How do Informed Investors Trade in the Options Market?*

Patrick Augustin, *McGill University - Desautels Faculty of Management*†
Menachem Brenner, *New York University - Leonard N. Stern School of Business*‡
Gunnar Grass, *HEC Montreal*§
Marti G. Subrahmanyam, *New York University - Leonard N. Stern School of Business*¶

June 1, 2018

Abstract

We analyze how informed investors trade in the options market ahead of corporate news when they receive private, but noisy, information about (i) the timing, and (ii) the potential impact on stock prices of these announcements. We propose a framework that ranks options trading strategies (option type, maturity, and strike price) based on their maximum attainable leverage, given market frictions. We exploit the heterogeneity in announcement characteristics across a large number of corporate announcements to demonstrate that informed trading measures derived from our framework incrementally contribute to the predictability of news events and stock returns.

Keywords: Corporate Announcements, Derivatives, Event Studies, Insider Trading, Market Microstructure

JEL Classification: G12, G13, G14, K42

---

*This paper benefited from helpful comments by Yakov Amihud, Robert Battalio, Tolga Cenesizoglu, Mathieu Fournier, Pascal François, Paul Whelan, Xiaofei Zhao, and participants of the 2015 OptionMetrics conference, the 2016 HEC - McGill Winter Finance Workshop, the 2016 China International Conference in Finance (CICF), the 2017 meeting of the Western Finance Association (WFA), and the 2017 meeting of the European Finance Association (EFA), as well as seminar participants at HEC Montreal, the University of Cologne, and the Securities and Exchange Commission (SEC). We are grateful to Dominique Boucher, Antoine Noël, and Siyang Wu for excellent research assistance. We thank the Montreal Institute of Structured Finance and Derivatives (IFSID) and the Global Risk Institute (GRI), as well as the Chicago Mercantile Exchange (CME) Group Foundation for generous financial support. Furthermore, Augustin acknowledges financing from McGill University and the Institute of Financial Mathematics of Montreal (IFM2) and Grass acknowledges financing from the Fonds de Recherche du Quebec sur la Société et la Culture (FRQSC).

†Patrick.Augustin@mcgill.ca, 1001 Sherbrooke St. West, Montreal, Quebec H3A 1G5, Canada.
‡mbrenner@stern.nyu.edu, 44 West 4th St., NY 10012-1126 New York, USA.
§gunnar.grass@hec.ca, 3000, chemin de la Côte-Sainte-Catherine, Montreal, Quebec H3T 2A7, Canada.
¶msubrahm@stern.nyu.edu, 44 West 4th St., NY 10012-1126 New York, USA.

How do Informed Investors Trade in the Options Market?

Abstract

We analyze how informed investors trade in the options market ahead of corporate news when they receive private, but noisy, information about (i) the timing, and (ii) the potential impact on stock prices of these announcements. We propose a framework that ranks options trading strategies (option type, maturity, and strike price) based on their maximum attainable leverage, given market frictions. We exploit the heterogeneity in announcement characteristics across a large number of corporate announcements to demonstrate that informed trading measures derived from our framework incrementally contribute to the predictability of news events and stock returns.

Key words: Corporate Announcements, Derivatives, Event Studies, Insider Trading, Market Microstructure
JEL classification: G12, G13, G14, K42

1. Introduction

Recent research extensively documents the prevalence of informed trading in the options market ahead of corporate news events. While many studies successfully identify the *existence* of informed trading, it is striking that the literature is not informative about *how* informed investors maximize their benefits from private information. Our objective is to understand how the nature of private information affects the strategy chosen by informed investors trading in the options market. The characterization of the optimal strategy can help improve the identification of informed trading, which has two key benefits. First, it may improve the prediction of future stock returns, based on patterns of unusual trading activity in the options market. Second, it may help regulators detect unusual informed trading activity around corporate news events and differentiate them from thousands of uninformed trades, to focus their more detailed investigation.

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 (i) the timing of the news announcement, and (ii) 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. Such heterogeneity across events affects an informed investor's trading strategy.[1] For instance, an investor who receives 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 and returns, due to the imprecision of the signal received. In contrast, an investor with private information about the deal premium paid in a merger and acquisition (M&A) transaction can predict the (typically large) price impact relatively precisely, but may not know the exact timing of the deal announcement. Any research that focuses on one specific category of corporate event, albeit in detail, is thus limited in its predictive power for understanding how this heterogeneity across corporate announcements affects the nature of informed trading. In 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.

As a first step, we propose a theoretical 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, which maximizes the expected returns from informed trading on a

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

noisy signal, in the presence of illiquid option markets. We posit that capital-constrained investors trading on private information in the options market do so since it enables them to leverage their exposure and, hence, potential returns. The maximization of expected returns can alternatively be interpreted as the maximization of leverage through options trading. We acknowledge that some informed investors would seek to hide their activities from other market participants or regulators tracking informed traders. The risk of detection may thus incentivize informed investors to deviate from the first best and avoid trades in the single option that maximizes expected returns. Our empirical application accounts for the possibility of deviations from the first best as it focuses on the top tercile of the options that maximize expected returns, instead of the first best strategy alone.

We assume that the private information received by the informed investor consists of two signals, information about the *timing* of an announcement, and information about the *announcement return* on the underlying stock in reaction to news.[2] 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 of the future stock price reaction to the announcement.

A central feature of our theoretical framework is that it accounts for two important frictions prevalent in the options market. First, most options trade with significant bid-ask spreads, which are typically a function of their moneyness. The minimum bid-ask spread is defined in dollar terms, implying substantially greater 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 (in terms of their implied volatility), and, therefore, severely limit the maximum leverage (and potential returns) that investors can attain in the options market. In addition, run-ups in implied volatilities ahead of scheduled news announcements can substantially increase the cost of setting up a trading strategy. Using numerical analysis, we illustrate that these three effects âĂŞbid-ask spreads, minimum prices, and run-up in implied volatilities – reduce the maximum attainable returns to informed trading from unrealistically high levels (i.e., returns of multi-million percent) to a more realistic magnitude of returns observed for informed trades that, according to the Securities and Exchange Commission (SEC), are based on private information.[3]

[2] We focus on a two-dimensional signal, for reasons of tractability. It would be possible to extend our analysis to account for private, but noisy, signals about changes in the second moment, i.e., the volatility of the underlying stock price distribution. We leave such an extension to future research.

[3] The website of the SEC publicly discloses the profits of trades pursued due to violation of insider trading rules at https://www.sec.gov/litigation/litreleases.shtml.

Furthermore, they can heavily affect the trading behavior of informed investors.

Our analysis reveals three main insights about the strategic option trading behavior of informed investors. 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. 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 an informed trader's option choice. Uncertainty about the announcement return, on the other hand, has limited impact on the strategic trading behavior of informed investors. 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. If informed investors have a very precise timing signal, leverage can be substantially increased by trading shortly ahead of the announcement and using a shorter maturity option. This effect may be partially offset by a run-up in implied volatility and an increase in bid-ask spreads ahead of scheduled events.

We apply the framework empirically in two steps. First, we use the framework to quantify the returns to informed options trading when investors receive private (but noisy) signals about future announcement returns and the timing of the announcement. We construct a sample of 30,975 "significant corporate news" (SCN) events between 2000 and 2014, by relying on the novel and comprehensive RavenPack news database. We classify SCNs into twelve different categories, which exhibit a substantial amount of heterogeneity with respect to their announcement characteristics. These diverse categories exhibit the variation in , the magnitude and the precision of private signals, which clearly affect the attainable returns to informed trading, as discussed earlier. We use two naive measures of informed trading to document that, consistent with our predictions, abnormal activity in options markets starts shortly prior to scheduled announcements and, well ahead of unscheduled announcements. The naive informed trading measures we use are the ratio of the implied volatility of OTM call options divided by that of OTM put options, and the daily firm-specific relative call volume, defined as the ratio of the total call options trading volume to the sum of both the call and put options trading volume.

In a second step, we use our framework to construct a novel measure of informed trading, with the aim of predicting returns and sentiment scores. We define the relative call volume (RCV) as the ratio of call volume in informed trading strategies to total options trading volume. Informed options strategies are those that, conditional on a noisy signal about a future price jump and news announcement date, yield high expected returns to informed investors, i.e., those options that maximize leverage. Similarly, relative put volume (RPV) is defined as the ratio of put volume in informed trading strategies relative to total options volume. In addition, we define RVD as the difference between relative call and put volumes, which is meant to capture the imbalance in informed trading strategies between calls and puts.

In the first step of our empirical analysis, we perform weekly cross-sectional Fama-MacBeth regressions in order to examine whether the informed trading measures have predictive power for subsequent stock returns in excess of the market's performance. This serves as a reality check in order to show that our measures do capture informed trading strategies, even in the presence of arbitrary noisy signals. We find, in particular, that RCV has positive predictive power for excess stock returns, and adds explanatory power beyond those accounted for by several measures of informed trading proposed in previous research. Thus, we show that existing measures of informed trading implied from option prices and volumes, even used in tandem, are unable to outperform the information captured by RCV. More specifically, we examine the Pan and Poteshman (2006) put-call volume ratio, the Johnson and So (2012) option-to-stock volume ratio, the Cremers and Weinbaum (2010) implied volatility spread, and the Xing et al. (2010) implied volatility smirk.

Second, we examine whether the same measures of informed trading also have predictive power for news sentiment, using the event sentiment score derived using textual news analysis from the RavenPack DowJones News Edition. We find that RPV has significant negative explanatory power for news sentiment, similar to the put-call and the option-to-stock volume ratios. RVD, on the other hand, positively predicts news sentiment. Thus, we find that the predicted signs are in line with those implied by existing measures of informed trading, and that neither of these is able to drive out the explanatory power of the newly proposed measures. Moreover, we find no evidence that existing measures of informed trading implied by prices have any significant explanatory power in the cross-section of stock returns or news, in contrast to our own measures.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and discusses our main contributions. Section 3 presents a novel framework for identifying option trades that maximize expected returns to informed traders with private, but noisy signals. In Section 4, we discuss the identification of significant corporate news events and categorize the heterogeneity in event characteristics across news categories. Section 5 discusses our novel measures of informed trading, reviews existing benchmark measures, and examines the predictability of excess returns and news sentiment. We conclude in Section 6.

2. Literature Review

A large body of theoretical literature from the past two decades suggests that informed investors may migrate towards the options markets, as they provide more "bang for the buck," i.e., leverage, especially for those with superior information (Boyer and Vorkink, 2014; Ge et al., 2016). This is especially true in the presence of frictions and market imperfections, such as capital constraints. Other motives include 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, underscored by informed trading activity ahead of corporate announcements, and, more generally, the predictive power of implied volatility and volume in the options markets for stock returns. Various studies pinpoint informed options trading ahead of 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., 2018), spin-offs (Augustin et al., 2015), leveraged buyouts (Acharya and Johnson, 2010), and the announcements of strategic trades by activist investors (Collin-Dufresne et al., 2015). We also relate our work to the vast literature that examines the predictive power of information-based measures derived from option trading volumes and prices 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; Driessen et al., 2012; Jin et al., 2012), put-call parity deviations (Cremers and Weinbaum, 2010), option-to-stock volume ratio (Johnson and So, 2012; Driessen et al., 2012), and hedging activity by option market makers (Hu, 2014).[4]

There are two key distinctions between the earlier literature and our present study. While previous work has successfully identified the existence of informed trading in the options market, the literature has not documented any details about the strategy an informed investor would implement to maximize her benefits from private information. Thus, we focus on the *type* of strategy, i.e., puts, calls, or a combination of both, as well as their *moneyness*, i.e., the strike price, and *time to expiration*, that the informed agent chooses. The choice of option strategy endogenously arises as a trade-off between the benefits of leverage, and the trading costs arising due to the significant illiquidity that characterizes the options market. Previous work has been suggestive of this trade-off for the choice of trading strategy (Chakravarty et al., 2004; Ge et al.,

[4]The focus on informed trading naturally relates this study also to the literature on insider trading, for which we refer to Bhattacharya (2014) for a thorough review.

2016) without explicitly formalizing the tradeoff and choice. In contrast, we explicitly model the option trading choice of an informed trader as a function of the characteristics of private signals that characterize the stock price reaction and uncertainty around future news announcements. For example, Chakravarty et al. (2004) argue that informed trading is driven towards ATM options when these are cheap to trade relative to OTM options. Similarly, Ge et al. (2016) 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.

The prior literature has emphasized how market frictions affect the choice of trading venue, e.g., the stock versus the option market. Instead, we focus on how such frictions, and the characteristics of private information, affect the investor's choice of option strategy, conditional on trading in the options market.[5]

Second, we examine the predictability of informed trading activity for SCNs using multiple events jointly. To the best of our knowledge, virtually all other studies on informed trading in options focus on one individual category of event, such as M&A transactions, corporate divestitures, or earnings announcements. One exception is work by Cremers et al. (2016), who distinguish between scheduled and unscheduled news items in their empirical analysis of informed trading activity. Heterogeneity in event characteristics influences the optimal trading decision. Thus, any study that does not take account these differences across events would be unable to explain how informed investors trade differentially as a function of the characteristics of corporate announcements.

3. Trading Strategies of Informed Investors

For an equal dollar investment, an informed investor obtains more "bang for the buck" in the options market than the stock market. This is because derivatives facilitate more leveraged exposures than the underlying cash market. To give an illustrative example, a few days ahead of a negative earnings surprise announced by Walgreen's on October 1, 2007, Thomas Flanagan, a former vice president at Deloitte and Touche LLP with material private information on multiple client firms, and his son, bought 485 put options

[5] A different perspective is taken by Anand and Sugato (2007), who show that the price impact of their trades can lead informed investors to split up their trades and engage in stealth trading. We focus on bid-ask spreads and minimum prices as central frictions to avoid additional assumptions about market depth.

on the stock at strike prices of \$45 and \$47.5, expiring in October 2007, for a total cost of \$46,619. When the firm announced its first earnings decrease (relative to the prior quarter) in almost a decade, its shares fell by 15% and the insiders realized an illicit profit of \$268,107, or 575% of their option investment.[6] As an alternative, taking a short stock position would have yielded profits of merely 15% before transaction costs. In this case, trading options thus enabled to leverage returns by a factor of almost 40.

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, the benefits from informed trading vary substantially across a wide spectrum of trading strategies, in terms of both strike price and maturity. Our objective is to improve the identification of informed trading by better understanding the trading strategies that maximize expected returns to investors with noisy private signals about the timing and stock price reaction of future news announcements. To achieve this objective, we first propose a general framework for calculating the expected returns to informed option trading as a function of the magnitude, quality, and strength of the private signal received by the informed trader. We then validate our framework by showing that measures of informed trading based on our approach predict corporate news events and stock returns quite well.

We acknowledge that some informed investors may trade strategically to mitigate the price impact and/or to avoid detection by other traders or the regulator. As a consequence of the incentives to hide their trades, informed investors may avoid the single option ranked highest in terms of expected returns, and deviate from the "first best" strategy. Even if some investors trade sub-optimally, we assume that such investors are, nevertheless, in pursuit of leverage to maximize the "bang for the buck." Our empirical analysis accounts for such strategic trades since we focus on the trading of options that rank in the top tercile of the options that maximize expected returns given the private but noisy signals.

3.1. Theoretical Framework

The objective of our study is to understand how informed investors choose to trade in option markets, given the strength and quality of their private signal. To do so, we assume that the informed agent's primary objective is to maximize her expected return by leveraging her private information. The choice of the option contracts she trades depends only on her expected return, net of transaction costs.[7] We calculate the expected

[6] In 2010, the SEC charged the Flanagans with insider trading on multiple occasions that resulted in total illicit profits of \$487,000. The suspects settled for a disgorgement of ill-gotten profits and a civil penalty of more than \$1.1 million.

[7] Assuming that the investor's primary objective is to maximize her leverage is in line with previous studies on informed trading in the options market, e.g., Acharya and Johnson (2010). All essential insights can be obtained from analyzing expected return. Our

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

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

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 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. We do not account for margin requirements as they are zero for long options positions, to which we restrict our analysis.[8] 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

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

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.[9] Similar to Cremers et al. (2016), we incorporate the run-up in implied volatility ahead of scheduled events as in Dubinsky and Johannes (2006) 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 σ_j the volatility of the jump anticipated by (uninformed) investors ahead of a scheduled event.

We next account for market frictions by introducing a bid-ask spread, α, and a minimum option price, P_{min}, to be consistent with a realistic trading setting. Whenever 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. It should be noted that the important variable is the bid-ask spread, which is determined by economic considerations while the minimum price, typically related to tick size, is determined by the

conclusions would be further strengthened when accounting for higher moments of the return distribution, and risk aversion, at the expense of the making the framework less tractable. We, therefore, leave such extensions for future research.

[8]Various studies document that margin requirements substantially increase the cost of trading in equity options (Hitzemann et al., 2016; Noel, 2017).

[9]Informed trading on anticipated changes in σ instead of κ (or in addition to) could be incorporated in future work. This would distract, however, from the focus of our study, while having only a marginal impact on predicted trading behavior. In other (unreported) results, we show that it can be rational to trade in "vega" or implied volatility strategies, e.g., straddles, if the information signal is very noisy, even though trading on changes in the implied volatility does not offer high expected returns to informed investors,.

exchange and has been reduced to a negligible number over time. [10] At time t_1, the informed investor will sell her position 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

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

Finally, we take into account 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 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 $\phi(\kappa, \Delta t)$,[11] the expected return to the option strategy is the probability-weighted average

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

Above, we have derived a simple expression for expected returns to informed trading in the presence of market frictions. Assuming that informed investors maximize their expected returns, we can use this expression to identify the strike price, maturity, and type of the option contract(s) they choose to trade. Before numerically evaluating the expected returns for alternative option strategies and varying private signals, we illustrate the implications of market frictions and noise in the private signal.

The two market frictions that we account for are the minimum option prices and bid-ask spreads, both of which reflect the limited liquidity in the options market. In Figure 1, we show the effect of market frictions on expected returns. Each graph plots the expected returns to informed trading in call options computed using Equation 4. For the purpose of illustration, we consider a signal that suggests an expected future price jump of $E[\kappa]$=20% in $E[\Delta_t]$=3 days, without any uncertainty about the magnitude of the jump or about the timing of the news announcement, i.e., σ_κ=0, $\sigma_{\Delta t}$=0. Furthermore, we fix S_0=10, r=0.03, and σ=0.4. The

[10] Apart from market liquidity, bid-ask spreads and minimum prices are driven by the minimum tick size dictated by the Chicago Board Options Exchange (CBOE), and other major options exchanges. Since the year 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, the first phase of which commenced on January 26, 2007. As part of that program, the minimum tick of heavily traded options was decreased to one and five cents for options priced below or above three dollars, respectively.

[11] We assume that κ follows a normal distribution, and that Δt follows a truncated normal distribution.

two upper graphs in Figure 1 are based on the assumption that there are no market frictions, i.e., 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 an OTM option at such a low price, and selling it once it is ITM after the news-induced jump, yields a return of more than 1.8 million percent, which is clearly unrealistic.

The introduction of market frictions emphasizes that it is impossible to generate such enormous returns in a more realistic trading environment. The lines in the two lower graphs of Figure 1 with the label "frictions" are based on a parameterization of the bid-ask spread equal to α of \$0.05 and a minimum price of \$0.10. All other parameters remaining unchanged. In addition to market frictions, increased option prices ahead of scheduled announcements can reduce the leverage investors can attain in the options market to more reasonable levels. The lines labeled "scheduled" assume a run-up in implied volatility ahead of the event, modeled as in Dubinsky and Johannes (2006). Even without this run-up, market frictions reduce maximum expected returns to more realistic values that are less than 2,000%.[12]

The stylized example underscores the importance of accounting for non-zero minimum prices, bid-ask spreads, and potential run-ups in implied volatility, as these restrict the leverage an informed investor can obtain in option markets. We now turn to discuss the magnitudes of these two market frictions over time. In Panel A of Figure 2, we plot the evolution of the bid-ask spreads of equity options listed in the OptionMetrics database. It is clear from the figure that the median (average) spread reduced substantially over time, from 25% (23%) in 1996 to 5% (10%) in 2010, with a spike in 2008, in the aftermath of the Lehman Brothers bankruptcy.

An option's minimum offer price is given by its minimum tick size. While this implies that DOTM options may be trading at a price of five cents, or, since 2007, one cent, if the option is part of the Penny Pilot Program, the minimum offer prices reported in the OptionMetrics database are larger than this lower bound for the vast majority of options. Panel B displays the evolution of the minimum (dotted line) and the first percentile (dashed line) of option prices below three dollars. The minima and percentiles are computed over all contract days with a trading volume of at least 100 options. Until 2007, the time series of observed minima reflects the described minimum CBOE tick size. The increase in the minimum price of options in the years 2008 to 2010 can be ascribed to the exceptional period of the financial crisis. Most of the time,

[12]The SEC's public record of insider trading litigations suggests that returns to option trades made by investors with private information are around 1,300%, on average. This estimate is based on the data described in Augustin et al. (2018).

however, as illustrated by the first percentile of option prices below three dollars, observed minimum prices are equal to or above 10 cents. Thus, the regulatory minimum prices do not seem to be a binding constraint .

The fact that DOTM options are rarely offered at the possible minimum price of 5 cents even if their "fair" (i.e. BSM) value is lower than that, may be explained by fat tails, risk aversion, informed trading, adverse selection, or other factors such as inventory costs and illiquidity. Writing DOTM options offers little return, but a potentially enormous downside to traders. Even for risk-neutral market makers, the cost of trading with an informed counterparty may prevent investors from offering DOTM options at the minimum regulatory price. Indeed, as shown by Goyenko et al. (2014), using intraday transactions data, 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) report that intermediaries expect substantial premia when writing OTM options and suggest that they "compensate intermediaries for bearing unhedgeable risk when accommodating investor demand for lottery-like options."[13]

Minimum prices render the trading of DOTM options expensive, which is also reflected in the high implied volatilities of most DOTM options and, perhaps, the low trading volume that may even be observed for OTM options. While it might be intuitive that informed traders, who expect a significant jump in stock prices, are best off purchasing DOTM or at least OTM options, we formally show that these do *not* always offer the highest expected return to informed investors. This is in particular true if the investor faces uncertainty about the magnitude of the future price jump and uncertainty about the timing of the jump. In other words, the choice of option strategy depends on the noise associated with the private signal. This provides a rationale for why, in most cases, it is optimal to trade in options that are only slightly OTM. These findings are consistent with trades identified to be informed, such as the previously highlighted trade by the Flanagans, who purchased put options with a strike price of USD 47.50, when the underlying stock was trading between 47 and 48 USD. The findings are also consistent with the comments made 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 in this paper is to explicitly formalize the strategic behavior of informed investors, which is implicit in the choice of option strike price and maturity. Hence, we are able to generate a trade-off, without appealing to the higher moments of the return distribution, investor

[13]This argument relates to prior work on the inelasticity of the option supply curve, along the lines analyzed theoretically by Garleanu et al. (2009) and empirically by Bollen and Whaley (2004) and Deuskar et al. (2011). For an earlier overview of research on empirical option pricing, see Bates (2013).

risk aversion or the price impact of informed trades.

The effect of uncertainty or *noise* in private information, i.e., uncertainty about κ and Δt, on expected returns, though important, is less significant than that of market frictions. The graphs in Figure 3 plot expected returns to informed trading in call options computed using Equation 4. We use the previous example to illustrate the impact of uncertainty about the jump size and timing of the announcement. Thus, we use an expected news-induced jump of $E[\kappa]$=20% in $E[\Delta_t]$=30 days. Bid-ask spreads are set equal \$0.05 and the minimum price to \$0.10. Furthermore, we set S_0=10, r=0.03, and σ=0.4. The left (right) graph of Figure 3 plots expected returns as a function of the time to maturity (strike price) of the option. On each side, the strike price (maturity) is chosen such that the graph shows the global maximum of the expected return function. This explains why the maxima of each function in the left and the right graph are identical. In each graph, the four lines represent different magnitudes of uncertainty.

For the given set of parameters, maximum expected returns decrease significantly in the uncertainty of the timing of the announcement, $\sigma_{\Delta t}$. The impact of uncertainty about the jump magnitude, σ_κ, on expected returns is positive, but it is less pronounced. Nevertheless, both $\sigma_{\Delta t}$ and σ_κ can have a significant impact on the parameters of the option that maximizes expected returns. Higher uncertainty about the timing of public news announcement incentivizes the investor to choose longer maturity options and deeper OTM options compared to the benchmark case, without any timing uncertainty. Higher uncertainty about the magnitude of the announcement results in a choice of shorter-term options that are further OTM.

3.2. Expected Returns of Different Trading Strategies and Private Signals

Having illustrated the effects of market frictions and noise in the private signal on expected returns, we now explore how the expected value and the noise of an informed investor's private signal affect the strike price, maturity, and type of the return-maximizing option contract. The two upper graphs in Figure 4 (Figure 5) plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in call options ahead of a positive event as a function of the expected time to announcement, $E[\Delta t]$ (the expected jump in stock prices, $E[\kappa]$). The lower graph displays the maximum expected return $E[R]^{max}$. In each figure, results are shown for three different parameter sets describing the private signal.

Figures 4 and 5 illustrate several key takeaways that can be obtained from our framework.[14] We refer to the upper, middle, and lower graphs in Figures 4 and 5 as Figures 4a, 4b, 4c, and 5a, 5b, 5c. The

[14]All plots are based on specific parameter combinations. The reported implications are unchanged for alternative parmeterizations.

first set of implications is related to the strike price that maximizes expected returns (K^{max}). The expected price jump of the stock following a news announcement, $E[\kappa]$, is a key determinant of expected returns (Figure 5c). Intuitively, one may assume that trading deeper OTM options increases expected returns, that is, leverage. However, for many parameter combinations, informed investors do not trade OTM options. For instance, for the parameter sets plotted in Figure 5a, informed investors will trade ATM or even ITM options for anticipated jumps of up to 10%. Furthermore, the kink in the function implies that, once $E[\kappa]$ reaches a certain threshold, informed investors will not trade deeper OTM. Thus, DOTM options do not always maximize returns to informed trading in the presence of market frictions. The kink arises due to the frictions incorporated in our framework. Their impact on informed trading is most pronounced for options with a low theoretical value, e.g., options with low implied volatility and a short time to maturity.[15] Amongst others, this explains why K^{max} shown in Figure 4a is lower for options with a short rather than for those with a medium time to maturity.

The second set of implications is related to the time to maturity of the option that maximizes expected returns (T^{max}). The longer the period between the time an informed investor trades and the expected time of the announcement, $E[\Delta t]$, the longer will be the contract maturity of the return-maximizing option (Figure 4b). A similar implication obtains if there is greater uncertainty around the announcement date, in other words, if the precision of the signal is low. In such cases, an informed trader will choose longer-dated options to reduce the likelihood that the trades expire worthless, prior to the announcement of news (Figure 4b). All else equal, the need to trade in longer term options decreases the expected returns to informed trading (Figure 4c).

We include additional graphs for the case of scheduled events, and for different trading strategies in the appendix of this paper. Figures A1 and A2 illustrate 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. When accounting for this effect, we assume a jump size volatility of $\sigma_j = 0.1$ for scheduled events. Figures A5 and A6 show that synthetic calls enable investors to reduce the impact of market frictions and substantially increase expected returns, as OTM, or even DOTM call options, can be created by trading the underlying together with ITM

[15]To sharpen the intuition about the impact of minimum prices on trading strategies, consider an investor who can choose to buy an OTM option at the minimum price, or an otherwise identical DOTM option that has a lower theoretical value, but that trades at the same price because of market frictions. All else equal, she will choose the OTM over the DOTM option.

or DITM put options, which are substantially less affected by market frictions, due to their higher values.[16] However, trading synthetic call options requires an investor to partly finance her positions by borrowing at the risk free rate, which is thus likely to be restricted to sophisticated investors.[17] Finally, Figures A3 and A4 demonstrate that the patterns observed for informed trading in call options are very similar for put option trading, implying that the above insights extend to the latter.[18]

To summarize, expected returns to informed trading in options can differ tremendously as a function of the level and precision of private signals. Using our framework can be useful to researchers, investors, and regulators trying to pinpoint informed trading ahead of various categories of corporate news.

4. Informed Trading Ahead of Significant Corporate News

We have proposed a conceptual framework of informed trading that identifies the options most likely to be traded by informed investors. We now turn to apply this framework empirically in two specific ways. First, we use the framework to quantify expected returns to informed trading in option markets ahead of SCNs. Doing so enables us to describe by how much investors can leverage their private information about different corporate events. We show that expected returns vary significantly as a function of event characteristics, just as informed trading activity exhibits differential patterns ahead of SCNs. Second, in Section 5, we propose new measures of informed trading derived from our framework and benchmark them against existing measures of informed trading to predict returns and news sentiments.

4.1. Identification of Significant Corporate News

We define SCNs as news events that can be linked to extreme price movements (EPMs) of stocks. The identification of SCNs involves two steps. First, we need to identify EPMs. Second, we need to associate EPMs with news. We describe these two steps in detail in the following sub-sections. We then follow this up with a detailed description of the heterogeneity in event characteristics in expected announcement returns,

[16]Even 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.

[17]We 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 ae dominated by the strategies considered here. We note that almost no (publicly reported) civil litigation initiated by the SEC refers to insider trading implemented through the use of synthetic options positions.

[18]Our framework also allows for the analysis of informed trading in volatility strategies such as straddles. We do not include results for the sake of brevity, but can provide them upon request.

the nature of their announcement (scheduled vs. unscheduled), as well as the uncertainty in announcement returns and announcement dates. These four dimensions reflect the main parameters of our framework.

Employing a diverse sample of SCNs instead of one specific event, such as the announcement of M&As or earnings news, has three advantages for the study of informed trading. First, using different categories of corporate events allows us to exploit the cross-sectional differences in announcement effects and their timing uncertainty. This expands the opportunity set of trading strategies for informed investors and, therefore, allows for a richer analysis of informed trading. In other words, we can exploit the heterogeneity in announcement characteristics to understand more granularly how informed investors can trade in the options market. We explore trading patterns ahead of different types of SCNs including analyst recommendations, earnings announcements, corporate guidance, M&As, product development, management changes, changes in dividends or financing, among others. Second, using SCNs rather than one category of corporate event yields a sample that is much larger than typical studies that focus on corporate announcements, and comprises of economically more meaningful opportunities of informed trading. This approach increases the statistical power of the analysis significantly . Third, given that we can observe the exact timing of both, the price reaction on a daily level and the news with a millisecond timestamp from RavenPack, we eliminate uncertainty about the announcement time. Doing so eliminates any potential upward-bias in computing the usual measures of informed trading activity due to event date uncertainty or news leakage prior to the actual corporate announcement.

4.1.1. Identification of EPMs

For the identification of SCNs, we first identify EPMs. We collect information on stock returns and prices, security type, the number of shares outstanding, and trading volume from CRSP. We retain all common stocks (sharecodes 10 and 11) that trade on the AMEX, Nasdaq or NYSE, for which all variables are available, resulting in a total of 17.5 million daily return observations. We exclude stock days with a lagged market capitalization (as of the previous trading day) below ten million USD, or a lagged stock price per share below five dollars, as such securities are often illiquid and exhibit higher levels of market microstructure noise. We further delete all stocks for which not even a single news headline is reported during our sample period. 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. This sample restriction, therefore, dictates the starting point of our analysis. These additional filters leave us with a sample of 11.4 million daily stock price observations.

From the remaining 11.4 million daily observations, we obtain a list of 138,121 EPMs. We classify a stock day observation as an EPM if it is a jump, as defined by the Lee and Mykland (2008) method for jump detection, or if the return on that day is above or below all returns observed during the preceding 252 trading days.[19] We additionally require the availability of stock market 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. 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.

4.1.2. Associating EPMs with News

Early doubts cast on the relevance of news for asset pricing were based largely on analyses with daily data and have recently been erased gradually with the release of more and more granular, high frequency data.[20] Boudoukh et al. (2013) use textual analysis to demonstrate that an improved identification of relevant news stories results in a tighter link between news and stock prices. Bradley et al. (2014) document that after correcting for the time stamps of analyst recommendations, news stories become an important determinant of stock price jumps. More anecdotally, Lee and Mykland (2008) report that only "one or two" of 24 detected jumps were not associated to news.

We, therefore, expect a significant part of EPMs to be driven by news that investors incorporate into prices. Understanding which news story (most likely) induces an EPM is important for our study, as the category of news can affect which informed trading strategy maximizes expected returns. In Section 3, we showed that the options trading strategy that maximizes returns depends on both the timing uncertainty and the magnitude of the stock price reaction relating to the future announcement. Both these parameters vary consistently across different categoris of events. For example, the timing uncertainty is zero for scheduled events, such as earnings announcements, but can be high for unscheduled events, such as a takeover announcement. Similarly, the sign and magnitude of an announcement return may be easier to predict for an M&A deal than for a change in a senior management position.

[19]Our 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. For details on the Lee and Mykland (2008) approach for jump detection, see Appendix A.

[20]See Roll (1988)'s presidential address to the AFA.

During our sample period, RavenPack features 7.98 million corporate news stories that involved 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 proceed as follows. Similar to Bradley et al. (2014), we estimate logistic regressions to separately identify the determinants of positive and negative EPMs. More 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, which has a straightforward interpretation. 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 as described in the previous section. For a given stock-day, 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. 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, which is a larger set than the categories of corporate announcements that the prior literature has focused on.

In Tables 1 and 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-statistics of 4.12. Overall, our results are intuitively appealing: For example, 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. Also, in line with Bradley et al. (2014), analyst-related news events are important determinants of EPMs. Armed with these findings, 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 1 and 2) can 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 an 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 assume only news published on earnings announcement days to be scheduled.[21]

Table 3 reports descriptive statistics for the sample of positive and negative SCNs for each news category. Not surprisingly, a news story about a firm being acquired is associated with the highest announcement returns, 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.

4.2. Expected Returns Attainable by Informed Trading on SCNs

We exploit the significant heterogeneity in event characteristics to understand how informed investors can leverage their private information that according to the magnitude and precision regarding timing and impact, expected for a particular SCN. In reality, and different from our previous numerical analysis, the choice of options investors can trade is limited, since there liquidity only a sub-set of the options listed on a particular stock. This section aims to quantify expected returns to informed trading that can be attained, given this restriction of availability. To do so, we examine the expected returns to hypothetical informed

[21]In related work, Cremers et al. (2016) assume only earnings news to be scheduled. However, many other news items, for instance related to financing or product releases that 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. We, therefore, consider all news released on earnings announcement dates as scheduled.

trading on SCNs. For the characterization of events, expected returns are computed based on the assumption that investors trade on a signal about a news announcement that occurs 10 days later for unscheduled announcements, and the following day for scheduled announcements. We assume that the uncertainty about the timing of the announcements is three days for unscheduled announcements, while there is no uncertainty for scheduled announcements. Table 4 reports expected returns to call (put) option trading around positive (negative) SCNs for each news category included in our sample. For each news category, we split all option days into terciles of the distribution of expected returns and report the average expected returns. When computing expected returns, the anticipated stock price reaction κ is set equal to the average stock return in each news category. Similarly, the uncertainty about the stock price reaction, σ_κ, is computed as the standard deviation of stock returns in a given category. These statistics are reported in Table 3.

Not surprisingly, the averages of expected returns to informed trading within each tercile are substantially higher for events with stronger stock price reactions, such as M&As, for example. In most instances, trading ahead of scheduled news enables a higher leverage. This is consistent with the high expected returns earned from trading in short-dated options briefly ahead of an announcement, as documented in Section 3. However, the empirical analysis reveals that the benefits of trading shortly ahead of an event are substantially lower than suggested by the numerical analysis. The fact that the expected returns from trading short-term options observed for the sample are lower than those observed in the numerical analysis is due to the severely limited availability of these options in practice. In theory, a precise timing signal enables informed traders to obtain substantial leverage by trading in options expiring just after an event. In practice, this effect is constrained by the limited number of option contracts expiring shortly after the event, as well as run-ups in implied volatility ahead of these events, as well as the poor liquidity in many of these contracts. For instance, the mean of expected returns to informed trading ahead of positive scheduled and unscheduled analyst opinions are equal to 124.7 and 107.5 percent for the second quantile, respectively. The difference between the sub-samples of scheduled and unscheduled events is larger for the third quantile. While the difference between the two sub-samples is statistically significant, its economic significance is lower than the one in our numerical analysis, given the constrained set of options actually available for trading.

Table 5 is created in the same way as Table 4, but reports the average moneyness for each expected return terciles for the news categories in our sample. We define option moneyness as the natural logarithm of the strike price relative to the spot price. For positive (negative) events, the expected returns are shown for call (put) options and positive moneyness thus correspond to OTM (ITM) options.

For each event category, the table indicates what degree of moneyness provides low, medium and high expected returns. We find that ahead of events with a moderate stock price reaction, 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. At the same time, the results confirm that investors would not trade deep OTM even ahead of events with extremely high stock price reactions, such as for target stocks in acquisitions. This is in line with the numerical results plotted in Figure 5, indicating that the benefits of trading deeper OTM are limited.

Table 6 reports the average time to maturity for expected return terciles and is created in the same way as Table 5. 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.

In contrast to the previous numerical analysis, all of the results reported in this section are affected by the availability of options for trading and are, thus, subject to noise that did not affect the numerical analysis. Still, all major conclusions drawn in the numerical analysis can be confirmed in this first section of our empirical analysis. In the next step, we will explore if our framework can be used to observe trading patterns that are consistent with informed trading. To do so, we will introduce a new measure of informed trading in the next step.

4.3. A New Measure of Informed Trading

We propose a new volume-based measure of informed trading implied by our framework. Accounting for bid-ask spreads and minimum option prices, we can rank the option strategies that maximize returns subject to (potentially noisy) signals about future price jumps κ and the arrival date of news Δt. The measure we propose 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

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

where C and P define the call and put volumes, respectively, and $\bar{R}$ defines 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 a lot of "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. Occasionally, we will also examine the imbalance in informed trading across call and put options, based on the relative difference volume, i.e., RVD, defined as

$$RVD_{i,t} = RCV_{i,t} - RPV_{i,t}. \tag{6}$$

4.4. Trading Patterns Prior to SCNs

In this section, we examine whether we can observe trading patterns ahead of EPMs and SCNs. We do so by simply plotting the time series of the previously introduced measures of informed trading ahead of events for different sub-samples. We indeed observe patterns that are consistent with informed trading activity. The results presented in this section are meant to motivate the subsequent use of our measure of informed trading for predictions in the broader cross section of stocks. If patterns of informed trading can be detected visually even in simple time series graphs, a multivariate analysis including relevant control variables should be able to identify any predictive power of our measures. This is indeed the case, as we report in Section 5

Our sample of SCNs is restricted to events that *jointly* feature both a significant price movement in the underlying stock and the announcement of news. Using stock price movements without news announcements is redundant, as, by default, there cannot be private information about news. Similarly, using news announcements with insignificant announcement effects is not helpful for the identification of informed trading. Focusing on large stock price reactions insures that the benefits from informed trading are economically meaningful.

Figure 6 plots RVD, the measure of informed trading that combines put and call option volumes, ahead of positive and negative EPMs, separately for those EPMs that can be associated to a news event, i.e., an

SCN, and those that cannot be associated with SCNs. The upper two figures show the sample of positive and negative EPMs that we can associate to a news event. The light grey (dark grey) line in the first figure shows that the difference between RCV and RPV notably increases (decreases) over the ten trading days before a positive (negative) news event. It also shows that the difference between RCV and RPV for positive and negative events begins to diverge approximately twenty trading days before the event with a distinct difference appearing approximately ten trading days before. The second figure plots the difference between the RVD for positive and negative news.

The lower two figures in Figure 6 plot RVD for the sample of positive and negative EPMs that we could not associate to a news event. As opposed to the sub-sample of EPMs associated to news, we do not observe any directional trend in either of the two sub-samples.

5. Cross-sectional Predictions of Excess Returns and News Sentiment

The evidence presented in the previous section suggests that there exists informed trading ahead of SCNs. As this analysis examines informed trading activity in a sample that is preconditioned on the occurrence of SCNs, one may be concerned with the existence of a selection bias. In this section, we address this concern by predicting (i) excess returns, and (ii) news sentiment scores in the entire cross-section of stocks. We first discuss the construction of our new measures of informed trading and then review existing measures of informed trading that serve as a benchmark for our analysis. We then describe the data, and subsequently present the results of weekly Fama-MacBeth regressions to predict abnormal returns and news sentiment.

5.1. Benchmark Measures of Informed Trading

In the previous section, we compute the informed trading measures RCV, RPV, and RVD in the run-up to SCNs, by calibrating their parameters to the characteristics that depend on the upcoming category of news. For the unconditional prediction of returns in the cross-section, such information is not yet available at the time that trading portfolios would be formed. To avoid any look-ahead bias, we compute our measures of informed trading by calibrating the parameters in a mechanical way that is identical for each stock in every week. More specifically, we calculate RCV and RPV based on expected returns that assume private signals about a hypothetical price jump of +10% and -10% for positive and negative news, respectively. These price jumps are anticipated to occur during any trading day of the next week. As opposed to the numerical analysis, for which we assumed a truncated normal distribution for the timing of the announcement, we adopt a uniform distribution for the timing of the news announcement in the context of return predictions. This implies that the stock price jump is expected to jump with equal probability on any given day of the week.

The existing literature has proposed other measures of informed trading that have proven successful in unconditional return predictions. Thus, we benchmark our measures against existing return predictors implied from option volume or price information.[22] We briefly review the existing benchmark measures against which we compare our proposed measures of informed trading.

Put-call ratios: Pan and Poteshman (2006) define the put-call ratio as the number of put contracts divided by the sum of both put and call contracts.[23]

$$PP_{i,t} = \frac{\sum_{j=1}^{N} P_{j,i,t}}{\sum_{j=1}^{N} P_{j,i,t} + \sum_{j=1}^{N} C_{j,i,t}} \tag{7}$$

Option to stock volume ratios: Johnson and So (2012) compute the ratio of total option to stock trading volume (OS) as a measure of informed trading. The authors argue that a high option to stock volume ratio is especially informative around negative news, as informed investors have a greater incentive to express their view through trading put options in the presence of costly short-sale constraints. We construct the OS ratio as

$$OS_{i,t} = \frac{\sum_{j=1}^{N} V^{O}_{j,i,t}}{\sum_{j=1}^{N} V^{S}_{j,i,t}}, \tag{8}$$

Where V^O and V^S refer to the trading volume in the options and stock market respectively.

Implied volatility spread: Cremers and Weinbaum (2010) argue that deviations from put-call parity, measured by the difference between the implied volatilities of call and put options, predict stock returns. Similar to them, we examine the implied volatility spread (IVS) as the volume-weighted average of the difference in implied volatilities between call and put options of the same strike price and time to maturity.

[22] We note that our measure has a very 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 can inform us about the likelihood that a particular trade is informed. A similar exercise is difficult with the existing measures of informed trading derived from options volume and price information.

[23] Pan and Poteshman (2006) rely on the CBOE put and call volume traded by non-market maker buyers to open new positions, as the CBOE disaggregates total trading volume according to trade type (buy to open, buy to close, sell to open, sell to close) and investor category. As we rely on unsigned volume information from OptionMetrics, we can only compute put-call ratios based on aggregate call and put volume.

Formally, $IVS_{i,t}$ for firm i on day t is constructed as

$$IVS_{i,t} = IV^C_{i,t} - IV^P_{i,t} = \sum_{j=1}^{N} \omega_{j,i,t} \left(IV^C_{j,i,t} - IV^P_{j,i,t} \right), \tag{9}$$

where in this instance j refers to pairs of call and put options, thereby indexing strike prices and maturities jointly, $\omega_{j,i,t}$ denotes the weights of the N valid option pairs, and IV defines the Black-Scholes-Merton implied volatility.

Implied volatility smirk: Xing et al. (2010) find that the skewness of the implied volatility smirk has predictive power for future stock returns. In particular, they find that stocks with a steep implied volatility slope underperform stocks with a shallower implied volatility slope over the subsequent six months. Similar to these authors, we define the volatility smirk as the difference between the implied volatilities of OTM puts and ATM calls

$$SKEW_{i,t} = IV^{OTMP}_{i,t} - IV^{ATMC}_{i,t} = \sum_{j=1}^{N} \omega_{j,i,t} \left(IV^C_{j,i,t} - IV^P_{j,i,t} \right), \tag{10}$$

where moneyness is defined as the ratio of the strike price over the stock price, with OTM options having a ratio below 0.95, and ATM options having a ratio between 0.95 and 1.05. The $SKEW$ measure incorporates the OTM and ATM options that have a moneyness ratio closest to 0.95 and 1 respectively.

5.2. Data Sources and Summary Statistics

For the construction of the informed trading measures, we source information from OptionMetrics, the dataset on option prices and volume that is most widely used in academic research. We match OptionMetrics 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. In addition to the prediction of returns, we attempt to predict news sentiment scores, which we also receive from the DowJones Edition of RavenPack News Analytics. The availability of sentiment scores in RavenPack starting in 2000 also dictates the starting point of our analysis.

Similar to the analysis on SCNs, we collect information on stock returns and prices, security type, the number of shares outstanding, and trading volume from CRSP. We retain all common stocks (sharecodes 10 and 11) that trade on the AMEX, Nasdaq or NYSE, and we exclude stock days with a lagged market value (the market value as of the previous trading day) below ten million USD or a lagged price per share below five dollars as such securities are often illiquid and exhibit higher levels of market microstructure noise. We keep only those stocks for which we can identify reliable option price and volume information in OptionMetrics, and balance sheet information and company characteristics in Compustat. We do not include stock-weeks for which we cannot compute lagged option trading measures. In particular, we require that option trading volume in calls and puts is positive.

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. To summarize, the 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.

Table 7 reports basic summary statistics on weekly cumulative returns in excess of the CRSP value weighted market return (CAR), and the average weekly event sentiment score (ESS). These are the two metrics we aim to predict and we accordingly report statistics for the measures as of next week ($t + 1$). The description and identification of SCNs will follow shortly. The table also describes statistics for all informed trading measures used in the analysis, as well information on standard control variables used in cross-sectional return predictions (see, for example, 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 pf the; 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. We compute RCV and RPV based on the expected returns computed by assuming that $\kappa = +10\%$ for positive, and $\kappa = -10\%$ for negative news.[24]

High expected returns are expected returns in the highest tercile of all attainable expected returns. 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

[24] An alternative computation using signals of +5% and -5% yields similar results.

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 8 reports correlations across all measures reported in the summary statistics.

We next use the new measures of informed trading to examine the predictability of excess returns and news sentiment. Doing so validates that the measure of informed trading derived from our framework indeed captures information, and enables us to benchmark its performance against existing measures of informed trading.

5.3. Predicting Returns

This section assesses how informative the different measures of informed trading are for explaining the cross-section of stock returns. To do so, we estimate weekly Fama-MacBeth regressions of weekly cumulative returns in excess of the market's performance on various measures of informed trading. All measures are lagged by one week. For each variable, Table 9 presents the average cross-sectional coefficient estimate. We report 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 (6) 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 2.24, 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%. Both PP and OS have negative predictive power for excess returns, with absolute t-statistics of 2.09 and 2.88, respectively. However, their improvement in explanatory power is only marginal. Based on the insignificant results in columns (5) and (6), we conclude that both price-based measures do not have predictive power for excess returns in our sample. In column (9), we examine whether RCV and PPV have any 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 slightly more to 5.65%. Column (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 7.87%, while also RVD is now significant at the 10% level. Given the base regression coefficient of 0.054 in column (2), our findings also 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%.

5.4. Predicting ESS

We also assess how informative the different measures of informed trading are for explaining the cross-section of news. To do so, we estimate weekly Fama-MacBeth regressions of next week's event sentiment score (ESS) on 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), 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 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 any of the other informed trading measures, as is demonstrated in columns (8), and (9).

In a nutshell, we have shown that our new measures of informed trading have predictive power for excess returns (RCV), and news sentiment (RPV and RVD). They have incremental explanatory power over existing measures of informed trading and are economically meaningful. This shows that our framework captures informed trading above and beyond existing measures.

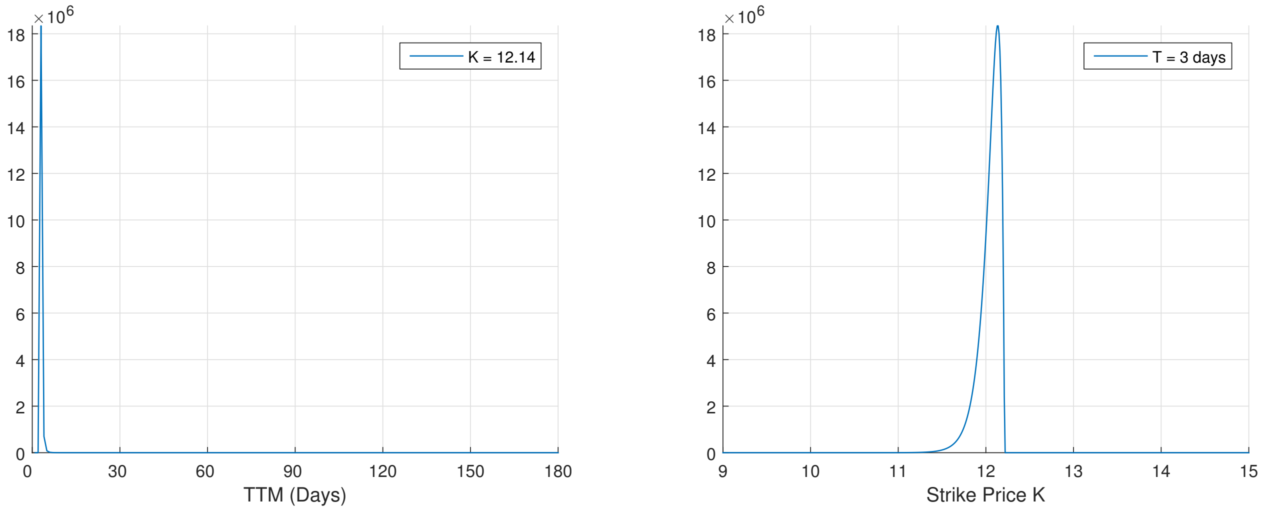
6. Conclusion

In this paper, 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 one 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 moneyness and expected return, without the need for modeling higher order effects, such as risk aversion, or more complex price impact frictions.

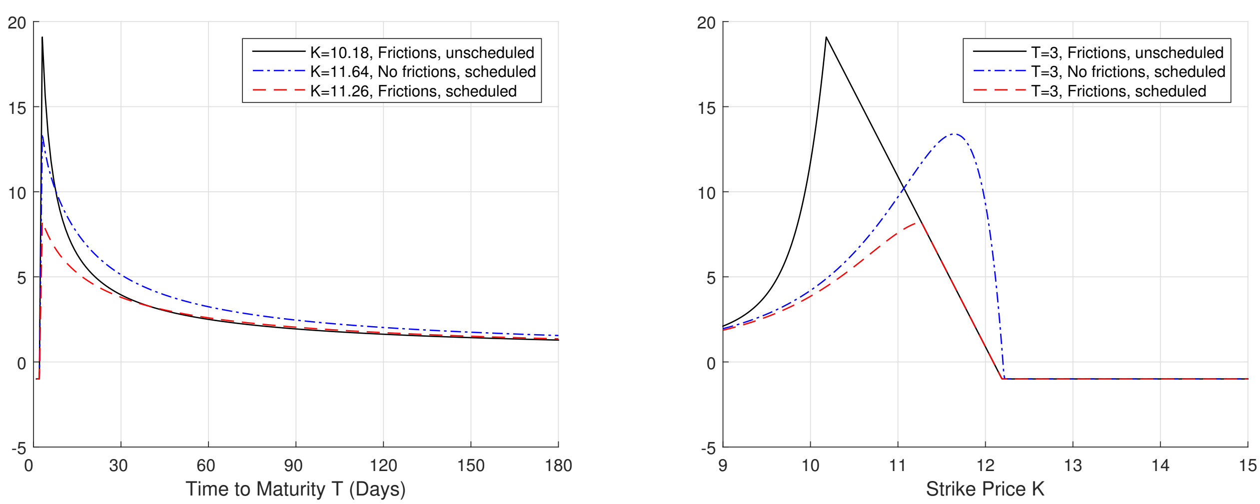
We empirically validate our proposed framework in two specific ways. We first use the framework to characterize attainable returns from informed options trading, and examine the ability of the framework to capture differential options strategies as a function of event characteristics. Using RavenPack's news database, we construct a sample of 30,975 significant corporate news by associating extreme price movements, i.e., jumps, with twelve different categories of important news announcements, reported over the years 2000-2014. We illustrate the heterogeneity in options trading strategies by emphasizing differences in expected returns from informed option strategies that vary in terms of option type, strike price, maturity, and timing of trade. Moreover, naive measures of informed trading ahead of different categories of significant corporate news further show differential options trading behavior as a function of event characteristics.

In a second step, we propose new measures of informed trading implied by our framework. In particular, we construct the ratio of informed call (put) volume to aggregate call (put) volume, where informed volume is defined as trading volume in options delivering high expected returns. We show that these measures improve the cross-sectional predictability of excess stock returns and news sentiment over existing measures of informed trading.

In sum, this paper provides a framework that identifies the option strategy that enables informed investors to maximize the leverage of their private signal under market frictions. This approach is useful to regulators for the detection of abnormal trading activity, to corporations to be more alert to the leakage of information about their announcements, and to investors for the prediction of excess stock returns

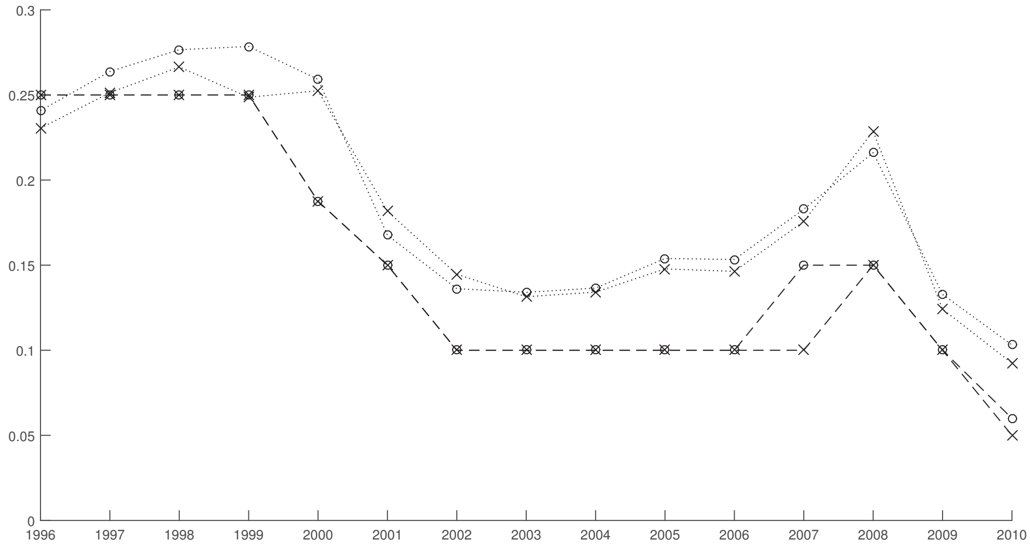


(a) Zero bid-ask spread and no minimum price, no IV run-up

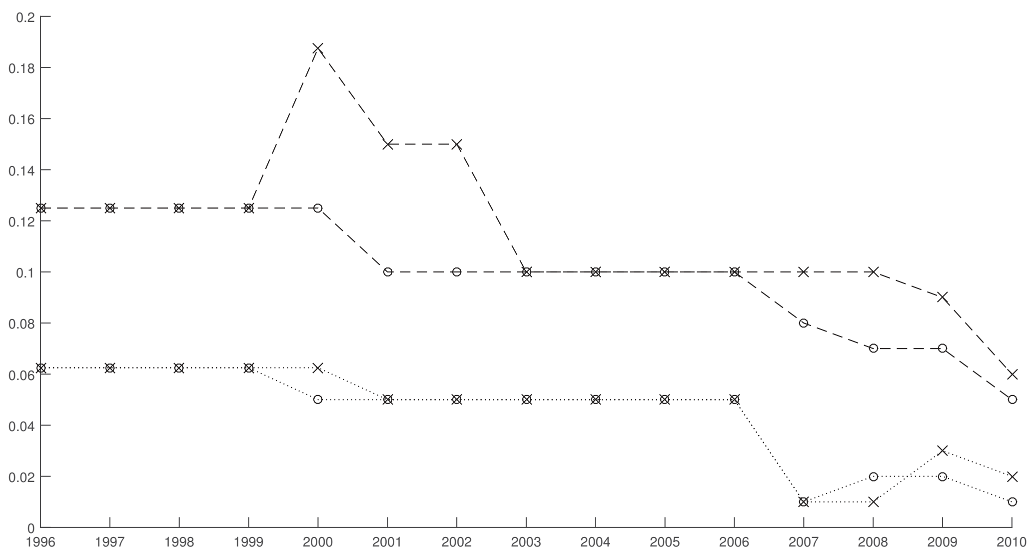


(b) Market frictions and IV run-up

Figure 1: The Effect of Market Frictions and Run-Ups in Implied Volatility on Expected Returns:
The graphs in this figure plot expected returns to informed trading in call options computed using the BSM framework. The upper two graphs are based on the assumption that there are neither market frictions nor a run-up in implied volatility. The bid-ask spread and the minimum price are equal to zero. The two lower graphs introduce market frictions and a run-up in implied volatility. The lines in the two lower graphs labelled "frictions" assume a bid-ask spread α of \$0.05 and a minimum price of \$0.10, all other parameters remaining equal. The lines labelled "scheduled" assume a Dubinsky and Johannes (2006) run-up in implied volatility ahead of the event. On each side, the strike price (maturity) is chosen such that the graph shows the global maximum of the expected return function. This explains why the maxima in the left and the right graphs are identical. The timing and magnitude of the news-induced jump are known with certainty ($E[\kappa]$=.2, $E[\Delta_t]$=3/360, σ_κ=0, $\sigma_{\Delta t}$=0), and S_0=10, r=.03, σ=.4.



(a) Panel A



(b) Panel B

Figure 2: Time Series of Bid-Ask Spreads and the Lowest 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. 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. Circles mark call options, crosses mark put options.

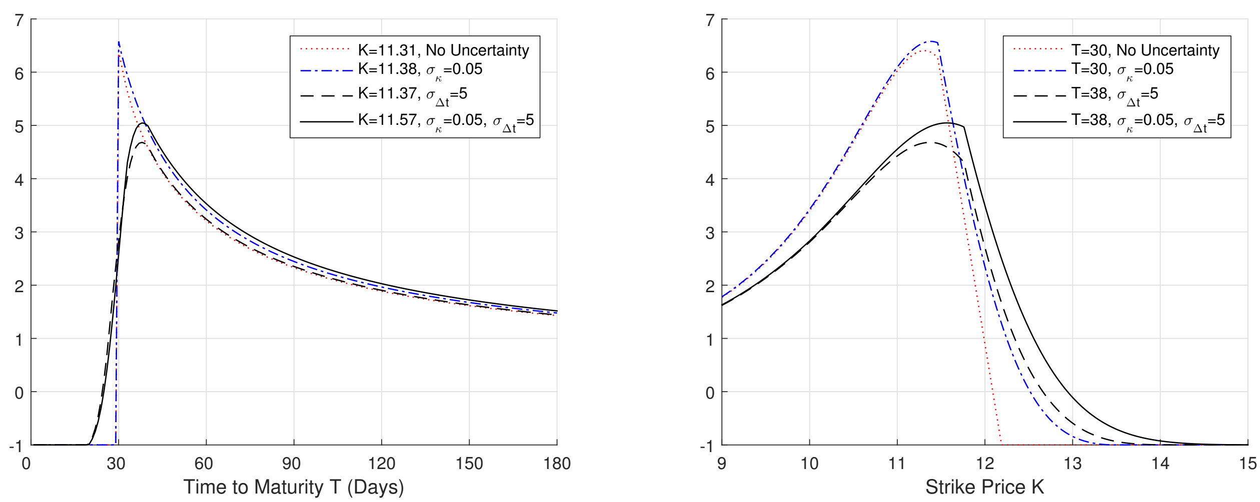


Figure 3: The Effect of Noise in the Private Signal on Expected Returns:
The graphs in this figure plot expected returns to informed trading in call options computed using the BSM framework. The left (right) graph plots expected returns as a function of the time to maturity (strike price) of the option. On each side, the maturity (strike price) is chosen such that the graph shows the global maximum of the expected return function. This explains why the maxima of each function in the left and the right graph are identical. In each graph, the four lines represent the case of no uncertainty (red dots), uncertainty about the event's effect on the stock price $\sigma_\kappa > 0$ (blue dash-dots) uncertainty about the time to announcement $\sigma_{\Delta t} > 0$ (dashed black line), and uncertainty in both dimensions (solid black line). Bid-ask spreads and minimum prices equal \$0.05 and \$0.10, respectively. Furthermore, $E[\kappa]$=.2, $E[\Delta_t]$=30/360, S_0=10, r=.03, σ=.4.

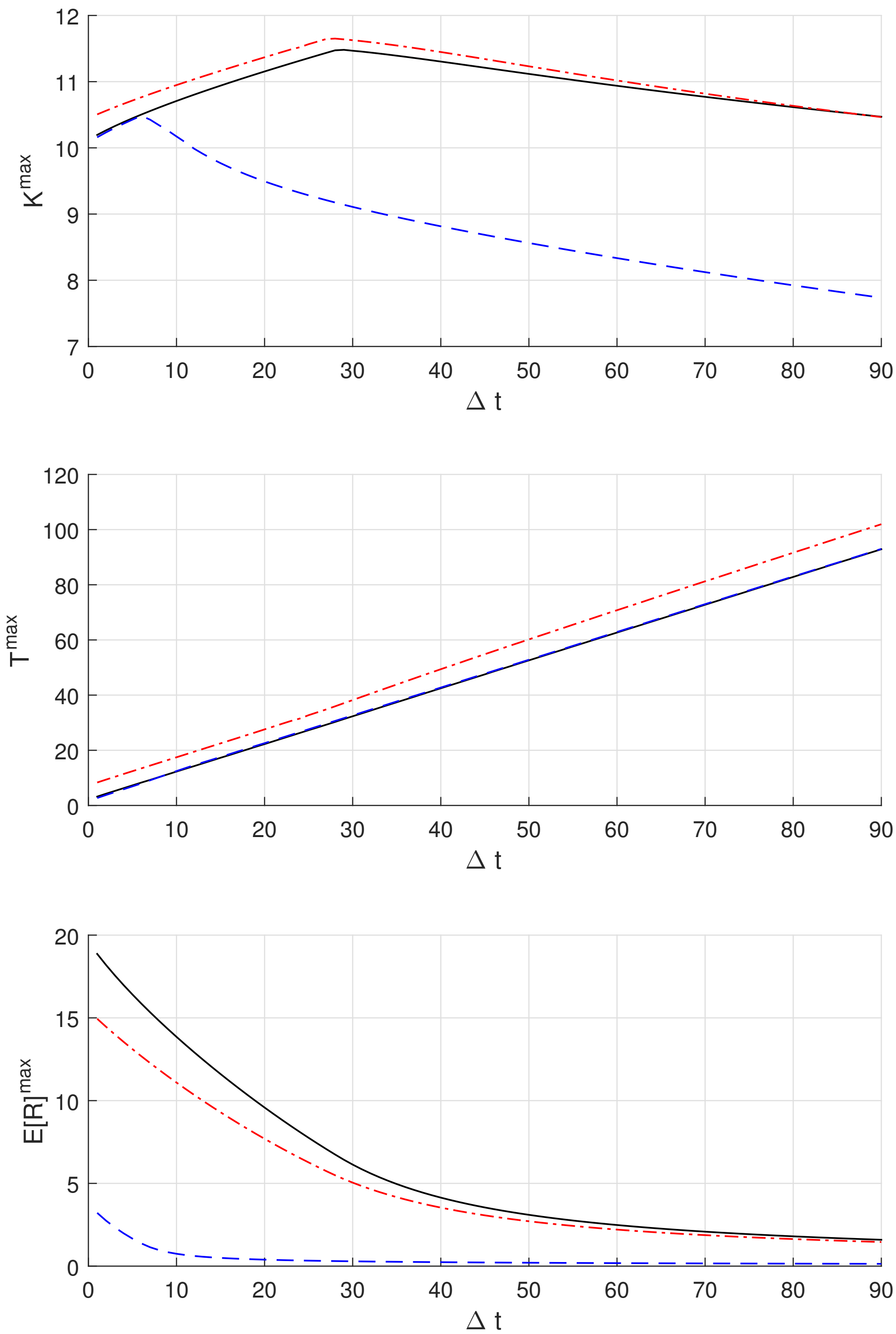


Figure 4: Maximizing Expected Returns to Informed Trading in *Call Options* depending on $E[\Delta t]$:
The upper two graphs in this figure plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in call options ahead of a positive event as a function of the expected time to announcement $E[\Delta t]$. The lower graph displays the maximum expected return $E[R]^{max}$. Results are shown for three parameter sets.
(1) black solid line: $\sigma_{\Delta t}$ = 1 *day*, $E[\kappa]$ = 0.2, $\sigma_\kappa 0.05$
(2) blue dashed line: $\sigma_{\Delta t}$ = 1 *day*, $E[\kappa]$ = 0.05, $\sigma_\kappa 0.05$
(3) red dash-dotted line: $\sigma_{\Delta t}$ = 5 *days*, $E[\kappa]$ = 0.2, $\sigma_\kappa 0.05$
In all plots, S_0=10, r=.03, σ=.4. Bid-ask spreads and minimum prices equal \$0.05 and \$0.10, respectively. Events are not scheduled, meaning that there is no run-up in implied volatilities preceding the event.

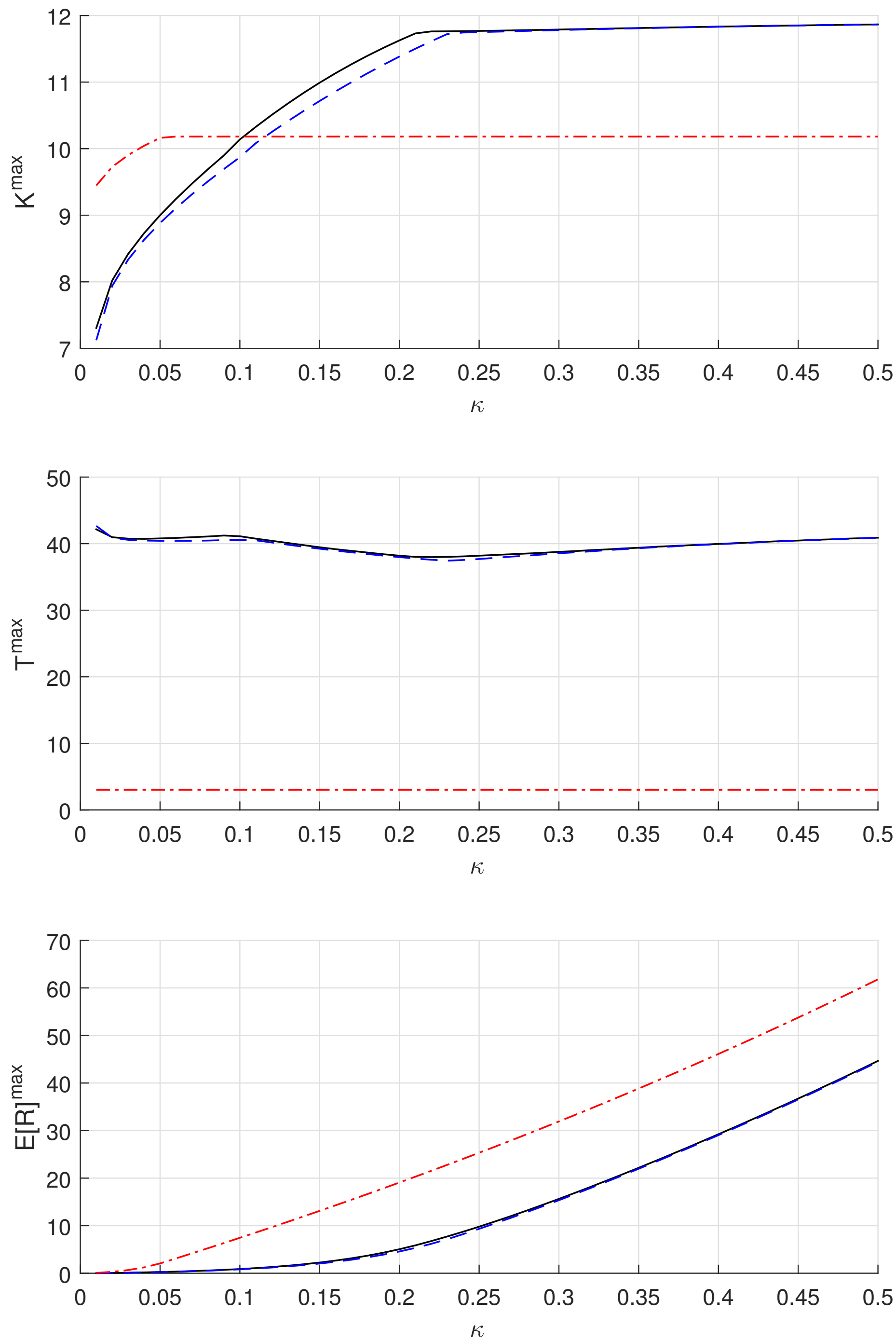


Figure 5: Maximizing Expected Returns to Informed Trading in *Call Options* depending on $E[\kappa]$:
The upper two graphs in this figure plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in call options ahead of a positive event as a function of the expected jump in stock prices, $E[\kappa]$. The lower graph displays the maximum expected return $E[R]^{max}$. Results are shown for three parameter sets.
(1) black solid line: $E[\Delta t]$ = 30 *days*, $\sigma_{\Delta t}$ = 5 *days*, $\sigma_\kappa 0.05$
(2) blue dashed line: $E[\Delta t]$ = 30 *days*, $\sigma_{\Delta t}$ = 5 *days*, $\sigma_\kappa 0.005$
(3) red dash-dotted line: $E[\Delta t]$ = 3 *days*, $\sigma_{\Delta t}$ = 0 *days*, $\sigma_\kappa 0.005$
In all plots, S_0=10, r=.03, σ=.4. Bid-ask spreads and minimum prices equal \$0.05 and \$0.10, respectively. Events are not scheduled, meaning that there is no run-up in implied volatilities preceding the event.

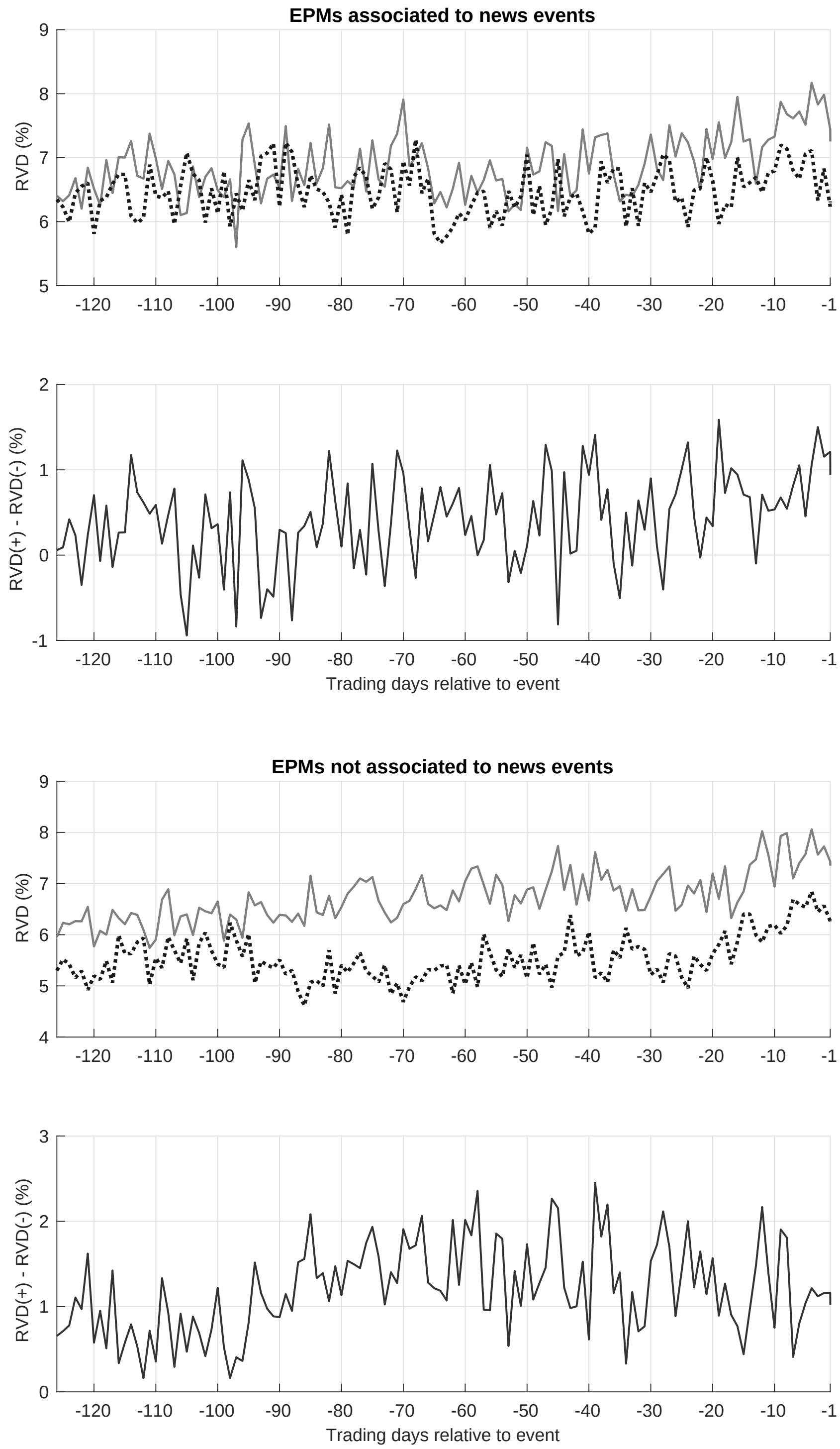


Figure 6: Informed Trading Activity ahead of News Events:
This figure plots directional trading activity for positive (grey) and negative (dotted) EPMs associated with news events (first graph) and EPMs not associated with news events (third graph) as well as the difference between the two (second and fourth graph). The measure of directional trading activity is the relative volume difference (RVD). RVD is the difference between relative call volume (RCV) and relative put volume (RPV). RCV (RPV) is the daily volume traded in call (put) options with high expected returns 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. The X-axis shows trading days relative to the event and does not include the day of the event itself.

Table 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-product-approval-granted	Drug & Product Development	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-expectations	Earnings	1.14	3.14	39.25	3694	2,293
earnings-per-share-below-expectations	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-expectations	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 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 & Product Development	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-expectations	Earnings	0.68	1.98	21.11	2,463	1,334
earnings-per-share-below-expectations	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-expectations	Earnings	0.52	1.68	17.16	3,213	48
revenue-below-expectations	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 3: *Significant Corporate News - Descriptive Statistics*
This table reports descriptive statistics for the sample of positive and negative 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.

Positive News			Return			
	N	% EAD	Avg.	Median	Std. Dev.	%High Vlm.
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

Negative News			Return			
	N	% EAD	Avg.	Median	Std. Dev.	%High Vlm.
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 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 Q1 through Q3 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 ten 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 3.

Positive News		***Scheduled***			***Unscheduled***	
	*Q*1	*Q*2	*Q*3	*Q*1	*Q*2	*Q*3
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

Negative News		***Scheduled***			***Unscheduled***	
	*Q*1	*Q*2	*Q*3	*Q*1	*Q*2	*Q*3
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: *Moneyness by Expected Return Tercile*

This table reports the average option moneyness 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. Moneyness is defined as the log of the ratio of the strike price over the spot price. The average moneyness is shown for each tercile Q1 through Q3 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 ten 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 3.

Positive News		***Scheduled***			***Unscheduled***	
	*Q*1	*Q*2	*Q*3	*Q*1	*Q*2	*Q*3
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

Negative News			***Scheduled***			***Unscheduled***
	*Q*1	*Q*2	*Q*3	*Q*1	*Q*2	*Q*3
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 Q1 through Q3 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 ten 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 3.

Positive News	***Scheduled***			***Unscheduled***		
	*Q*1	*Q*2	*Q*3	*Q*1	*Q*2	*Q*3
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

Negative News	***Scheduled***			***Unscheduled***		
	*Q*1	*Q*2	*Q*3	*Q*1	*Q*2	*Q*3
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: *Measures of Informed Trading - Descriptive Statistics.*
This table presents the average, standard deviation, and the 5th, 25th, 50th, 75th, and 95th percentile 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 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 Poteshman (2006) measure of put volume scaled by total volume, O/S the Johnon 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 logged market capitalization (in mio 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. The first two rows include the dependent variables of our analysis, ESS and CAR as of next week (t+1). All other variables are reported for t. Further details on the construction of these measures are included in Sections 4.3 and 5.1.

	Avg	*Std*	5	25	50	75	95	N
ESS_{t+1}	53.043	9.950	38.600	48.000	50.500	59.333	69.286	654,407
CAR_{t+1}	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
CAR	0.083	6.406	−8.861	−2.565	−0.051	2.560	9.422	1,198,917
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 8: *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 scaled by total call (put) volume. RVD is the difference between RCV and RPV. PP is the Pan Poteshman (2006) measure of put volume scaled by total volume, O/S the Johnon 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 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 but SIZE and ESS are multiplied by 100. The first two rows include the dependent variables of our analysis, ESS and CAR as of next week (t+1). All other variables are reported for t. Further details on the construction of these measures are included in Sections 4.3 and 5.1

	1	2	3	4	5	6	7	8	9	10	11	12	13
(1) ESS_{t+1}	1.000												
(2) CAR_{t+1}	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) CAR	−0.013	−0.008	0.010	0.038	−0.028	−0.111	0.013	−0.060	0.040	1.000			
(11) SIZE	0.070	0.000	0.502	0.479	0.006	0.061	0.164	0.142	0.087	0.033	1.000		
(12) ILLIQ	−0.019	−0.002	−0.208	−0.196	−0.005	0.004	−0.050	−0.103	−0.039	0.002	−0.473	1.000	
(13) MOM	0.001	0.006	0.005	0.045	−0.038	−0.057	0.039	−0.031	0.002	0.004	0.035	−0.022	1.000
(14) MB	0.008	−0.010	−0.011	0.005	−0.012	−0.024	0.158	−0.045	−0.044	0.051	0.105	−0.044	0.247

Table 9: *Predicting returns in the weekly cross-section.*
This table presents results from weekly Fama-MacBeth regressions of next week's cumulative market adjusted returns on measures of informed trading and a set of control variables. For each variable, the average coefficient estimate is reported in the upper row and the *t*-statistic based on Newey-West standard errors adjusted for three autocorrelation lags in the lower row. 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. RVD is the difference between RCV and RPV. PP is the Pan Poteshman (2006) measure of put volume scaled by total volume, O/S the Johnon 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 these measures are included in Sections 4.3 and 5.1. [a,b,c] indicate statistical significance at the one, five, or ten percent level, respectively

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.033	0.056	0.034	0.033	0.026	−0.057	−0.091	−0.031	−0.048
	(0.859)	(1.235)	(0.873)	(0.838)	(0.644)	(−.918)	(−1.733)	(−.565)	(−1.012)
RCV		0.054[b]						0.114[a]	
		(2.24)						(3.746)	
RPV		0.025						0.03	
		(1.265)						(1.12)	
RVD			0.01						0.027[b]
			(1.356)						(1.997)
PP				−0.021[b]				0.007	−0.003
				(−2.093)				(0.465)	(−.159)
O/S					−0.077[a]			−0.036	−0.048[c]
					(−2.878)			(−1.525)	(−1.918)
IVS						0.016		0.105[a]	0.115[a]
						(0.21)		(5.164)	(5.549)
SKEW							−0.048	−0.046	−0.027
							(−1.248)	(−1.574)	(−.737)
CAR	−0.06[a]	−0.063[a]	−0.06[a]	−0.063[a]	−0.059[a]	0.759	0.348	−0.063[a]	−0.062[b]
	(−2.836)	(−3.143)	(−2.823)	(−2.963)	(−2.80)	(0.973)	(0.864)	(−2.769)	(−2.563)
SIZE	−0.016	−0.047[b]	−0.016	−0.013	−0.008	0.263	0.121	−0.076[c]	−0.018
	(−.476)	(−2.075)	(−.505)	(−.416)	(−.241)	(0.911)	(1.091)	(−1.936)	(−.402)
ILLIQ	−0.014	−0.016	−0.014	−0.014	−0.013	−0.079	−0.028	−0.041	−0.014
	(−.901)	(−1.059)	(−.884)	(−.867)	(−.787)	(−1.127)	(−.484)	(−.803)	(−.254)
MOM	0.018	0.012	0.018	0.015	0.017	0.429	0.169	−0.005	−0.002
	(0.339)	(0.257)	(0.339)	(0.294)	(0.336)	(1.048)	(0.835)	(−.111)	(−.028)
MB	−0.064[b]	−0.054[b]	−0.064[b]	−0.064[b]	−0.058[b]	0.027	−0.035	−0.04	−0.034
	(−2.225)	(−2.023)	(−2.231)	(−2.248)	(−2.055)	(0.28)	(−.493)	(−1.154)	(−1.137)
Adj. R2	4.558	5.381	4.57	4.626	4.782	6.175	6.172	7.872	6.824
Avg N	1531	1531	1531	1531	1531	714	714	714	714

Table 10: *Predicting news sentiment in the weekly cross-section.*
This table presents results from weekly Fama-MacBeth regressions of next week's event sentiment scores (ESS) on measures of informed trading and a set of control variables. For each variable, the average coefficient estimate is reported in the upper row and the *t*-statistic based on Newey-West standard errors adjusted for three autocorrelation lags in the lower row. 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 scaled by total call (put) volume. RVD is the difference between RCV and RPV. PP is the Pan Poteshman (2006) measure of put volume scaled by total volume, O/S the Johnon 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 these measures are included in Sections 4.3 and 5.1. [a,b,c] indicate statistical significance at the one, five, or ten percent level, respectively

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	53.408[a]	53.445[a]	53.405[a]	53.401[a]	53.396[a]	53.095[a]	53.164[a]	52.984[a]	52.929[a]
	(336.33)	(343.614)	(336.543)	(340.017)	(331.073)	(242.023)	(253.996)	(213.863)	(212.197)
RCV		0.017						0.247[a]	
		(0.559)						(3.798)	
RPV		−0.119[a]						−0.224[a]	
		(−4.271)						(−4.75)	
RVD			0.068[a]						0.218[a]
			(3.331)						(3.02)
PP				−0.185[a]				−0.303[a]	−0.334[a]
				(−10.565)				(−3.524)	(−4.236)
O/S					−0.069			0.017	0.019
					(−1.331)			(0.409)	(0.457)
IVS						0.091		0.064	0.115[a]
						(1.44)		(0.992)	(2.797)
SKEW							−0.098[c]	−0.059	−0.054
							(−1.673)	(−.889)	(−.844)
CAR	−0.174[a]	−0.168[a]	−0.170[a]	−0.198[a]	−0.174[a]	−0.223[a]	−0.225[a]	−0.247[a]	−0.242[a]
	(−5.364)	(−5.072)	(−5.204)	(−6.123)	(−5.405)	(−6.342)	(−6.468)	(−6.981)	(−6.86)
SIZE	0.718[a]	0.770[a]	0.720[a]	0.737[a]	0.724[a]	0.964[a]	0.984[a]	0.982[a]	1.037[a]
	(21.81)	(21.389)	(21.808)	(22.68)	(20.975)	(23.177)	(23.67)	(22.261)	(13.565)
ILLIQ	0.359[a]	0.370[a]	0.363[a]	0.369[a]	0.362[a]	0.862[a]	0.868[a]	0.855[a]	0.833[a]
	(9.434)	(9.741)	(9.591)	(9.677)	(9.495)	(7.431)	(7.381)	(7.236)	(7.135)
MOM	−0.04	−0.027	−0.036	−0.054	−0.039	−0.121[b]	−0.138[a]	−0.131[b]	−0.135[b]
	(−.855)	(−.584)	(−.777)	(−1.153)	(−.84)	(−2.316)	(−2.642)	(−2.448)	(−2.568)
MB	0.095[b]	0.085[b]	0.093[b]	0.092[b]	0.102[b]	−0.037	−0.04	0.086[c]	0.067[c]
	(2.363)	(2.165)	(2.352)	(2.316)	(2.577)	(−.422)	(−.462)	(1.929)	(1.739)
Adj. R2	1.245	1.34	1.266	1.283	1.277	1.592	1.657	1.892	1.791
Avg N	836	836	836	836	836	440	440	440	440

Appendix

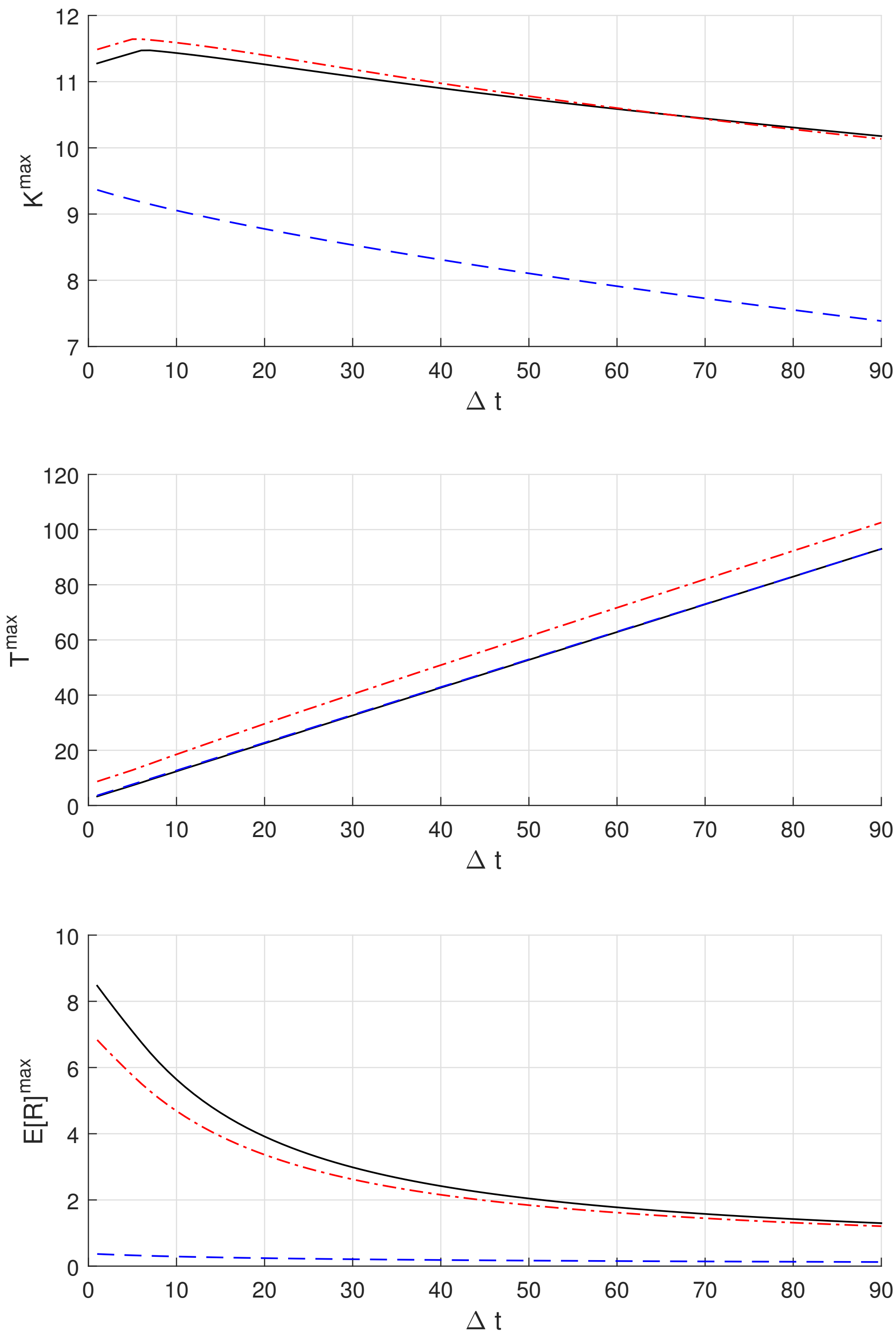


Figure A1: Maximizing Expected Returns to Informed Trading in *Call Options* ahead of Scheduled Events, depending on $E[\Delta t]$: The upper two graphs in this figure plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in call options ahead of a positive event as a function of the expected time to announcement $E[\Delta t]$. The lower graph displays the maximum expected return $E[R]^{max}$. Results are shown for three parameter sets.

(1) black solid line: $\sigma_{\Delta t} = 1$ *day*, $E[\kappa] = 0.2$, $\sigma_\kappa 0.05$

(2) blue dashed line: $\sigma_{\Delta t} = 1$ *day*, $E[\kappa] = 0.05$, $\sigma_\kappa 0.05$

(3) red dash-dotted line: $\sigma_{\Delta t} = 5$ *days*, $E[\kappa] = 0.2$, $\sigma_\kappa 0.05$

In all plots, S_0=10, r=.03, σ=.4. Bid-ask spreads and minimum prices equal \$0.05 and \$0.10, respectively. Events are scheduled, meaning that there is a run-up in implied volatilities preceding the event.

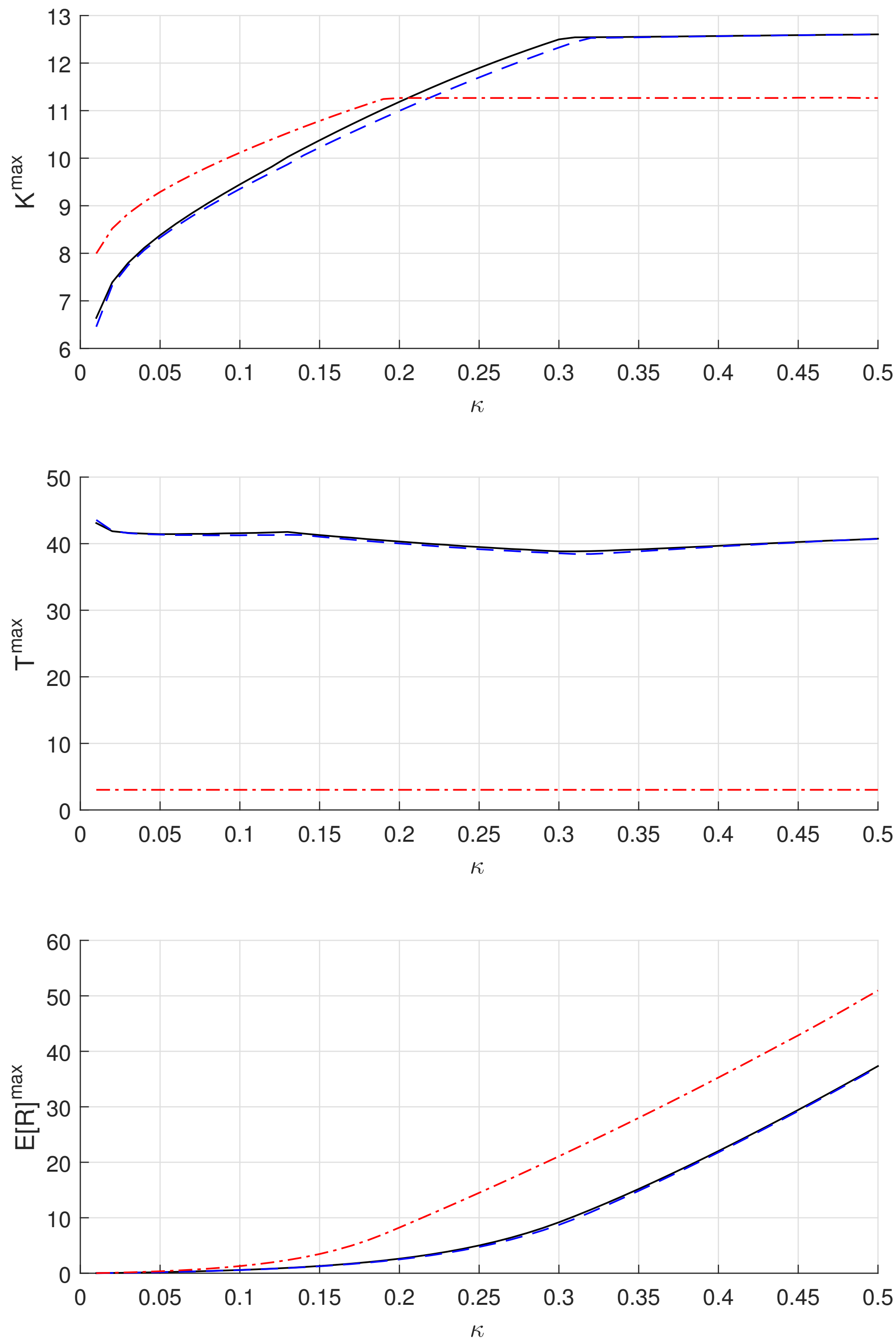


Figure A2: Maximizing Expected Returns to Informed Trading in *Call Options* ahead of Scheduled Events, depending on $E[\kappa]$: The upper two graphs in this figure plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in call options ahead of a positive event as a function of the expected jump in stock prices, $E[\kappa]$. The lower graph displays the maximum expected return $E[R]^{max}$. Results are shown for three parameter sets.

(1) black solid line: $E[\Delta t]$ = 30 *days*, $\sigma_{\Delta t}$ = 5 *days*, $\sigma_\kappa 0.05$

(2) blue dashed line: $E[\Delta t]$ = 30 *days*, $\sigma_{\Delta t}$ = 5 *days*, $\sigma_\kappa 0.005$

(3) red dash-dotted line: $E[\Delta t]$ = 3 *days*, $\sigma_{\Delta t}$ = 0 *days*, $\sigma_\kappa 0.005$

In all plots, S_0=10, r=.03, σ=.4. Bid-ask spreads and minimum prices equal \$0.05 and \$0.10, respectively. Events are scheduled, meaning that there is a run-up in implied volatilities preceding the event.

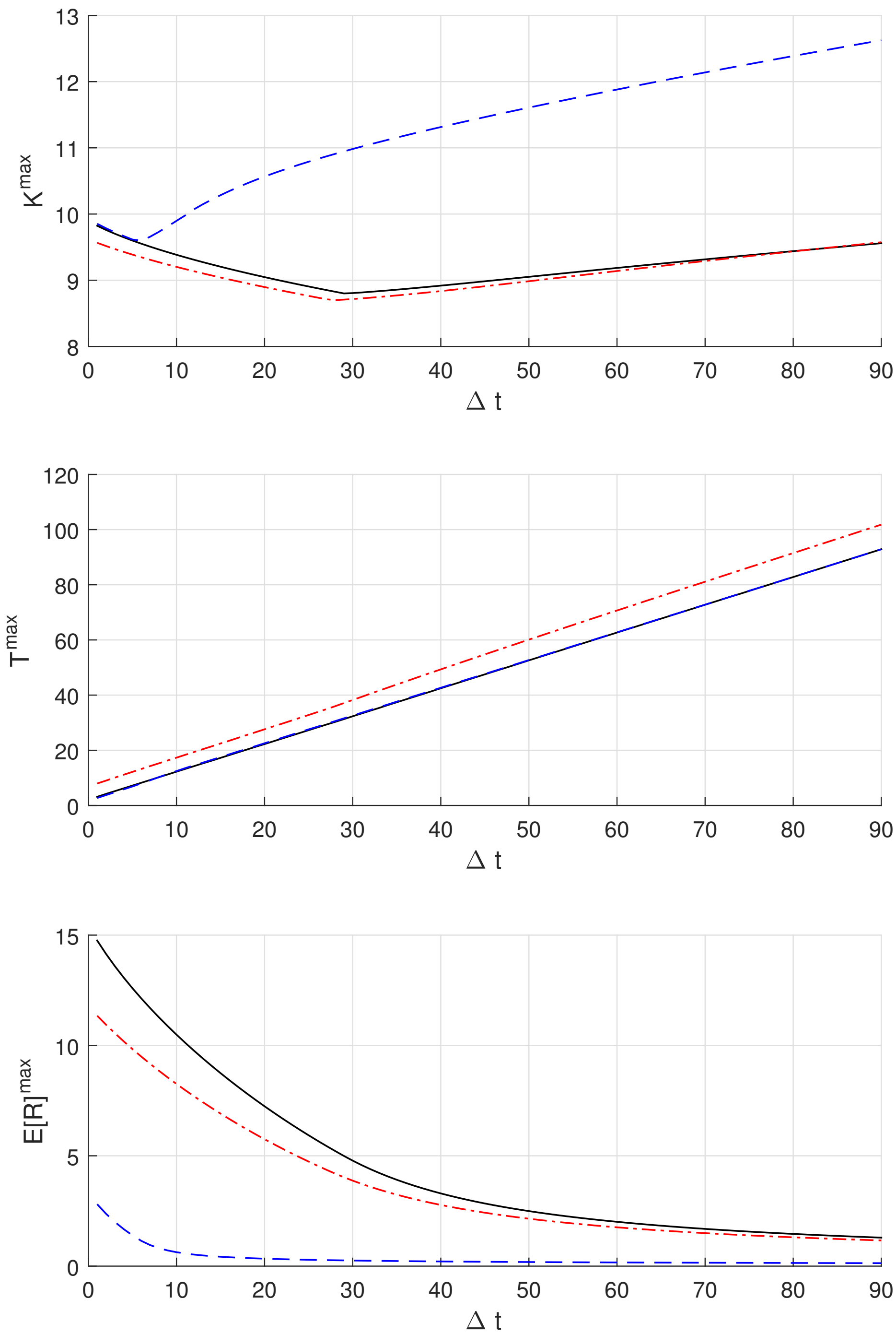


Figure A3: Maximizing Expected Returns to Informed Trading in *Put Options* depending on $E[\Delta t]$:
The upper two graphs in this figure plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in put options ahead of a positive event as a function of the expected time to announcement $E[\Delta t]$. The lower graph displays the maximum expected return $E[R]^{max}$. Results are shown for three parameter sets.
(1) black solid line: $\sigma_{\Delta t} = 1\ day$, $E[\kappa] = -0.2$, $\sigma_\kappa 0.05$
(2) blue dashed line: $\sigma_{\Delta t} = 1\ day$, $E[\kappa] = -0.05$, $\sigma_\kappa 0.05$
(3) red dash-dotted line: $\sigma_{\Delta t} = 5\ days$, $E[\kappa] = -0.2$, $\sigma_\kappa 0.05$
In all plots, S_0=10, r=.03, σ=.4. Bid-ask spreads and minimum prices equal \$0.05 and \$0.10, respectively. Events are not scheduled, meaning that there is no run-up in implied volatilities preceding the event.

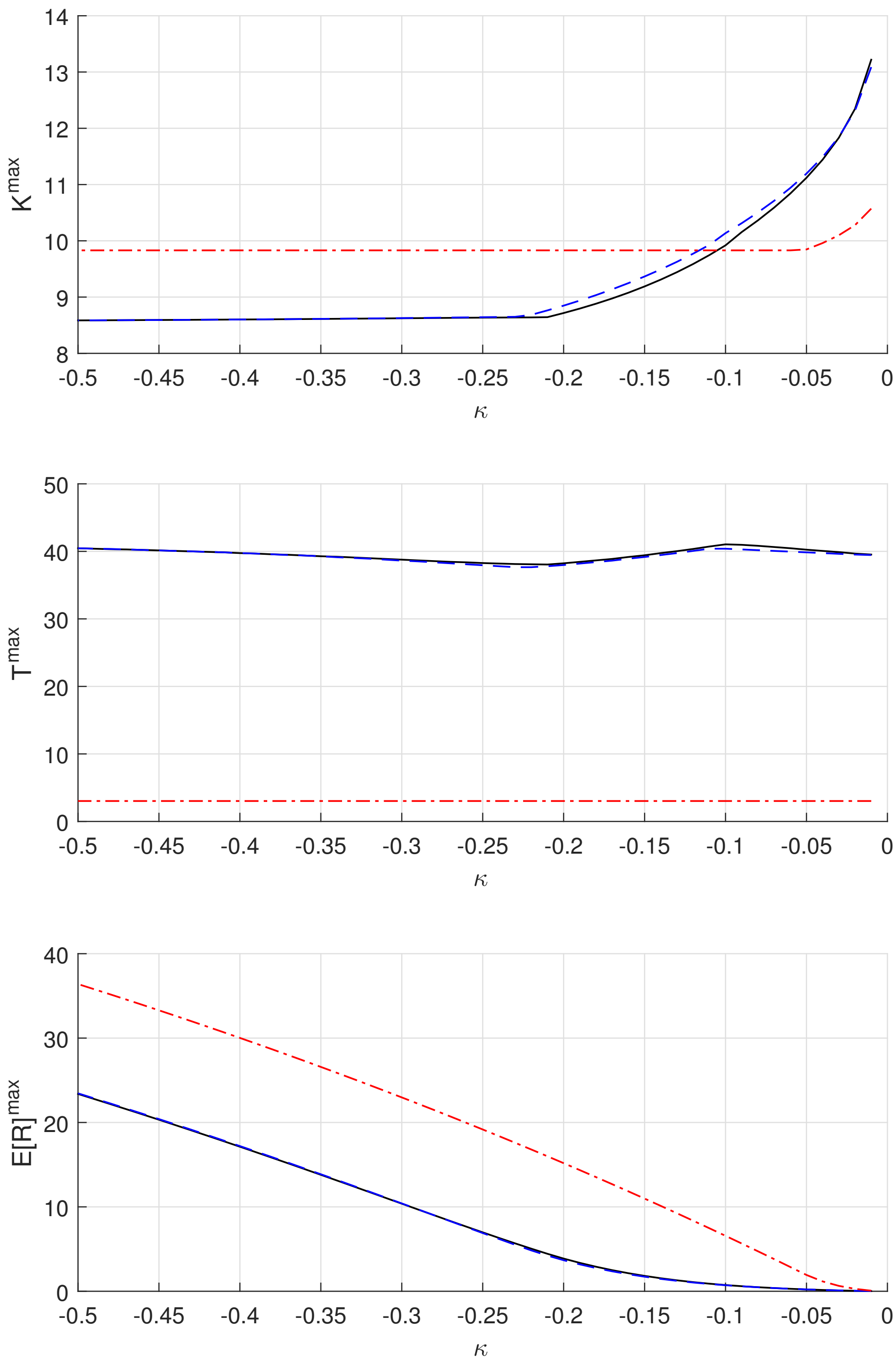
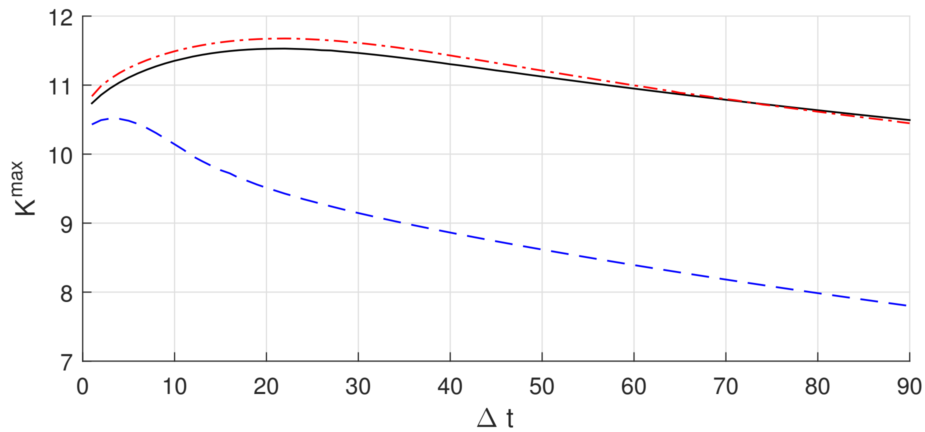
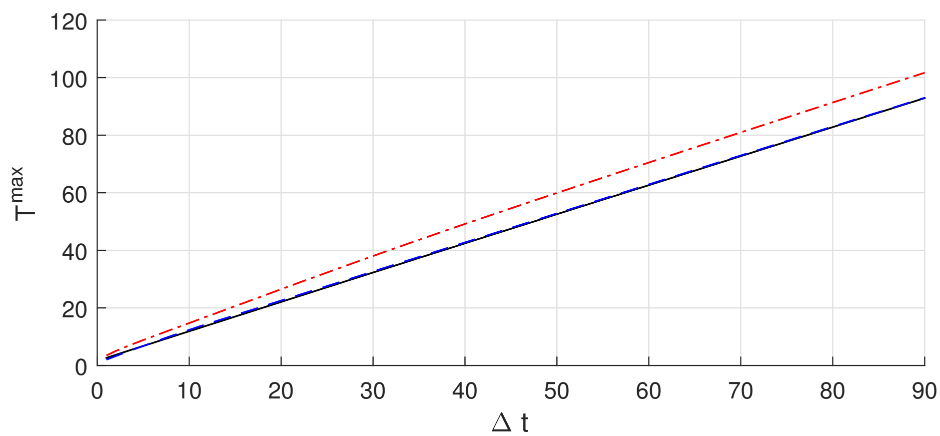


Figure A4: Maximizing Expected Returns to Informed Trading in *Put Options* depending on $E[\kappa]$:
The upper two graphs in this figure plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in put options ahead of a positive event as a function of the expected jump in stock prices, $E[\kappa]$. The lower graph displays the maximum expected return $E[R]^{max}$. Results are shown for three parameter sets.
(1) black solid line: $E[\Delta t] = 30\ days$, $\sigma_{\Delta t} = 5\ days$, $\sigma_{\kappa}0.05$
(2) blue dashed line: $E[\Delta t] = 30\ days$, $\sigma_{\Delta t} = 5\ days$, $\sigma_{\kappa}0.005$
(3) red dash-dotted line: $E[\Delta t] = 3\ days$, $\sigma_{\Delta t} = 0\ days$, $\sigma_{\kappa}0.005$
In all plots, S_0=10, r=.03, σ=.4. Bid-ask spreads and minimum prices equal \$0.05 and \$0.10, respectively. Events are not scheduled, meaning that there is no run-up in implied volatilities preceding the event.





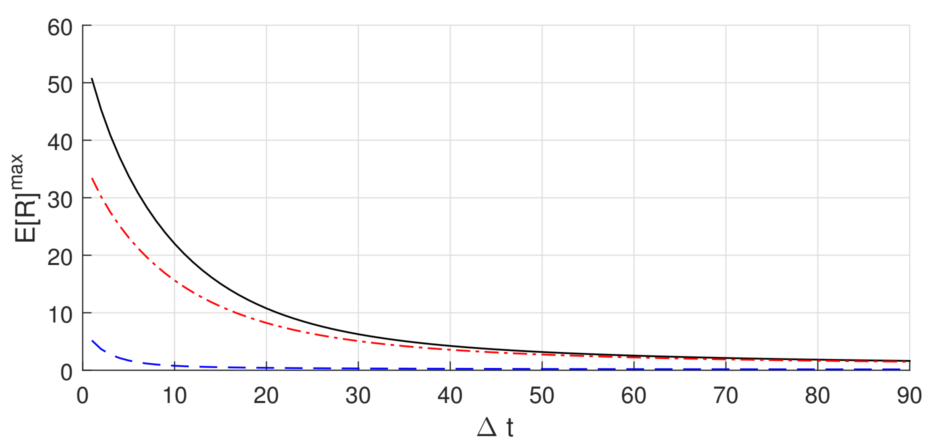


Figure A5: Maximizing Expected Returns to Informed Trading in *Synthetic Call Options* depending on $E[\Delta t]$:
The upper two graphs in this figure plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in synthetic call options ahead of a positive event as a function of the expected time to announcement $E[\Delta t]$. The lower graph displays the maximum expected return $E[R]^{max}$. Results are shown for three parameter sets.
(1) black solid line: $\sigma_{\Delta t}$ = 1 *day*, $E[\kappa]$ = 0.2, $\sigma_\kappa 0.05$
(2) blue dashed line: $\sigma_{\Delta t}$ = 1 *day*, $E[\kappa]$ = 0.05, $\sigma_\kappa 0.05$
(3) red dash-dotted line: $\sigma_{\Delta t}$ = 5 *days*, $E[\kappa]$ = 0.2, $\sigma_\kappa 0.05$
In all plots, S_0=10, r=.03, σ=.4. Bid-ask spreads and minimum prices equal \$0.05 and \$0.10, respectively. Events are not scheduled, meaning that there is no run-up in implied volatilities preceding the event.

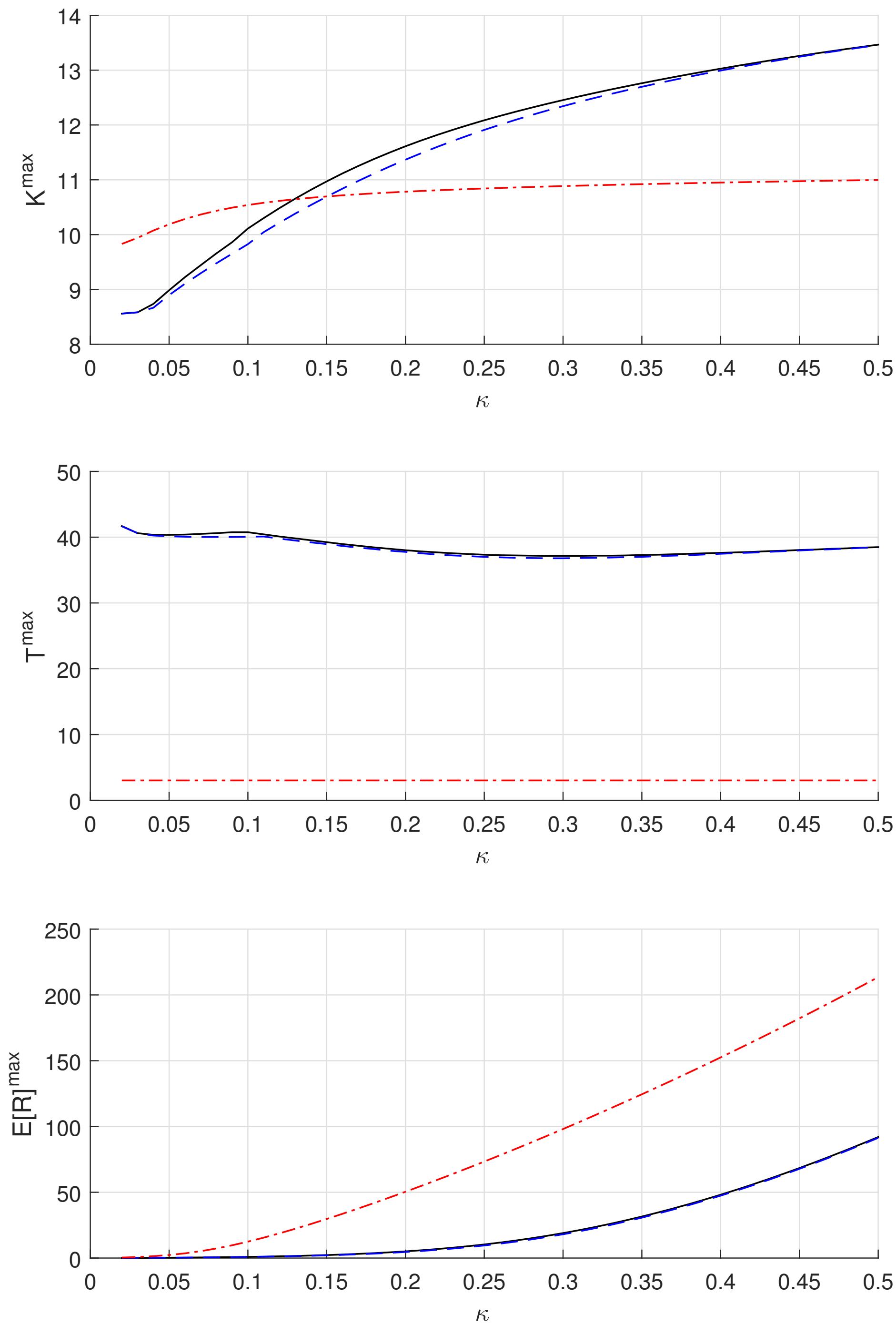


Figure A6: Maximizing Expected Returns to Informed Trading in *Synthetic Call Options* depending on $E[\kappa]$:
The upper two graphs in this figure plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in synthetic call options ahead of a positive event as a function of the expected jump in stock prices, $E[\kappa]$. The lower graph displays the maximum expected return $E[R]^{max}$. Results are shown for three parameter sets.

(1) black solid line: $E[\Delta t] = 30\ days$, $\sigma_{\Delta t} = 5\ days$, $\sigma_\kappa 0.05$

(2) blue dashed line: $E[\Delta t] = 30\ days$, $\sigma_{\Delta t} = 5\ days$, $\sigma_\kappa 0.005$

(3) red dash-dotted line: $E[\Delta t] = 3\ days$, $\sigma_{\Delta t} = 0\ days$, $\sigma_\kappa 0.005$

In all plots, S_0=10, r=.03, σ=.4. Bid-ask spreads and minimum prices equal \$0.05 and \$0.10, respectively. Events are not scheduled, meaning that there is no run-up in implied volatilities preceding the event.

A. 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 £$_i$ as the ratio of the (continuous) stock price return to the instantaneous volatility:

$$\mathcal{L}_t = \frac{R_t}{\hat{\sigma}_t} \tag{11}$$

where volatility is the realized bipower variation:

$$\hat{\sigma}_t^2 = \frac{1}{K-2} \sum_{j=t-k+2}^{t-1} \left|R_j\right| * \left|R_{j-1}\right| \tag{12}$$

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:

$$\frac{\max_{t \in \bar{A}_n} |\mathcal{L}_t| - C_n}{S_n} \longrightarrow \xi \tag{13}$$

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

$$C_n = \frac{\sqrt{2\log(n)}}{c} - \frac{\log(\pi) + \log(\log(n))}{2c\sqrt{2\log(n)}} \tag{14}$$

$$S_n = \frac{1}{c\sqrt{2\log(n)}} \tag{15}$$

$$c = \sqrt{\frac{2}{\pi}}. \tag{16}$$

n stands for the number of observations. $\bar{A}_n$ is the time series indexes such as 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.[25] Following Lee and Mykland's recommendation, we set $K = 16$ to compute the statistics $\mathcal{L}_t$ from daily returns.

[25]For example, see Cremers et al. (2014).

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.

References

Acharya, V. V., Johnson, T. C., 2010. More insiders, more insider trading: Evidence from private-equity buyouts. Journal of Financial Economics 98 (3), 500–523.

Anand, A., Sugato, 2007. Stealth trading in options markets. Journal of Financial and Quantit.

Augustin, P., Brenner, M., Hu, J., Subrahmanyam, M. G., 2015. Are corporate spinoffs prone to insider trading? Working Paper.

Augustin, P., Brenner, M., Subrahmanyam, M. G., 2018. Informed options trading ahead of takeover announcements: Insider trading? Management Science Forthcoming.

Bali, T. G., Hovakimian, A., 2009. Volatility spreads and expected stock returns. Management Science 55 (11), 1797–1812.

Bates, D. S., 2013. Empirical option pricing: A retrospection. Journal of Econometrics 113 (1), 387–404.

Bernile, G., Hu, J., Tang, Y., 2016. Can information be locked up? informed trading ahead of macro-news announcements. Journal of Financial Economics Forthcoming.

Bhattacharya, U., 2014. Insider trading controversies: A literature review. Annual Review of Financial Economics 6 (1), 385–403.

Black, F., Scholes, M., 1973. The pricing of options and corporate liabilities. Journal of Political Economy 81 (3), 637–654.

Bollen, N. P. B., Whaley, R. E., Apr. 2004. Does net buying pressure affect the shape of implied volatility functions? The Journal of Finance 59 (2), 711–753.

Boudoukh, J., Feldman, R., Kogan, S., Richardson, M., 2013. Which news moves stock prices? a textual analysis. NBER Working Paper No. 18725.

Boyer, B. H., Vorkink, K., 2014. Stock options as lotteries. The Journal of Finance 69 (4), 1485–1527.

Bradley, D., Clarke, J., Lee, S., Ornthanalai, C., 2014. Are analysts' recommendations informative? intraday evidence on the impact of time stamp delays. The Journal of Finance 69 (2), 645–673.

Brogaard, J., Carrion, A., Moyaert, T., Riordan, R., Sokolov, A. S. K., 2018. High-frequency trading and extreme price movements. Journal of Financial Economics 128 (2), 253–265.

Cao, C., Chen, Z., Griffin, J. M., 2005. Informational content of option volume prior to takeovers. The Journal of Business 78 (3), 1073–1109.

Cao, H. H., Ou-Yang, H., 2009. Differences of opinion of public information and speculative trading in stocks and options. Review of Financial Studies 22 (1), 299–335.

Chakravarty, S., Gulen, H., Mayhew, S., 2004. Informed trading in stock and option markets. The Journal of Finance 59 (3), 1235–1258.

Chan, K., Ge, L., Lin, T.-C., 2015. Informational content of option trading on acquirer announcement return. Journal of Financial and Quantitative Analysis 50 (5), 1057–1082.

Collin-Dufresne, P., Fos, V., Muravyev, D., 2015. Informed trading and option prices: Theory and evidence from activist trading. Working Paper.

Cremers, M., Fodor, A., Weinbaum, D., 2016. Where do informed traders trade first? option trading activity, news releases, and stock return predictability. Working Paper.

Cremers, M., Hayalling, M., Weinbaum, D., 2014. Aggregate jump and volatility risk in the cross-section of stock returns. The Journal of Finance 70 (2), 577–614.

Cremers, M., Weinbaum, D., 2010. Deviations from put-call parity and stock return predictability. The Journal of Financial and Quantitative Analysis 45 (2), 335–367.

Deuskar, P., Gupta, A., Subrahmanyam, M. G., 2011. Liquidity effect in otc options markets: Premium or discount? Journal of Financial Markets 14 (1), 127–160.

Driessen, J., Tse-Chun, L., Xiaolong, L., 2012. Why do option prices predict stock returns? Working Paper.

Dubinsky, A., Johannes, M., 2006. Fundamental uncertainty, earning announcements and equity options. Working Paper Columbia University.

Easley, D., O'Hara, M., Srinivas, P. S., 1998. Option volume and stock prices: Evidence on where informed traders trade. The Journal of Finance 53 (2), 431–465.

Garleanu, N., Pedersen, L. H., Poteshman, A. M., 2009. Demand-based option pricing. Review of Financial Studies 22 (10), 4259–4299.

Ge, L., Lin, T.-C., Pearson, N. D., 2016. Why does the option to stock volume ratio predict stock returns? Journal of Financial Economics 120 (3), 601–622.

Goyenko, R., Ornthanalai, C., Tang, S., 2014. Trading cost dynamics of market making in equity options. Working Paper.

Hitzemann, S., Hofmann, M., Uhrig-Homburg, M., Wa, C., 2016. Margin requirements and equity option returns. Working Paper.

Hu, J., 2014. Does option trading convey stock price information? Journal of Financial Economics 111 (3), 625–645.

Jin, W., Livnat, J., Zhang, Y., 2012. Option prices leading equity prices: Do option traders have an information advantage?. Journal of Accounting Research 50 (2), 401–432.

John, K., Koticha, A., Narayanan, R., Subrahmanyam, M. G., 2003. Margin rules, informed trading in derivatives and price dynamics. NYU Working Paper No. FIN-01-038.

Johnson, T. L., So, E. C., 2012. The option to stock volume ratio and future returns. Journal of Financial Economics 106 (2), 262–286.

Kadan, O., Michaely, R., Moulton, P. C., 2018. Speculating on private information: Buy the rumor, sell the news. Working Paper Forthcoming.

Kedia, S., Zhou, X., 2014. Informed trading around acquisitions: Evidence from corporate bonds. Journal of Financial Markets 18, 182–205.

Lee, S., Mykland, P., 2008. Jumps in financial markets: A new nonparametric test and jump dynamics. Review of Financial Studies 21 (6), 2535–2563.

Lee, S., Mykland, P., 2012. Jumps in equilibrium prices and market microstructure noise. Journal of Econometrics 168 (2), 396–406.

Merton, R. C., 1973. The pricing of options and corporate liabilities. The Journal of Political Economy 81 (3), 637–654.

Noel, A., 2017. Informed trading across strikes. Working Paper.

Pan, J., Poteshman, A. M., 2006. The information in option volume for future stock prices. The Review of Financial Studies 19 (3), 871–908.

Roll, R., 1988. R2. The Journal of Fina 43 (2), 541–566.

Roll, R., Schwartz, E., Subrahmanyam, A., 2010. O/s: The relative trading activity in options and stock. Journal of Financial Economics 96 (1), 1–17.

Xing, Y., Zhang, X., Zhao, R., 2010. What does the individual option volatility smirk tell us about future equity returns?. Journal of

Financial & Quantitative Analysis 45 (3), 641–662.