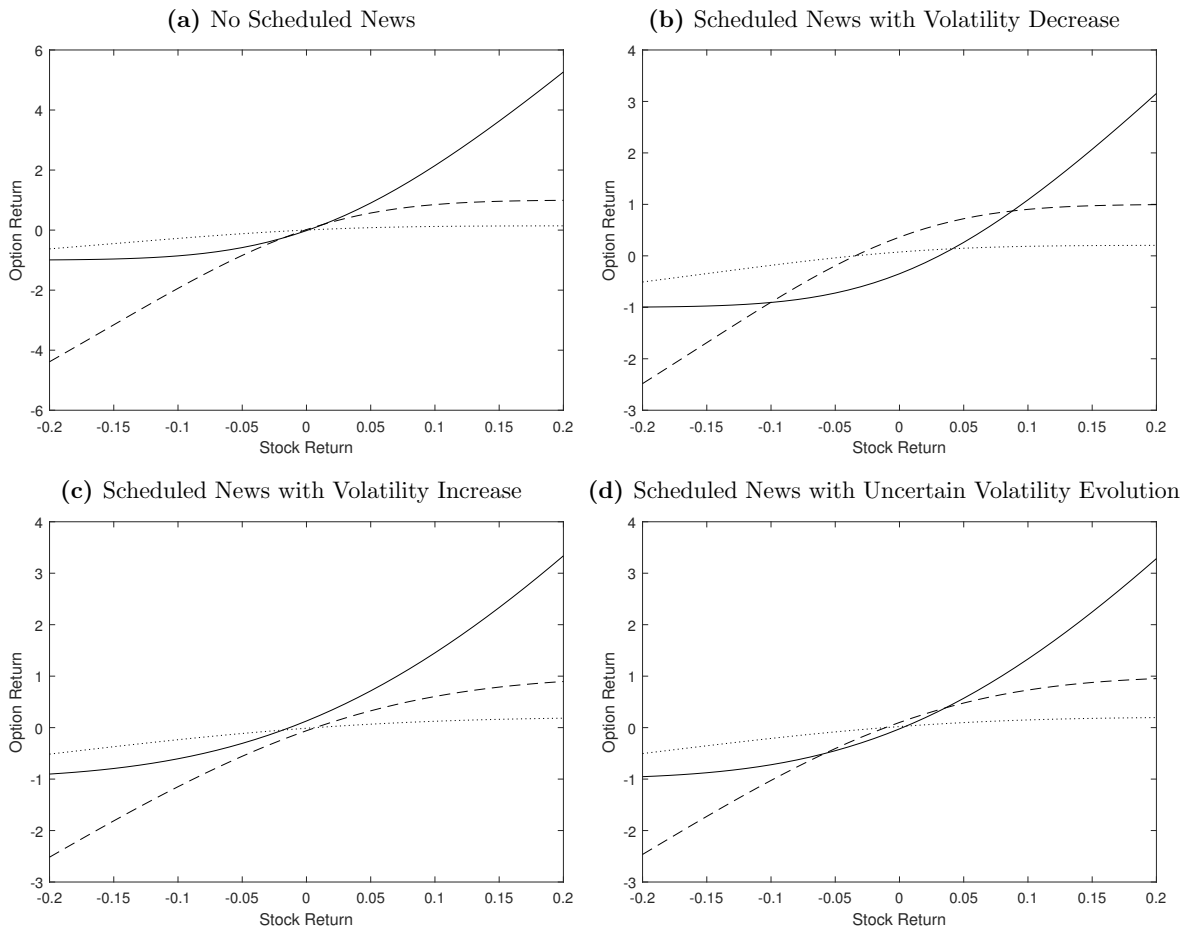
Consistent with the findings in Cremers et al. (2021), Panel (a) shows that long call option positions dominate short put positions for unscheduled news, because the call returns are always above the short put option returns regardless of the price jump. That graph shows that margins flatten the returns for short put positions (less negative for stock price drops and less positive for stock price increases).

Panel (b) shows the corresponding return when news is scheduled to be released the next day. We extend the range of stock price jumps to price drops/increases of up to 20%. This figure illustrates that, even for scheduled news, long call option returns dominate short put option returns when stock prices jumps are large.

In Panel (c), we consider scheduled news and a volatility increase of 10% after the announcement. Even though volatility decreases on average after scheduled news, there is uncertainty about the evolution of the post-event volatility. A deterministic increase in volatility after the scheduled news announcement would again imply that call option returns dominate short put option returns. In Panel (d), we incorporate uncertainty in the evolution of volatility following the announcement of scheduled news, that is, volatility could either go up or down. In that case, long call option returns once again dominate short put option returns.

Figure B-5: The Impact of Margin Requirements on Option Returns.

These figures provide alterations of Figure 1 in Cremers et al. (2021). In each graph, the solid (dashed) line denotes long call (short put option returns) in an extension of the Black and Scholes (1973) option pricing model augmented with randomly sized but deterministically timed jumps, as in Dubinsky et al. (2019). The dotted line accounts for institutional margin requirements as described in the CBOE margin manual. Panel (a) shows the one-day option return as a function of the daily underlying stock return when no news is scheduled to be released during the life of the option. Panel (b) shows the corresponding return when news is scheduled to be released the next day. Jumps that occur on predetermined dates can be interpreted as scheduled news releases. Jump size is log-normally distributed. The options are at the money and have one month to expiration, diffusive volatility of 30%, and jump size volatility of 10%. Option positions are held for one day. In Panel (c), we consider scheduled news and a volatility increase of 10% after the announcement. In Panel (d), we incorporate uncertainty in the evolution of volatility following the announcement of scheduled news.



C Construction of significant corporate news

We define Significant Corporate News (SCNs) as news events that can be linked to extreme price movements (EPMs) of stocks. The identification of SCNs involves two steps. First, we identify EPMs. Second, we associate EPMs with news. To identify news, we use RavenPack News Analytics, which employs textual analysis to identify companies, news categories, and news relevance with millisecond time stamps in Dow Jones news articles and press releases published since 2000, which dictates the start of our sample period.

We collect from the CRSP Center for Research in Security Prices information on common stocks (sharecodes 10 and 11) that trade on the AMEX, Nasdaq or NYSE with available information on stock prices, security type, number of shares outstanding, and trading volume. From the initial sample of 17.5 million daily return observations, we exclude observations if the previous trading day's market capitalization is below ten million USD or if the lagged price per share is below five dollars, as such securities are often illiquid and exhibit higher levels of market microstructure noise. After filtering out all stocks without news during our sample period, we obtain a sample of 11.4 million daily stock price observations.

We classify a stock day observation as an EPM if it is a jump following the Lee and Mykland (2008) method for jump detection (see Appendix D), or if the return on that day is above or below all returns observed during the preceding 252 trading days.¹⁴ Out of the 11.4 million daily observations, we identify 138,121 EPMs.

We further require available stock price data for at least 189 of the past 252 trading days. We exclude all EPMs of stocks without information on options price and volume, and require a minimum of one option trade during the 63 trading days prior to the EPM. We further delete observations that we cannot match to the Compustat database for company fundamentals. Our final sample includes 83,653 EPMs – 50.9 percent of which are negative – observed for 4,131 securities on 3,761 different dates between 2000 and 2014.

Next, we associate EPMs with news. RavenPack features 7.98 million corporate news stories that involve a US-based firm. We discard all news stories for which the relevance or novelty score is below its maximum of 100, as well as all stories of firms that we are not able to identify in the CRSP and Compustat database. Finally, we delete all news about stock trading, including articles on stock gains and losses, order imbalance, and technical analysis, as these may have been the result rather than the cause of large moves in stock prices. These filters leave us with 3.3 million news stories.

To associate the 3.3 million specific news stories from RavenPack with EPMs, we follow Bradley et al. (2014) and estimate logistic regressions to separately identify the determinants of positive and negative EPMs. Specifically, we regress an indicator of positive or negative EPMs on variables indicating the RavenPack news categories. The coefficients obtained from these regressions are the log of the odds-ratio. For coefficient i , the odds ratio indicates by what factor the odds of observing an EPM changes if news are reported in category i .

The sample includes all 11.4 million stock-days included in the sample, for which we estimate EPMs. For a given stock-day, a news indicator is set equal to one if a news story

¹⁴Our definition of EPMs is closely related to Brogaard et al. (2018), who define EPMs at ten-second intervals as jumps identified by the Lee and Mykland (2012) methodology. In robustness checks, Brogaard et al. (2018) define EPMs as ten-second returns with a magnitude in the 99.99th percentile of the return distribution.

in that category was reported for the stock between 4 p.m. on the previous trading day and 4 p.m. on the given day. There are 527 news categories in the RavenPack database, and we ignore all categories for which not a single news observation is made on a positive (negative) EPM day. We include indicator variables for all 80 (81) remaining categories, a larger set than the categories of corporate announcements used in prior literature.

In Tables A-1 and A-2, we report statistics only for indicator variables that are significant at the one percent level. To allow for the testing of multiple hypotheses, we use Bonferroni-adjusted p -values, implying a minimum t -statistic of 4.12. Events that are typically associated with large and significant announcement returns, such as M&A announcements, or negative news about clinical trials, have high odds ratios. Consistent with Bradley et al. (2014), analyst-related news events are also important determinants of EPMs.

We use these results to associate news and EPMs. First, we assume that only news events that are significant determinants of EPMs (i.e., all news in the categories reported in Tables A-1 and A-2) explain EPMs. Second, in case two or more news headlines for a firm are published between the end of the previous trading date and the day of the EPM, we associate the one with the highest odds ratio with the EPM. The difference between the number of news occurrences in the regression, (N_{reg}) and the number of news events used in the main analysis (N_{final}) is due to the fact that only a part of all news occurs contemporaneously with an EPM as previously defined. We define a SCN as an EPM that we can explain with a news headline, using this approach. Out of 41,092 (42,561) positive (negative) EPMs, 15,211 (15,764) are associated with SCNs.

We complement the RavenPack database with information on earnings news from Compustat's Capital IQ Key Development (CIQKD) database, and quarterly earnings announcement dates from the Compustat Quarterly files. We use this information to distinguish between scheduled SCNs – which are defined as SCNs on the day, or the day after (if reported in the after-trading hours), an earnings announcement – and unscheduled SCNs that do not occur with earnings. This matters for our analysis, as there is a run-up in implied volatilities ahead of scheduled SCNs. We consider all news released on earnings announcement dates as scheduled. In related work, Cremers et al. (2021) assume only earnings news to be scheduled. However, many other news items, for instance related to financing or product releases are also published on earnings announcement dates. Investors trading in options ahead of these news will also face the pre-earnings run-up in implied volatilities, which affects their expected returns.

D Jump classification

One of multiple criteria used in our definition of an EPM is the prevalence of a jump as defined by Lee and Mykland (2008). We compute the statistic \mathcal{L}_i as the ratio of the (continuous) stock price return to the instantaneous volatility $\mathcal{L}_t = R_t/\hat{\sigma}_t$, where volatility is the realized bipower variation

$$\hat{\sigma}_t^2 = \frac{1}{K-2} \sum_{j=t-k+2}^{t-1} |R_j| * |R_{j-1}|. \quad (\text{D-6})$$

Assuming that the drift and diffusion coefficients of the stochastic process describing the stock price do not vary a lot when Δt (the increment) approaches zero, the authors derive the limiting distribution of the maximums

$$\frac{\max_{t \in \bar{A}_n} |\mathcal{L}_t| - C_n}{S_n} \longrightarrow \xi, \quad (\text{D-7})$$

where ξ has a cumulative distribution function $P(\xi \leq x) = \exp(-\exp(-x))$ and

$$C_n = \frac{\sqrt{2 \log(n)}}{c} - \frac{\log(\pi) + \log(\log(n))}{2c\sqrt{2 \log(n)}}; \quad S_n = \frac{1}{c\sqrt{2 \log(n)}}; \quad c = \sqrt{\frac{2}{\pi}}. \quad (\text{D-8})$$

The parameter n denotes the number of observations. \bar{A}_n defines the time series indices such that there is no jump between two consecutive time points. While Lee and Mykland show that misclassification rates decrease in data frequency, it can also be applied to daily data (e.g., Cremers et al., 2014). Following Lee and Mykland (2008), we set $K = 16$ to compute the statistic \mathcal{L}_t from daily returns. As in their study, we use a significance level of 5%. The threshold is hence equal to $-\log(-\log(0.95)) \approx 2.97$. For each stock, we obtain a time series of \mathcal{L}_t . If $|\mathcal{L}_t|$ exceeds $2.97 * S_n + C_n$, the return is classified as a jump.

E Option elasticity

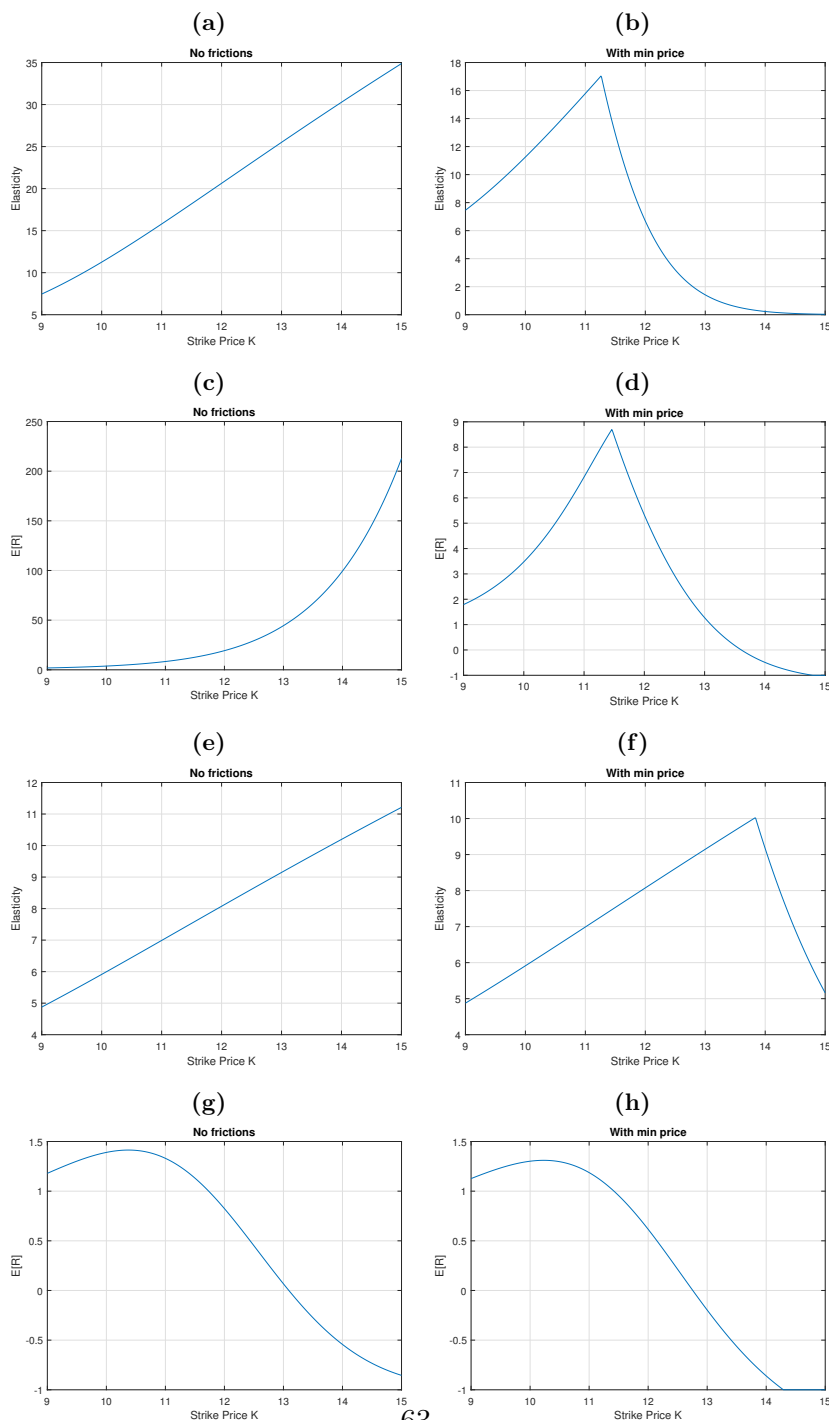
Denote by V the value of an option. The option elasticity Ω , is defined as the product of the option delta Δ and the ratio of the value of the underlying asset to the option price, i.e., $\Omega = \Delta \frac{S}{V}$ in the case of a call option. It measures the percentage change in an option's value with respect to the percentage change in the underlying price.

In Figure E-6, we compare the option elasticity measure Ω to maximize expected returns to informed trading $E[R]^{max}$ for different levels of moneyness. We plot elasticity in Panels (a), (c), (e) and (f), and maximum expected returns in Panels (c), (d), (g), and (h). Panels (a), (c), (e), and (g) ((b), (d), (f), and (h)) report results without (with) frictions. In all graphs, we use the calibration $S_0 = 10$, $r = 0.03$, $T_0 = 30$ days, and $\kappa = 0.2$. In Panels (a) to (d), we further use the calibration $\sigma = 0.40$, and $\Delta t = 3$ days. In Panels (e) to (h), we use the calibration $\sigma = 0.80$, and $\Delta t = 25$ days.

Panels (a) to (d) suggest that, using a particular parameter calibration, elasticity and our measure of maximum expected returns can be strongly positively correlated. However, Panels (e) to (h) similarly suggest that, using a different parameter calibration, both measures can also be negatively correlated. These examples underscore that maximum expected returns from informed trading are not just a monotonic transformation of option elasticity.

Figure E-6: Option Elasticity and Maximum Expected Returns to Informed Trading.

These figures compare the option elasticity measure Ω to maximize expected returns to informed trading $E[R]^{max}$ for different levels of moneyness. Ω is defined as $\Omega = \Delta \frac{S}{V}$, where $\Delta = \partial V / \partial S$, S is the underlying asset price, and V is the value of the option. We plot elasticity in Panels (a), (b), (e) and (f), and maximum expected returns in Panels (c), (d), (g), and (h). Panels (a), (c), (e), and (g) ((b), (d), (f), and (h)) report results without (with) frictions. In all graphs, we use the calibration $S_0 = 10$, $r = 0.03$, $T_0 = 30 \text{ days}$, and $\kappa = 0.2$. In Panels (a) to (d), we further use the calibration $\sigma = 0.40$, and $\Delta t = 3 \text{ days}$. In Panels (e) to (h), we use the calibration $\sigma = 0.80$, and $\Delta t = 25 \text{ days}$.



F Predictions of excess returns & news sentiment

We extend our analysis to the unconditional prediction of returns and news sentiment scores in the broader cross-section of stocks without considering the specific event characteristics of SCNs. That exercise is akin to limiting the usefulness of the information signals. On the one hand, this exercise reduces the look-ahead bias associated with the information signals in comparison to other informed trading measures. On the other hand, it forces us to make, ex-ante, specific assumptions about the magnitude and uncertainty about the anticipated stock price jumps.

F.1 Data sources and summary statistics

We source information from OptionMetrics, which we match with stock price information from the Chicago Center for Research in Security Prices (CRSP). We further source information on company characteristics and balance sheets from the quarterly files in Compustat. Our sample comprises all stock-days reported in the CRSP database over the years 2000-2014 that are common stocks with a minimum stock price of USD 5, a market value of more than USD 10 million, with positive trading volume, and for which contract-specific call and put volume data are available from the OptionMetrics database.

Using this sample, we first construct weekly returns using Friday-to-Friday closing prices. We compute weekly returns in excess of the CRSP value weighted market return. Second, we compute the informed trading measures. To operationalize our framework, we calculate RCV and RPV based on expected returns that assume private signals about a hypothetical price jump in the subsequent week of +10% and -10% for positive and negative news, respectively, with a jump uncertainty of 5%.¹⁵ Since there is uncertainty with respect to the timing of the price jumps, we allow for the possibility that the jumps occur on any trading day of the week during which we predict returns and news. Since price jumps and news may arrive with equal probability on any day of the week, we adopt a uniform distribution for the expected timing of the news announcement in the numerical computation of expected option returns.

We compute RCV and RPV based on the volume of those options that rank in the highest tercile of all attainable expected option returns. We also examine the imbalance in informed trading across call and put options, based on the relative difference volume, defined as $RVD_{i,t} = RCV_{i,t} - RPV_{i,t}$.

In addition to the prediction of returns, we attempt to predict weekly news sentiment scores, which we also receive from the DowJones Edition of RavenPack News Analytics. A main variable of interest from RavenPack is the event sentiment score ESS . The metric ESS ranges between 0 and 100, and is meant to capture news sentiment. Values above 50 reflect a bullish sentiment, while those below 50 indicate that a news item reflects bearish sentiment. We drop all news with a neutral score of 50. We compute weekly ESS as the equally weighted average ESS of all firm-specific news in a stock week. Weeks without news are excluded from the analysis.

Table F-5 reports summary statistics on weekly returns in excess of the CRSP value weighted market return (CAR), and the weekly event sentiment score (ESS). The table also describes statistics for other benchmark measures of informed options trading used in the

¹⁵An alternative computation using signals of +5% and -5% yields similar results.

analysis, as well as information on standard control variables used in cross-sectional return predictions (e.g., Ge et al., 2016). The variable *CAR0* defines weekly cumulative returns in excess of the CRSP value weighted market return; *SIZE* is the logged market capitalization in 1,000 USD; *ILLIQ* refers to the Amihud illiquidity ratio winsorized at the 5th and 95th percentiles of the distribution; *MOM* denotes the stock's holding period return over the past six months; and *MB* defines the market-to-book ratio.

The average weekly news sentiment score is 53, implying that overall, news is slightly tilted towards bullish sentiment. This is consistent with a weekly cumulative excess return over the market that is 0.041%, on average, with a standard deviation of 6.3%. ESS ranges between 38.6 and 69.3 at the 5th and 95th percentiles of the distribution. The second block of variables describes the measures of informed trading.

RCV is, on average, 42.07. However, trading in those options that provide high expected returns to informed investors can be zero (5th percentile) to 98.745% (95th percentile). The average *RPV* is a bit lower with 36.3%, but features similar cross-sectional heterogeneity. *RVD*, which reflects the imbalance in the *RCV* and *RPV* measures, is slightly positive, (on average 5%), consistent with evidence that informed trading is more prevalent in call options (Cao et al., 2005). We do not explicitly comment on the benchmark informed trading measures PP, O/S, IVS, and SKEW, but summary statistics are consistent with sample statistics reported by the respective authors. The average firm in the sample has a market capitalization of \$2.1 billion, but the firm at the 95th percentile of the distribution has a market capitalization of \$31.6 billion. Table F-6 reports correlations across all measures reported in the summary statistics.

F.2 Predicting returns

To validate that the measures of informed trading derived from our framework capture information, we assess how informative the different measures of informed trading are for explaining the cross-section of stock returns. We estimate Fama-MacBeth regressions using weekly returns in excess of the market's performance and various measures of informed trading, which are lagged by one week. For each variable, we report in Table F-7 the average cross-sectional coefficient estimate with *t*-statistics based on Newey-West standard errors adjusted for three lags in parentheses. We have 1,531 cross-sectional regressions for volume-based measures, and 714 cross-sectional regressions for price-based (implied volatility) measures of informed trading.

In column (1), we provide a benchmark regression to evaluate the improvement in explanatory power of the regressions. Columns (2) to (7) independently examine the predictability of all informed trading measures. Column (2) suggests that it is, in particular, *RCV* that has positive predictive power for excess returns, with a *t*-statistic of 2.21, while *RPV* is insignificant, as is *RVD* in column (3). In particular column (2) shows that the *RCV* helps improve the predictability power, as the adjusted R^2 of the regression increases from 4.6% to 5.4%. The fact that only *RCV* is significant in explaining the cross-section of returns could be consistent with the evidence that informed trading is generally more prevalent in call options (e.g. Cao et al., 2005; Ge et al., 2016; Augustin et al., 2019). Both PP and OS have negative predictive power for excess returns, with absolute *t*-statistics of -2.06 and -2.88 , respectively. However, their improvement in explanatory power is marginal. Based on the

insignificant results in columns (6) and (7), we conclude that both price-based measures do not have predictive power for excess returns in our sample.

In column (8), we examine whether *RCV* and *PPV* have predictability after we control for existing volume-based measures of informed trading. The coefficient for *RCV* continues to be significant and positive, while the adjusted R^2 increases to 5.67%. Columns (8) and (9) compare the new measures of informed trading against existing ones derived from option prices. In this smaller sample, *RCV* is significant at the 1% level, and the adjusted R^2 is 6.87%, while *RVD* is significant at the 5% level. Given the base regression coefficient of 0.054 in column (2), our findings suggest that the coefficient of *RCV* is economically meaningful. In particular, a one standard deviation increase in *RCV* predicts an increase of future excess returns of 1.9255%.

F.3 Predicting ESS

We further assess how informative the different measures of informed trading are for explaining the cross-section of news. To do so, we estimate Fama-MacBeth regressions using weekly event sentiment score (ESS) and the lagged values of the previously described set of variables. For each variable, we present the average cross-sectional regression coefficient together with the t -statistic in parentheses based on Newey-West standard errors adjusted for three lags. News sentiment is significantly predicted by informed trading in puts, as illustrated by the statistically significant negative coefficient on *RPV* in column (2) in Table F-8, and *PP* in column (4). Also the imbalance in informed call and put trading (*RVD*) is statistically significant at the 1% level (see column (3)). In all instances, the explanatory power increases, although only marginally. The OS ratio is insignificant, as are the coefficients for price-based measures of informed trading (columns (6) and (7)). Importantly, the statistical significance of neither *RPV* nor *RVD* is driven out by the other informed trading measures, as is demonstrated in columns (8), and (9).

Table F-5: Measures of Informed Trading - Descriptive Statistics.

This table presents the average, standard deviation, and the 5th, 25th, 50th, 75th, and 95th percentiles of the distribution of informed trading measures and additional variables used in our empirical analysis together with the number of observations for which data is available. ESS is a measure of the news tone. Values below, equal to, and above 50 represent negative, neutral, and positive news, respectively. CAR is the weekly market adjusted return. Relative call volume RCV (relative put volume, RPV) is the weekly volume traded in call (put) options with high expected returns (top tercile) to informed trading scaled by total call (put) volume. Expected returns are computed for call and put options for a private signal about a hypothetical price jump of +10% and -10% anticipated for any day over the next trading week. High expected returns are expected returns in the highest tercile of the pooled distribution. RVD is the difference between RCV and RPV. PP is the Pan and Poteshman (2006) measure of put volume scaled by total volume, O/S is the Johnon and So (2012) ratio of option to stock volume, IVS is the Cremers and Weinbaum (2010) call minus put implied volatility spread, and SKEW is the Xing et al (2010) measure of the volatility smirk. Following Ge et al. (2016), our set of control variables includes the natural logarithm of market capitalization (in million USD) SIZE, the Amihud illiquidity ratio ILLIQ, the stock's market adjusted return over the past six months MOM, and the market to book ratio MB. All variables but SIZE and ESS are multiplied by 100. Further details on the construction of our informed trading measure are included in Section 3.5.

	Avg	Std	5th	25th	50th	75th	95th	N
ESS	53.043	9.950	38.600	48.000	50.500	59.333	69.286	654,407
CAR	0.041	6.296	-8.827	-2.575	-0.048	2.517	9.235	1,198,917
RCV	42.071	35.658	0.000	2.222	39.969	75.474	98.745	1,198,917
RPV	36.254	37.439	0.000	0.000	23.744	71.910	100.000	1,198,917
RVD	5.817	31.449	-48.046	-3.204	0.000	19.088	63.082	1,198,917
PP	38.123	22.871	5.007	20.110	35.948	52.711	81.516	1,198,917
O/S	4.071	9.495	0.014	0.367	1.439	4.432	15.982	1,198,917
IVS	-0.944	4.322	-5.968	-1.440	-0.432	0.344	2.581	558,390
SKEW	1.170	0.304	1.009	1.073	1.128	1.208	1.430	558,390
SIZE	14.565	1.495	12.396	13.473	14.400	15.495	17.268	1,198,917
ILLIQ	5.959	13.225	0.305	0.836	2.386	6.228	22.234	1,198,917
MOM	10.625	48.960	-42.632	-11.258	6.031	24.218	72.486	1,198,917
MB	2.532	1.481	0.826	1.418	2.148	3.255	5.736	1,198,917

Table F-6: Correlations between Measures of Informed Trading.

This table presents averages of cross-sectional correlations between informed trading measures and additional variables used in our empirical analysis. ESS is a measure of the news tone. Values below, equal to, and above 50 represent negative, neutral, and positive news, respectively. CAR is the weekly market adjusted return. Relative call volume RCV (relative put volume, RPV) is the weekly volume traded in call (put) options with high expected returns to informed trading (top tercile) scaled by total call (put) volume. RVD is the difference between RCV and RPV. PP is the Pan and Poteshman (2006) measure of put volume scaled by total volume, O/S is the Johnon and So (2012) ratio of option to stock volume, IVS is the Cremers and Weinbaum (2010) call minus put implied volatility spread, and SKEW is the Xing et al. (2010) measure of the volatility smirk. Following Ge et al. (2016), our set of control variables includes the natural logarithm of market capitalization SIZE, the Amihud illiquidity ratio ILLIQ, the stock's market adjusted return over the past six months MOM, and the market to book ratio MB. All variables but SIZE and ESS are multiplied by 100. The first two rows include the dependent variables of our analysis, ESS and CAR, which are compared to lagged independent variables. Further details on the construction of our informed trading measures are included in Section 3.5.

	1	2	3	4	5	6	7	8	9	10	11	12	13
(1) ESS	1.000												
(2) CAR	0.125	1.000											
(3) RCV	0.034	0.009	1.000										
(4) RPV	0.027	0.007	0.565	1.000									
(5) RVD	0.007	0.001	0.440	-0.486	1.000								
(6) PP	-0.011	-0.003	0.077	0.060	0.014	1.000							
(7) O/S	0.011	-0.009	0.033	0.032	-0.001	0.030	1.000						
(8) IVS	0.022	0.019	0.108	0.142	-0.055	-0.044	-0.108	1.000					
(9) SKEW	0.002	-0.004	0.168	0.181	-0.025	0.037	-0.054	-0.208	1.000				
(10) SIZE	0.070	0.000	0.502	0.479	0.006	0.061	0.164	0.142	0.087	1.000			
(11) ILLIQ	-0.019	-0.002	-0.208	-0.196	-0.005	0.004	-0.050	-0.103	-0.039	-0.473	1.000		
(12) MOM	0.001	0.006	0.005	0.045	-0.038	-0.057	0.039	-0.031	0.002	0.035	-0.022	1.000	
(13) MB	0.008	-0.010	-0.011	0.005	-0.012	-0.024	0.158	-0.045	-0.044	0.105	-0.044	0.247	1.000

Table F-7: Predicting Returns in the Weekly Cross-Section.

This table presents results from weekly Fama-MacBeth regressions of weekly market adjusted returns on lagged measures of informed trading and a set of control variables. For each variable, we report coefficient estimates with t -statistics based on Newey-West standard errors adjusted for three autocorrelation lags. Relative call volume RCV (relative put volume, RPV) is the weekly volume traded in call (put) options with high expected returns to informed trading (top tercile) scaled by total call (put) volume. RVD is the difference between RCV and RPV. PP is the Pan and Poteshman (2006) measure of put volume scaled by total volume, O/S the Johnson and So (2012) ratio of option to stock volume, IVS is the Cremers and Weinbaum (2010) call minus put implied volatility spread, and SKEW is the Xing et al. (2010) measure of the volatility smirk. Following Ge et al. (2016), our set of control variables includes the lagged weekly market adjusted return CAR0, the natural logarithm of market capitalization SIZE, the Amihud illiquidity ratio ILLIQ, the stock's market adjusted return over the past six months MOM, and the market to book ratio MB. All variables except the dependent one are normalized. Further details on the construction of our informed trading measures are included in Section 3.5. ***,**,* indicate statistical significance at the one, five, or ten percent level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	0.032 (0.83)	0.055 (1.20)	0.033 (0.84)	0.032 (0.82)	0.025 (0.61)	-0.086 (-1.44)	-0.113** (-2.02)	0.045 (0.98)	-0.033 (-0.57)	-0.063 (-1.20)
RCV		0.054** (2.21)						0.053** (2.19)	0.113*** (3.68)	
RPV		0.026 (1.27)						0.024 (1.20)	0.030 (1.11)	
RVD			0.010 (1.30)							0.026* (1.93)
PP				-0.020** (-2.06)				-0.023** (-2.46)	0.007 (0.46)	-0.003 (-0.18)
O/S					-0.078*** (-2.88)			-0.073** (-2.56)	-0.035 (-1.51)	-0.046* (-1.89)
IVS						0.030 (0.43)			0.105*** (5.15)	0.114*** (5.50)
SKEW							-0.069 (-1.59)		-0.047 (-1.63)	-0.029 (-0.77)
CAR0	-0.063*** (-2.95)	-0.065*** (-3.24)	-0.062*** (-2.94)	-0.065*** (-3.08)	-0.062*** (-2.91)	0.787 (0.95)	0.338 (0.85)	-0.067*** (-3.33)	-0.064*** (-2.80)	-0.062** (-2.56)
SIZE	-0.011 (-0.37)	-0.042* (-1.86)	-0.012 (-0.40)	-0.010 (-0.31)	-0.004 (-0.12)	0.278 (0.94)	0.117 (1.07)	-0.032 (-1.38)	-0.074* (-1.91)	-0.023 (-0.52)
ILLIQ	-0.003 (-0.17)	0.002 (0.13)	-0.003 (-0.16)	-0.003 (-0.19)	-0.000 (-0.01)	-0.267 (-1.56)	-0.173 (-1.30)	0.004 (0.25)	-0.071 (-0.55)	-0.103 (-0.82)
MOM	0.015 (0.28)	0.010 (0.22)	0.015 (0.28)	0.012 (0.24)	0.015 (0.28)	0.432 (1.01)	0.181 (0.91)	0.009 (0.18)	-0.006 (-0.12)	-0.002 (-0.03)
MB	-0.064** (-2.25)	-0.055** (-2.05)	-0.064** (-2.25)	-0.065** (-2.27)	-0.058** (-2.08)	0.019 (0.20)	-0.028 (-0.40)	-0.050* (-1.91)	-0.040 (-1.15)	-0.034 (-1.13)
Adj. R2	4.53	5.38	4.54	4.60	4.76	6.19	6.19	5.65	7.93	6.84
Avg N	1531	1531	1531	1531	1531	714	714	1531	714	714

Table F-8: Predicting News Sentiment in the Weekly Cross-Section.

This table presents results from weekly Fama-MacBeth regressions of weekly event sentiment scores (ESS) on lagged measures of informed trading and a set of control variables. For each variable, we report coefficient estimates with t -statistic based on Newey-West standard errors adjusted for three autocorrelation lags. ESS is a measure of the news tone. Values below, equal to, and above 50 represent negative, neutral, and positive news, respectively. Relative call volume RCV (relative put volume, RPV) is the weekly volume traded in call (put) options with high expected returns to informed trading (top tercile) scaled by total call (put) volume. RVD is the difference between RCV and RPV. PP is the Pan and Poteshman (2006) measure of put volume scaled by total volume, O/S is the Johnson and So (2012) ratio of option to stock volume, IVS is the Cremers and Weinbaum (2010) call minus put implied volatility spread, and SKEW is the Xing et al. (2010) measure of the volatility smirk. Following Ge et al. (2016), our set of control variables includes the weekly market adjusted return CAR0, the natural logarithm of market capitalization SIZE, the Amihud illiquidity ratio ILLIQ, the stock's market adjusted return over the past six months MOM, and the market to book ratio MB. All variables except the dependent one are normalized. Further details on the construction of our informed trading measures are included in Section 3.5. ***,**,* indicate statistical significance at the one, five, or ten percent level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	53.433*** (335.94)	53.460*** (341.18)	53.430*** (336.13)	53.426*** (339.33)	53.421*** (330.37)	53.498*** (244.78)	53.558*** (257.42)	53.441*** (338.02)	53.341*** (216.58)	53.308*** (216.55)
RCV		0.043 (1.47)						0.054* (1.83)	0.278*** (4.28)	
RPV		-0.108*** (-3.88)						-0.106*** (-3.74)	-0.202*** (-4.32)	
RVD			0.073*** (3.62)							0.218*** (3.01)
PP				-0.177*** (-10.20)				-0.176*** (-10.04)	-0.299*** (-3.48)	-0.328*** (-4.15)
O/S					-0.069 (-1.31)			-0.064 (-1.20)	0.022 (0.51)	0.021 (0.51)
IVS						0.099 (1.57)			0.064 (1.00)	0.120*** (2.95)
SKEW							-0.110* (-1.86)		-0.077 (-1.16)	-0.064 (-1.00)
CAR0	-0.171*** (-5.29)	-0.165*** (-4.97)	-0.166*** (-5.12)	-0.194*** (-6.03)	-0.171*** (-5.35)	-0.223*** (-6.32)	-0.225*** (-6.45)	-0.185*** (-5.62)	-0.247*** (-7.02)	-0.242*** (-6.87)
SIZE	0.716*** (21.93)	0.748*** (21.21)	0.718*** (21.85)	0.732*** (22.78)	0.723*** (21.13)	0.975*** (22.59)	0.996*** (23.31)	0.764*** (21.12)	0.972*** (22.11)	1.046*** (13.44)
ILLIQ _{w5}	0.530*** (10.60)	0.518*** (10.66)	0.535*** (10.75)	0.528*** (10.64)	0.534*** (10.68)	2.731*** (8.33)	2.710*** (8.42)	0.522*** (10.81)	2.620*** (8.00)	2.628*** (7.89)
MOM	-0.025 (-0.55)	-0.013 (-0.28)	-0.021 (-0.46)	-0.039 (-0.85)	-0.025 (-0.54)	-0.105** (-2.01)	-0.120** (-2.30)	-0.026 (-0.56)	-0.116** (-2.17)	-0.120** (-2.30)
MB	0.096** (2.40)	0.089** (2.26)	0.094** (2.39)	0.093** (2.35)	0.103*** (2.62)	-0.021 (-0.24)	-0.025 (-0.28)	0.094** (2.44)	0.090** (2.00)	0.068* (1.77)
Adj. R2	1.27	1.36	1.29	1.31	1.30	1.64	1.69	1.43	1.93	1.83
Avg N	835	835	835	835	835	440	440	835	440	440