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How do Informed Investors Trade in the Options Market?☆

Patrick Augustin
McGill University

Menachem Brenner
New York University

Gunnar Grass*
HEC Montreal

Marti G. Subrahmanyam
New York University

Abstract

We characterize *how* informed investors trade in the options market ahead of corporate news when they receive private information about (i) the timing of the announcement and (ii) its impact on stock prices. A simple framework determines the optimal strategy in terms of option type, maturity, and strike price that yields the greatest leverage to informed investors. Accounting for uncertainty in the private information signal, as well as market frictions including minimum prices and bid-ask spreads, we can rank strategies without the need to model risk aversion or price impact. We demonstrate empirically that (i) heterogeneity in unusual options activity ahead of significant corporate news (SCNs) is consistent with the predictions of our framework and (ii) informed trading measures derived from our framework improve the predictability of significant corporate news events.

Key words: Insider Trading, Market Microstructure, Corporate Announcements, Extreme Price Movements, Equity Options
JEL classification: G12, G13, G14, K42

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*Corresponding author. Email: gunnar.grass@hec.ca

1. Introduction

Recent research thoroughly 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 the 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. This can improve the identification of informed trading, which has two key benefits. First, it enables the prediction of future stock returns. In addition, it can help regulators detect illegal insider trading.

Informed investors trade based on private information, i.e., 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 impact on stock prices. Across different types of corporate events, both dimensions of the private signal vary in terms of their expected value, as well as their uncertainty, and this heterogeneity affects an informed investor's choice of trading strategy.[1] For instance, an investor who receives private information about a scheduled earnings announcement knows precisely when the news will be published, but may find it difficult to estimate the (typically moderate) impact of the earnings news on stock prices. In contrast, an investor with private information about the deal premium paid in an 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 type of corporate event, albeit in detail, is thus limited in its predictive power for understanding how this heterogeneity affects informed trading. Our study is much broader in scope, since we study trading strategies of informed investors ahead of numerous types of announcements.

In a first step, we propose a theoretical framework for identifying optimal option trading strategies to privately informed investors. In other words, we identify the combination of option type, strike price, and maturity which maximizes expected returns to informed trading on a noisy signal and in illiquid markets. We

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

posit that investors trading on private information in the options market do so as it enables them to leverage their exposure. The maximization of expected returns can alternatively be interpreted as the maximization of leverage. We assume that the private information 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 value*, we also consider the *precision* of the two signals, characterized by the uncertainty in the timing of the future announcement, and the uncertainty of the future stock price reaction. One 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*. Their 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, given their lower prices. Second, most options do not trade below a *minimum price* of ten cents. Both of 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 leverage investors can attain in the options market.[3] In addition, run-ups in implied volatilities ahead of scheduled news can substantially increase the cost of setting up a trading strategy. Using numerical analysis, we illustrate that these effects 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 illegal trades observed by the Securities and Exchange Commission (SEC).[4] Furthermore, they can heavily affect the trading behavior of informed investors. Importantly, a simple framework that takes into account minimum prices and transaction costs is able to generate a trade-off for informed investors without the need for risk aversion, price impact, or other potential frictions.

The analysis reveals three main insights about the strategic trading behavior of informed investors. First,

[2]It is possible to extend our analysis to account for private but noisy signals about changes in the volatility of the underlying stock price distribution. This dimension is relevant in the presence of volatility trades on M&A acquiring companies, as suggested by Augustin et al. (2014). In this paper, we focus on a two-dimensional signal for tractability.

[3]Multiple studies document that OTM options are overpriced relative to standard pricing models. Boyer and Vorkink (2014) report that intermediaries expect substantial premia when writing OTM options. Goyenko et al. (2014) show that the bid-ask spreads of OTM options are inflated by information asymmetry and demand pressures arising ahead of earnings announcements.

[4]We can provide descriptive statistics about illegal insider trades documented by the SEC upon request.

market frictions, including lower price bounds and bid-ask spreads, typically lead informed investors to trade options that are near-the-money rather than DOTM. 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. Everything else equal, a higher 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. This effect may be partially be offset by a run-up in implied volatility and an increase in bid-ask spreads ahead of scheduled events.

We empirically verify whether our framework enables the identification of informed trading in the options market by testing its ability to predict "significant corporate news" (SCNs) in the aggregate cross-section of stocks. We construct a rich sample of 30,975 SCNs between 2000 and 2014 by relying on the novel and comprehensive RavenPack news database. We classify SCNs into twelve different categories, which feature a substantial amount of heterogeneity with respect to their announcement characteristics.

We then use two naive measures of informed trading to document that, consistent with our predictions, abnormal activity in options markets starts shortly before scheduled announcements and earlier 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.

We show that measures of informed trading that give greater weight to those options enabling the greatest leverage predict corporate news announcements with a horizon of up to ten days. More precisely, we compute the expected return for each call and put option-day for a hypothetical +10% (-10%) price jump occurring over the next 3 or 10 days. For each stock-day, we then aggregate across all call and put options and compute the ratio of the volume of call (put) options with a high expected return to the total call (put) volume, i.e., the "informed volume ratio". Additionally, we calculate the "informed IV ratio" as the implied volatility of high expected return options divided by that of options with a low expected return. We define options with a high (low) expected return as those in the top decile (all other deciles) of the expected return distribution. We then estimate a multinomial logistic regression to document that the measures of informed trading in call (put) options predict positive (negative) SCNs. The economic significance of this predictability is especially meaningful for a horizon of three trading days. These findings show that our theoretical framework enables us to identify informed trading activity in the options market.

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. Section 4 describes the construction of the sample of significant corporate news events. Section 5 proceeds with an empirical analysis based on the framework, including the prediction of corporate news announcements based on model-implied informed trading measures. We conclude in Section 6.

2. Literature Review

A large body of theoretical literature suggests that frictions and market imperfections lead informed investors to migrate towards the options markets, especially in the presence of capital constraints, as option markets provide more "bang for the buck," i.e., leverage (Boyer and Vorkink, 2014; Ge et al., 2016). 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 exists also a substantial amount of 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 predictability of stock returns by implied volatility and volume in the options markets. Various studies pinpoint informed options trading ahead of analyst recommendations (Kadan et al., 2014), 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., 2014), 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 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 (Xing et al., 2010; Driessen et al., 2012; Jin et al., 2012), put-call parity deviations (Cremers and Weinbaum, 2010), the option-to-stock volume ratios Johnson and So (2012), Driessen et al. (2012), hedging activity by option market makers (Hu, 2014).[5]

There are two key distinctions between the earlier literature and our 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 the 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 costs due significant illiquidity, that characterize the options market. While previous work has been suggestive of this trade-off for the choice of trading strategy (Chakravarty et al., 2004; Ge et al., 2016; Johnson and So, 2012), we explicitly model the option 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.[6]

[5]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.

[6]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."

While previous work has emphasized how frictions affect the choice of trading venue, while we focus on how frictions and the characteristics of private information affect the choice of option strategy, conditional on trading in the options market. As this is the first step towards towards identifying the strategic choice, we focus on the liquidity in the options market as the most important frictions, and we do not take into account price impact, which may lead informed investors to split up their trades and engage into stealth trading (Anand and Sugato, 2007).

Second, we examine the predictability of informed trading activity for significant corporate news announcements (SCN) using multiple events jointly. To the best of our knowledge, virtually all other studies on informed trading in options focus on *one* individual type of event, such as M&A transactions, corporate divestitures, or earnings announcements.[7] Heterogeneity in event characteristics influences the optimal trading decision. Thus, any study that does not take account these cross-sectional differences 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 allow for 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 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

[7] A notable exception is the article by Cremers et al. (2016), who study how the difference between scheduled and unscheduled news affects an informed investor's trading behaviour.

by 15% and the insiders realized an illicit profit of \$268,107, or 575% of their option investment.[8]

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 illegal insider trading vary substantially across the wide spectrum of insider 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 type, quality, and strength of the private signal received by the informed trader. We then validate our framework by showing that measures of informed trading in options expected to attract informed investors can predict corporate news events and stock returns.

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 leverage her private information. The choice of option contracts she trades depends only on her expected return net of transaction costs. We calculate the expected return to 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 bid and observed ask prices of all securities in the

[8] 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.

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. In the Black-Scholes-Merton (BSM) framework (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 denotes the expected change in the stock price between time t_0 and t_1, expressed as a continuous return. Similar to Cremers et al. (2016), we incorporate the run-up in implied volatility ahead of scheduled events based on Dubinsky and Johannes (2006) by defining $\sigma_0 = \sqrt{\sigma^2 + \frac{\sigma_j^2}{T_0}}$. For unscheduled events, $\sigma_0 = \sigma$. σ is the usual implied volatility excluding run-up and σ_j the volatility of the jump anticipated by (uninformed) investors ahead of a scheduled event.[9] Throughout this paper, we follow Cremers et al. (2016) and assume a jump size volatility of $\sigma_j = 0.1$ for scheduled events.

We next account for market frictions by introducing bid-ask spreads α and a minimum option price P_{min} to be consistent with a realistic trading setting by using the following rule: 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 the minimum price. [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 execute the option(s) otherwise. We can thus

[9]Informed trading on anticipated changes in σ can easily be incorporated in a simple extension of our framework. This would distract us, however, from the focus of our study, while having only a marginal impact on predicted trading behavior, if any. Results not reported in this article reveal that while trading on changes in the implied volatility does not offer high expected returns to informed investors, it can still be rational to trade in vega strategies, e.g., straddles, if their signal is very noisy. These results are available upon request.

[10]Beyond market liquidity, bid-ask spreads and minimum prices are driven by the minimum tick size dictated by the Chicago Board Options Exchange (CBOE). Since the year 2000, the minimum tick size for most options equals five cents if 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.

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. As we assume that she 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. Both of these signals may be noisy. Denoting their joint probability density function by $\phi(\kappa, \Delta t)$, the expected return to the option strategy is the probability-weighted average

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

We have established a simple expression for expected returns to informed trading under 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 in. Before examining the expected returns for alternative option strategies and varying private signals, we illustrate the implications of market frictions and noise in the private signal.[11]

The two *market frictions* that we account for are minimum option prices and bid-ask spreads, both of which reflect the limited liquidity in the options market. Figure 1 shows 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 a future price jump of κ=20% in Δ_t=3 days, without any uncertainty about the magnitude of the jump or about the timing of the

[11]The informed investor's problem presented in this paper cannot be solved analytically. All of our results are based on numerical solutions.

news announcement, i.e., σ_κ=0, $\sigma_{\Delta t}$=0. Furthermore, S_0=10, r=0.03, and σ=0.4. The upper two 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! The introduction of market frictions highlights that it is impossible to generate such enormous returns in a more realistic setting. The lines in the two lower graphs that are labelled "market frictions" assume a bid-ask spread α of \$0.05 and a minimum price of \$0.10, all other parameters remaining equal. In addition to market frictions, increased option prices ahead of scheduled announcements can reduce the leverage investors can attain in the options market. The lines labelled "scheduled" assume a run-up in implied volatility ahead of the event, modeled following Dubinsky and Johannes (2006). Even without this run-up, market frictions reduce maximum expected returns to less than 2,000%, clearly, a more realistic value.[12]

The illustrative 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 realistically obtain in option markets. We now turn to discuss the magnitudes of these two market frictions. Panel A of Figure 2 plots the evolution of the average (dotted line) and median (dashed line) 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 contracts and non-negative bid-ask spreads. Circles mark call options, crosses mark put options. Median (average) spreads reduced substantially over time, from 25% (23-24%) in 1996 to 5% (10-11%) in 2010, with a spike in 2008.

An option's minimum offer price is given by its minimum tick size. While this implies that DOTM options may be traded at five cents – or since 2007 even at one cent if they are part of the Penny Pilot

[12]For instance, in insider trading cases documented by the SEC, insider trading around M&A announcements commonly produces returns of around 1,300%. Descriptive statistics about illegal insider trades documented by the SEC are not included in this paper but are available upon request.

Program – the minimum offer prices reported in the OptionMetrics database are higher 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. 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 in the years 2008 to 2010 can be ascribed to the exceptional period of the financial crisis. Most of the time, however, as illustrated by the first percentile of option prices below three dollars, empirically 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 risk aversion, informed trading, adverse selection, or other factors such as inventory costs and illiquidity. Writing DOTM options offers little return, but a potentially tremendous 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 prices. 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 increasing 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 in even 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

[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 (2003).

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. We rationalize why in most cases it is optimal to trade in options that are only slightly OTM. These findings are consistent with observed illegal insider trades, such as the previously highlighted trade by the Flanagans, who purchased put options with a strike price of USD 47.5, when the underlying was trading between 47 and 48 USD. The findings are also consistent with the comments made by Chakravarty et al. (2004) and Ge et al. (2016), who argue that while OTM options appear to offer an informed trader the highest leverage, informed trading is driven to ATM or even ITM options when these are cheap to trade relative to OTM options. Our contribution is to explicitly formalize the strategic behavior of informed behaviors, which is implicit in the choice of option strike and maturity. Importantly, we are able to generate a trade-off without the need for investor risk aversion or price impact.

Though important, the effect of uncertainty or *noise* in private information, i.e., uncertainty about κ and Δt, on expected returns 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 κ=20% in Δ_t=30 days. Bid-ask spreads equal \$0.05 and the minimum price is \$0.10. Furthermore, S_0=10, r=0.03, and σ=0.4. The left (right) graph 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. Bid-ask spreads equal \$0.05 and minimum price \$0.10. 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. Thus, higher uncertainty about the timing of public news announcement reduces expected returns and incentivizes the investor to choose longer maturity options and deeper OTM options compared to the benchmark case, without any timing uncertainty. On the other hand, higher uncertainty about the magnitude of the announcement *increases* the expected returns and 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 upper two 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 time to announcement, Δt (the expected jump in stock prices, κ).[14] 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 derive from our framework.[15] We refer to the upper, middle, and lower graphs in Figures 4 and 5 as Figures 4a, 4b, 4c, and 5a, 5b, 5c. The first set of implications is related to the strike price maximizing expected returns (K^{max}). The expected price jump of the stock following a news announcement, κ is a key determinant of expected returns (Figure 5c). Naturally, the lower the price reaction, i.e., κ, the higher the leverage an investor needs to implement in order to yield the same return (Figure 5a). Yet, 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 for anticipated jumps of up to 10%. Furthermore, the kink in the function implies that once κ reached a certain threshold level, informed investors will only marginally increase their leverage for an additional increase in

[14]Expected returns are computed according to Equation 4.

[15]Of course, the plots are restricted to a limited number of parameter combinations. However, the main takeaways discussed in this section are robust to changes in parameters. We can provide additional results upon request.

announcement returns. Thus, DOTM options do not always maximize returns to informed trading in the presence of market friction. The kink is due to the market frictions incorporated in our framework. Their impact on informed trading is most pronounced for options with a low theoretical value, for instance options with low implied volatility and a short time to maturity. Amongst others, this explains why K^{max} shown in Figure 4a is lower for options with a short than for those with a medium time to maturity.

The second set of implications is related to the time to maturity of the option maximizing expected returns (T^{max}). The longer the period between the time an informed investor trades and the time of the anticipated announcement Δt, the longer will be the contract maturity of the return-maximizing option (Figure 4b). A similar implication obtains if there is a high uncertainty around the announcement date, in other words, if the precision of the signal is weak. In such cases, an informed trader will choose longer dated options to avoid 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 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 section of this paper. Figures A1 and A2 illustrate that expected returns to informed trading in call options are lower 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 options can be created by trading the underlying together with ITM or DITM options, which are substantially less affected by market frictions.[16] However, trading synthetic call options requires an investor to partly finance his positions by borrowing at the risk free rate and is thus likely restricted to sophisticated investors.[17] Accordingly, 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. Finally, Figures A3 and A4 demonstrate

[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 irrelevant to the pricing of ITM options.

[17]We ignore 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. While these can be incorporated in our framework, this is beyond the scope of our analysis. In brief, any significant margin requirement will substantially reduce an investor's leverage and thus, heavily reduce returns to informed trading.

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. Researchers, investors, and regulators trying to pinpoint informed trading can account for this variation using a framework as proposed in this study.

4. Constructing a Sample of Significant Corporate News

We define SCNs as news events that we can link to extreme price movements (EPMs) of stocks. Using a diverse sample of SCNs instead of one specific event, such as the announcement of M&As or earnings news, features several advantages for the study of informed trading. First, using different types of corporate events allows us to exploit the significant cross-sectional differences in terms of announcement effects and timing uncertainty, which increases the opportunity set of strategic behaviors by informed investors, and therefore allows for a richer analysis. In other words, we can exploit the heterogeneity in announcement characteristics to understand more granularly *how* informed investors trade in the options market. Indeed, 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 as a starting point yields a sample that is larger and comprises economically more meaningful opportunities of informed trading. This increases the statistical power of the analysis. Third, we have access to the millisecond timestamp of intraday news announcements. Therefore, we can link EPMs more precisely to SCNs, thereby avoiding any bias that may arise because of news leakage. Including events with news leakage would upward bias measures of informed trading activity. In the following, we first describe how we identify EPMs, and then outline how we associate them with news events to finally obtain a sample of SCNs.

[18]Our framework also allows 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.

4.1. Identification of EPMs

Our sample period begins in 2000, the first year for which information from RavenPack, our primary news data set, is available, and ends in 2014. To obtain a list of EPMs, we collect information on stock returns and prices, security type, the number of shares outstanding, and trading volume from the Center for Research in Security Prices (CRSP). We retain all common stocks (sharecode 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 value (the market value as of the previous trading day) below ten million USD or a lagged stock price below five dollars as such securities are often illiquid and exhibit higher levels of market microstructure noise. Furthermore, we delete all stocks for which not a single news headline is reported in the RavenPack news database during our sample period.

We obtain a list of 138,121 EPMs from the remaining 11.4 million daily observations. 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. We additionally require the availability of stock market data for at least 189 of the past 252 trading days.[19] In sum, our definition of EPMs is most closely related to the one used by Brogaard et al. (2015). They define EPMs at ten-second intervals as jumps identified by the approach proposed in Lee and Mykland (2012), which is more suitable for such high frequencies than the Lee and Mykland (2008) method used in this paper.[20] In a final step, we match this list of EPMs to OptionMetrics for option price and volume information, and to Compustat for balance sheet information and company characteristics. As we are interested in informed trading in option markets, we exclude all EPMs of stocks without options, and we require a minimum of one option trade during the 63 trading days prior to the EPM. We further delete observations which we cannot match to Compustat. Our final sample includes 83,653 EPMs – 50.9 percent

[19]For details on the Lee and Mykland (2008) approach for jump detection, see Appendix A. Amongst others, the method is used by Bradley et al. (2014) to examine the impact of analyst recommendations on stock prices.

[20]In robustness checks, they alternatively label ten-second returns with a magnitude in the 99.99th percentile.

of which are negative – observed for 4,131 securities on 3,761 different dates between 2000 and 2014.

4.2. Associating EPMs with News

Early doubts cast on the relevance of news for asset pricing have recently been rectified.[21] Boudoukh et al. (2013) use textual analysis to demonstrate that an improved identification of relevant news stories results in a tighter link between stock prices and news. Bradley et al. (2014) document that after correcting the time stamps of analyst recommendations, these 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 what news story (most likely) induces an EPM is important for our study, as the type of news can affect which informed trading strategy maximizes expected returns. In Section 3, we showed that the return-maximizing options trading strategy depends on the timing uncertainty and the magnitude of the stock price reaction of the future announcement. Both these parameters vary across different types of events. For example, the timing uncertainty is zero for scheduled events, such as earnings announcements, but it can be high for unscheduled events. The direction and magnitude of an announcement return may be easier to predict for an M&A deal than for a change of a senior management position.

Our primary source for news data is the RavenPack News Analytics DowJones Edition. RavenPack employs textual analysis to identify companies, news categories, and news relevance in Dow Jones news articles and Press Releases published since the year 2000. Each news story has a milisecond precise time stamp. Over our sample period, the data includes 7.98 million corporate news stories for which a US based firm and a category were identified. 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 which we are not able to identify in the CRSP and Compustat database. Finally, we delete all news about the stock, including articles on stock gains and losses,

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

order imbalance, and technical analysis, as these may have been caused by an EPM rather than being the reason for the EPM. These criteria result in 3.3 million news stories.

Especially large firms appear in the news frequently and not all news stories that co-occur with EPMs caused them. To associate specific news stories 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 RavenPack news categories. The coefficients obtained from these regressions are the log of the odds-ratio, which has a straightforward interpretation. For coefficient i, it indicates by what factor the odds of observing an EPM changes if news are reported (only) in category i. For instance, on a day with no other reported news, the odds of observing an EPM increase by a factor of 3.14 if news are published that earnings per shares are above expectations.

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 news in that category were reported for the stock between 4 p.m. on the previous trading date and 4 p.m. of 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.

Tables 1 and 2 only report statistics for all 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. Overall, results are intuitively appealing. 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. In line with Bradley et al. (2014), analyst related news are important determinants of EPMs. We use these results to associate news and EPMs. First, we assume that only news 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. *We define an SCN as an EPM that we can explain by a news headline using this approach.*

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 an earnings announcement – and unscheduled SCNs that do not occur with earnings. This matters in our analysis, as there is a run-up in implied volatilities ahead of scheduled SCNs. Similar to Cremers et al. (2016), we assume only news published on earnings announcement days to be scheduled.[22]

Table 3 reports descriptive statistics for the sample of positive and negative SCNs for each news category. Not surprisingly, news about a firm being acquired are associated with the highest announcement returns, and almost always induce a significant amount of trading activity. Negative news about drug developments are comparable, even though the subsample is substantially smaller, i.e., 103 SCNs relative to 780 for targets in merger/takeover deals. EPMs which we cannot associate to news using the above approach (and which we thus do not classify as SCNs) often do not occur on days with high trading volume, 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 the subsequent analysis, as such events may be noise that does not enable informed trading.

[22]The authors assume only earnings news to be scheduled. However, many other news, for instance related to financing, product releases etc are published on earnings announcement dates. Investors trading in options ahead of these will also face the pre-earnings run-up in implied volatilities, which affects expected returns. We therefore consider all news released on earnings announcement dates as scheduled.

5. Empirical Analysis

Our objective is to exploit our conceptual framework of informed trading to improve the identification of unusual trading activity in the options market. In the subsequent empirical analysis, we employ it to quantify expected returns to trading on significant corporate news (SCNs), to explain trading patterns prior to these, and to predict such news.

5.1. Expected Returns Attainable by Informed Trading on SCNs

We exploit the significant heterogeneity in event characteristics to understand how informed investors can leverage private information that differs in terms of type and precision. In reality, and different from our previous numerical analysis, the choice of options investors can trade is limited. This section aims to quantify expected returns to informed trading that can be attained given this restriction. To do so, we examine expected returns to hypothetical informed trading on SCNs. 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. In the subsequent section, we proceed to a more systematic analysis that computes the informed trading measure on a rolling basis, allowing for different trading horizons.

Table 4 reports expected returns to call (put) option trading around positive (negative) SCNs for each news category included in our sample. As indicated, expected returns are computed using 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 is set equal to the average return in each category. Similarly, the signal uncertainty is computed as the standard deviation of the return. These statistics are reported in Table 3.

Both the median and 90th percentile of expected returns to informed trading are substantially higher for events with stronger stock price reactions, such as M&As, for example. In most instances, trading ahead of scheduled news enables a higher leverage. This is consistent with the high expected returns earned from trading in short-dated options traded 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 limited benefits of trading short-term options is due to the limited availability of short-term options. 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 informed investors can trade in. For instance, the median expected returns to informed trading ahead of positive scheduled and unscheduled analyst opinions are equal to 120.2 and 103.8 percent, respectively. The difference between the subsamples of scheduled and unscheduled events is larger for the 90th percentile. While the difference between the two subsamples is statistically significant, its economic significance is lower than the one in our numerical analysis given the constrained set of options available for trading.

5.2. Informed Trading Prior to SCNs

The sample of SCNs is restricted to events that jointly feature a significant price movement in the underlying stock and the announcement of news. Using stock price movements without news announcements is redundant, as there cannot be private information about news by default. Furthermore, focusing on large stock price reactions insures that the benefits from informed trading are economically meaningful. Before we validate that the informed trading measures based on the framework that identifies the optimal trading strategy to informed investors, we provide supporting evidence that SCNs are, indeed, preceded by informed trading.

Figure 6 plots measures of directional trading activity ahead of positive and negative events, together with the difference between the two subsamples. The two measures of directional trading activity are the ratio of call volume to total option volume and the implied volatility of OTM call options to that of OTM put options. These measures are certainly very naive measures of informed trading. However, the evidence of informed options trading ahead of news is well documented in recent studies [23] Amongst others, these measures do not capture whether option positions are closed or opened, and they are partly based on datasets not used in this study. Evidence for unusual trading activity based on our simple measures can be expected to be more pronounced for more informative measures.

As expected, we observe an increase in directional trading activity ahead of SCNs. The ratio of call to total option volume drops substantially ahead of negative news, meaning that the relative amount of traded put options, enabling bets on negative price movements, increases. This pattern cannot be observed ahead of positive events, ahead of which there is no significant change in the volume-based measure. The difference in the average volume measure between positive and negative subsamples increases substantially during the days before negative news. The lower two panels of Figure 6 provide additional support for the assertion that informed trading takes place ahead of SCNs. It shows that the average ratio of OTM call to OTM put implied volatility does not differ significantly between the subsamples of positive and negative SCNs until around thirty to forty trading days ahead of the SCN. During the last weeks preceding the event, however, the measure increases significantly for the subsample of positive SCNs. This indicates that the pricing of call options, on average, increases relative to that of put options ahead of positive news. In contrast, the measure slightly decreases for the subsample of negative events, meaning that put options become relatively more expensive ahead of negative events.

In a next step, we examine whether the above patterns are significantly different between the subsample of scheduled and unscheduled SCNs, and whether the differences are consistent with our expectations. We classify any event as scheduled if it falls on a quarterly earnings announcement date. Figure 7 plots the difference between the average directional trading measures ahead of announcements with positive and negative stock price reactions. The two measures of directional trading activity correspond to those plotted in Figure 6. We observe that the previously documented patterns exist in both subsamples. More importantly,

[23] For instance, see Pan and Poteshman (2006), Roll et al. (2010), Johnson and So (2012), and Ge et al. (2016).

we document that the increase in the difference of both measures between the subsample of positive and negative events increases sharply on the one to three days preceding a scheduled event. In contrast, this increase stretches over a longer time period ahead of unscheduled news. These observations are consistent with our prediction that informed investors trade (i) briefly ahead of scheduled events – despite potential run-ups in implied volatility, and (ii) further ahead of unscheduled events with uncertain timing.

5.3. Predicting SCNs

The empirical evidence presented previously supports the notion that there is directional informed trading ahead of SCNs, and that investors trade closer to the announcement date if news are scheduled, and earlier if the announcements is unscheduled. Once concern may be that we are picking up uninformed speculation. For instance, speculators may bet that firms approaching financial distress declare bankruptcy by acquiring put options. As our sample includes those observations for which an actual news event, such as a bankruptcy, occurred, our previous results may be biased. In the following subsection, we address this concern by predicting SCNs in the aggregate cross-section of stocks, using the framework that identifies the optimal trading strategy in options following noisy signals about upcoming announcements.

Table 5 reports results from multinomial logistic regressions of a categorical variable that flags stock-days on which there is (i) no news, (ii) negative news, or (iii) positive news over the next 1-3 days (columns 1 and 2), over the next 1-10 days (columns 3 and 4). This variable is regressed on explanatory variables capturing trading activity in call and put options offering high expected returns to informed traders. The reference case is the one without news, coefficients for negative (positive) events are reported in columns 1 and 3 (2 and 4). 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 10mio with positive trading volume and for which contract specific call and put volume data from are available from the OptionMetrics database.

As opposed to the previous naive analysis, the explanatory variables in this exercise are implied from our theoretical framework. Relative call (put) volume is defined as the volume of call (put) options with high expected returns to informed trading scaled by total call (put) volume. Expected returns are computed using Equation 4 for call and put options for a private signal about a price jump of +10% and -10% anticipated for the next day (columns 1 and 2) or in ten days from now (columns 3 and 4). High expected returns are expected returns in the highest decile of the pooled distribution. Similarly, the relative call (put) implied volatility (Rel. Call IV or Rel. Put IV) is computed as the average implied volatility of call (put) options with a high expected return divided by that of all other options. On stock-days for which information about implied volatilities is missing, even though options were traded, we set the value of Rel. Call IV (Rel. Call IV) equal to the average value of the pooled sample.

We find that the measures of informed trading that overweight the volume or prices of those options that are return-maximizing to informed investors significantly predict negative and positive SCNs in the aggregate cross-section. Consistent with the evidence presented previously, we show that the put option volume ratio predicts negative corporate news, while the call option IV ratio predicts positive corporate news. Using this approach, we can predict positive and negative news in the short term (over the next three trading days) and even over the next ten trading days.[24] These results cannot be explained by a potential sample selection bias and indicate that our theoretical framework enables us to identify informed trading activity in the options market.

6. Conclusion

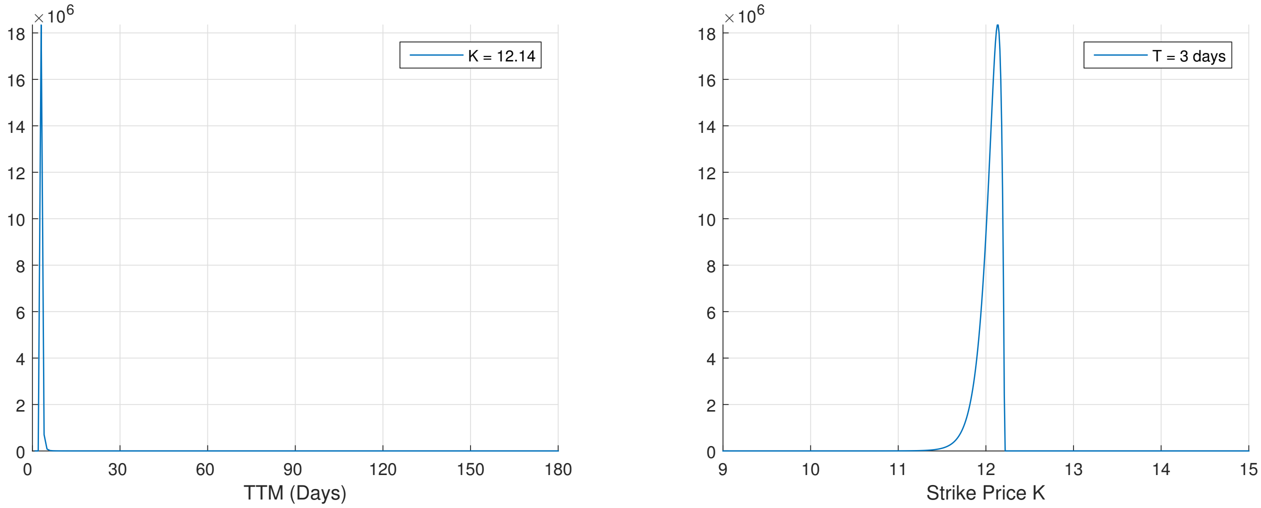
In this paper, we propose a framework for describing *how* informed investors can leverage their private information in the options market. Informed investors receive private signals which include information about the *timing* of future news events, and their *impact on stock prices*. Since this information can be uncertain, the signal's quality influences the choice of option strategy as well as the returns to informed

[24]The negative coefficient of the call volume measure in the fourth column can be explained with the fact that we compute the ten days measure assuming that events are expected to occur in ten days, whereas the dependent variable in our regression flags events over the next ten rather than in ten days.

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 behaviour of informed investors, and introduces a trade-off without the need for modeling risk aversion or more complex price impact frictions. Amongst others, the framework predicts that informed investors would often trade ATM rather than OTM options.

In our empirical analysis, we use the comprehensive RavenPack news database to explain extreme price movements by news stories and create a sample of 30,975 significant corporate news from twelve different news categories, reported over the years 2000-2014. We then validate our framework in two main ways. First, we document that naive measures of directional trading in the options market behave differently ahead of positive versus negative news events, which confirms the presence of informed trading. Patterns in this suspicious trading activity are consistent with the trading behavior of informed investors predicted by our theoretical framework. Second, we show that measures capturing trading activity in call (put) options with high expected returns computed using our framework predict significant positive (negative) corporate news in the aggregate cross-section of stocks. 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 (i) regulators for the detection of suspect trading activity, and to (ii) private 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

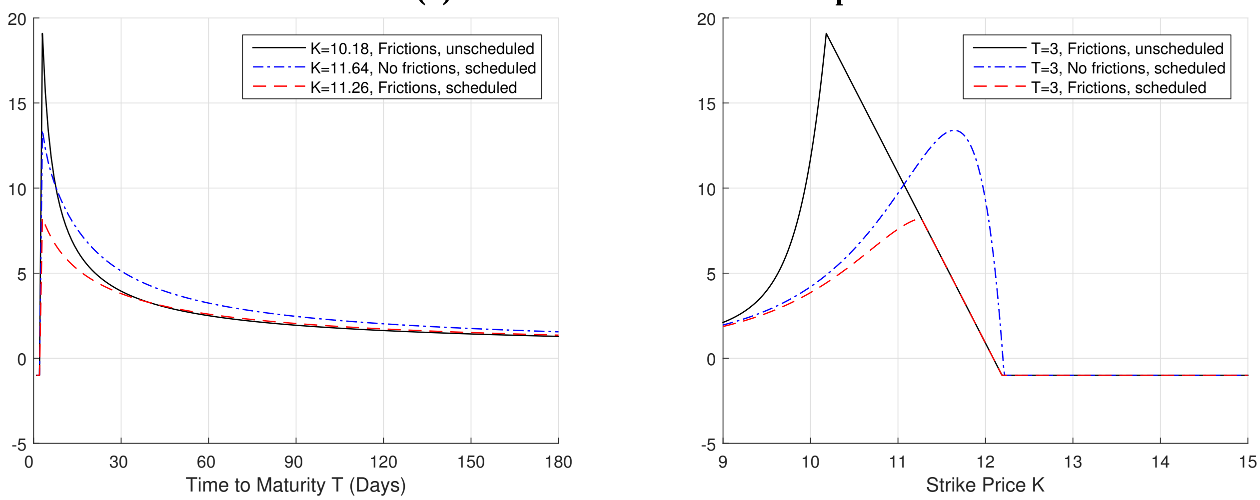
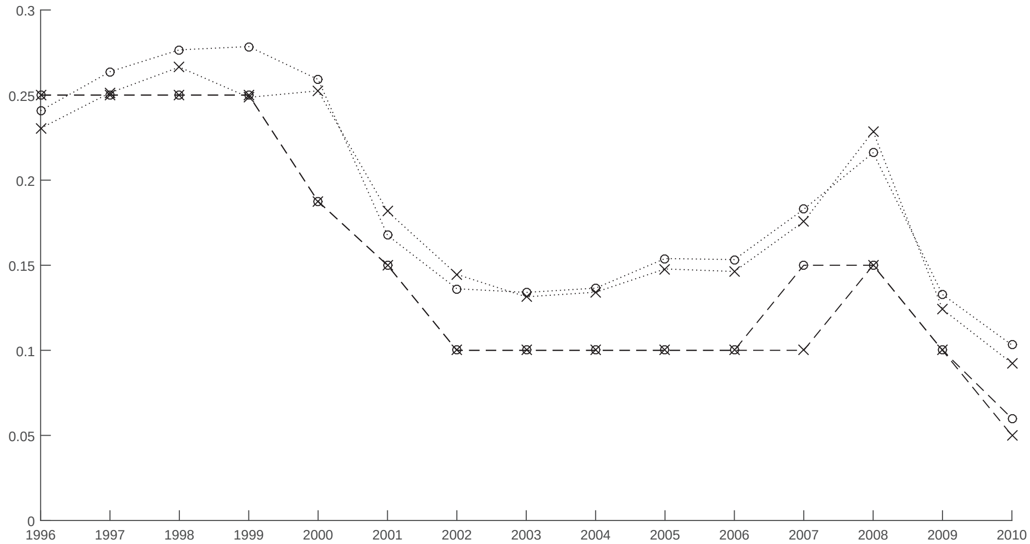
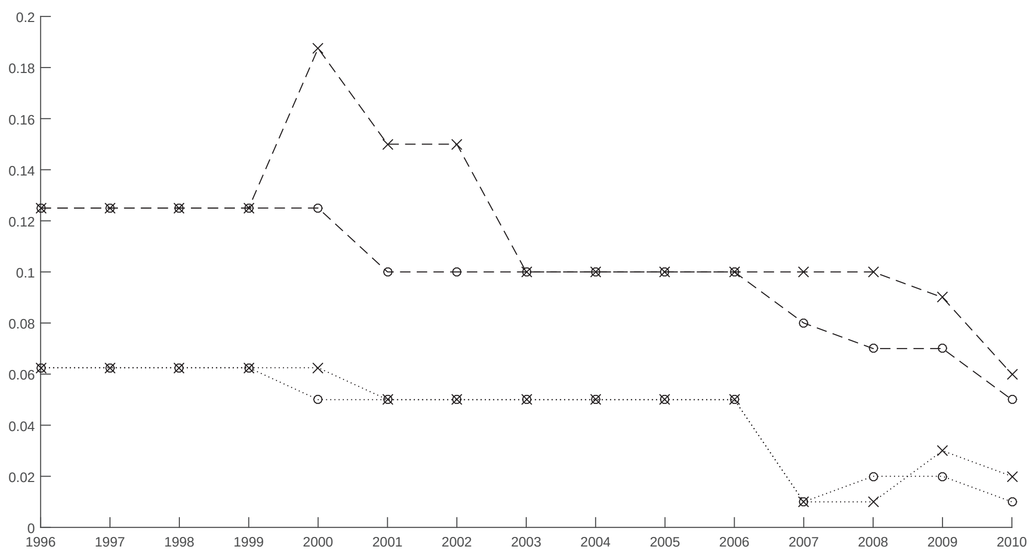


Figure 1: The Effect of Market Frictions and Run-Ups in Implied Volatility on Expected Returns:
The graphs in this figure plot expected returns to informed trading in call options computed using the BSM framework. The upper two graphs are based on the assumption that there are neither market frictions nor a run-up in implied volatility . The bid-ask spread and the minimum price are equal to zero. The lines in the two lower graphs that are labelled "market 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 (κ=.2, Δ_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. 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.

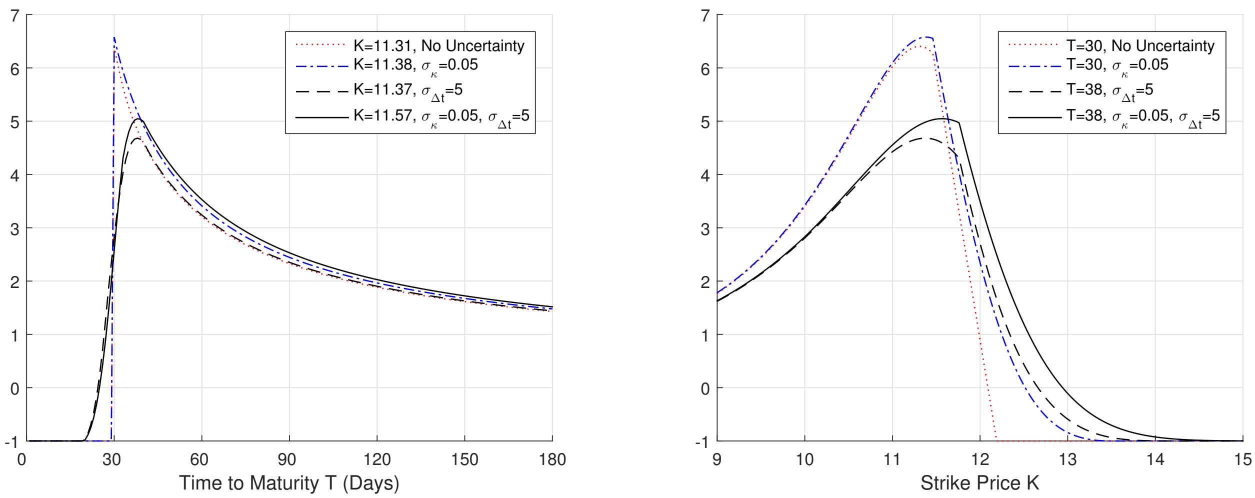


Figure 3: The Effect of Noise in the Private Signal on Expected Returns:
The graphs in this figure plot expected returns to informed trading in call options computed using the BSM framework. The left (right) graph plots expected returns as a function of the time to maturity (strike price) of the option. On each side, the 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 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, κ=.2, Δ_t=30/360, S_0=10, r=.03, σ=.4.

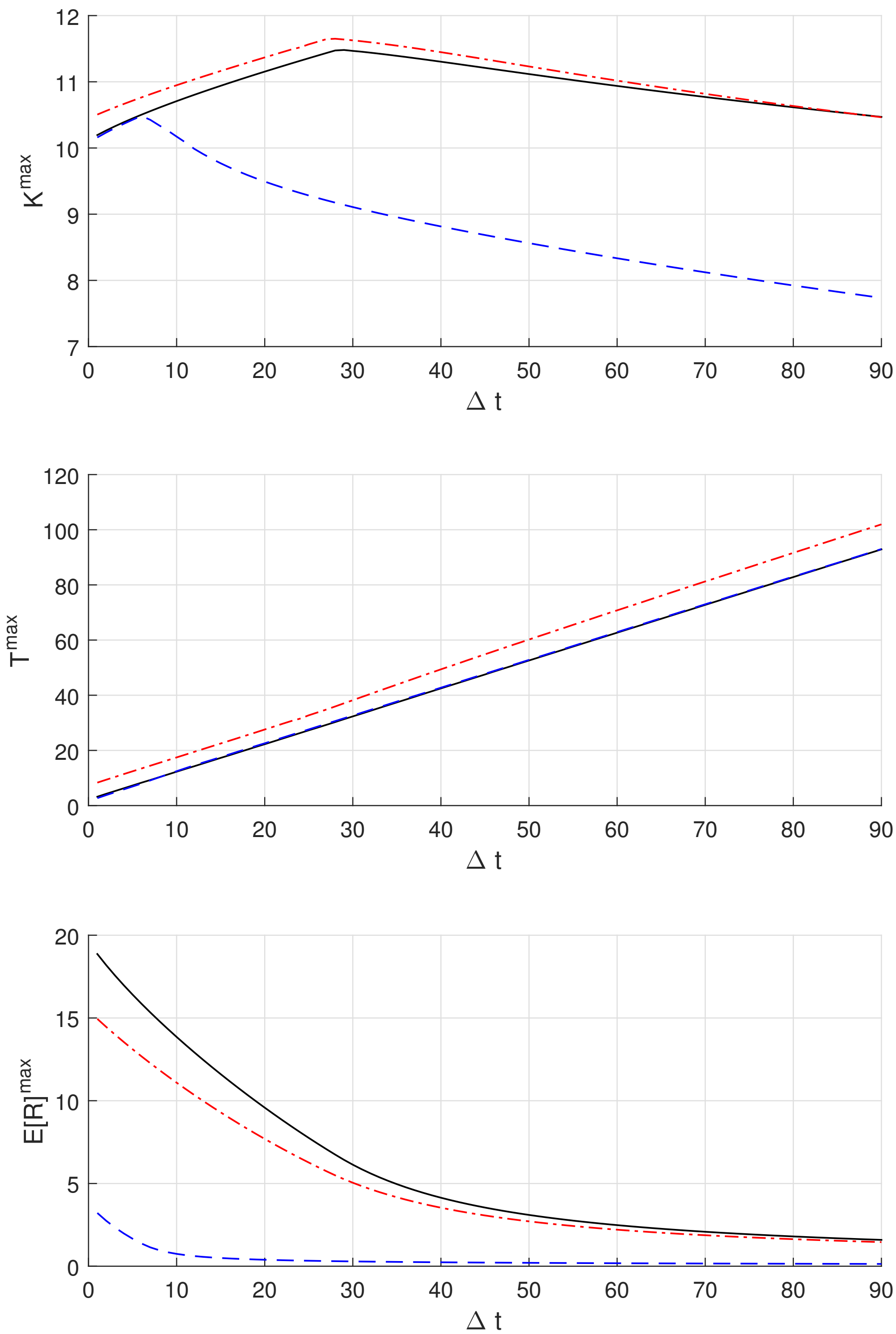


Figure 4: Maximizing Expected Returns to Informed Trading in *Call Options* depending on Δt:
The upper two graphs in this figure plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in call options ahead of a positive event as a function of the time to announcement Δt. The lower graph displays the maximum expected return $E[R]^{max}$. Results are shown for three parameter sets.
(1) black solid line: $\sigma_{\Delta t} = 1\ day$, $\kappa = 0.2$, $\sigma_\kappa 0.05$
(2) blue dashed line: $\sigma_{\Delta t} = 1\ day$, $\kappa = 0.05$, $\sigma_\kappa 0.05$
(3) red dash-dotted line: $\sigma_{\Delta t} = 5\ days$, $\kappa = 0.2$, $\sigma_\kappa 0.05$
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.

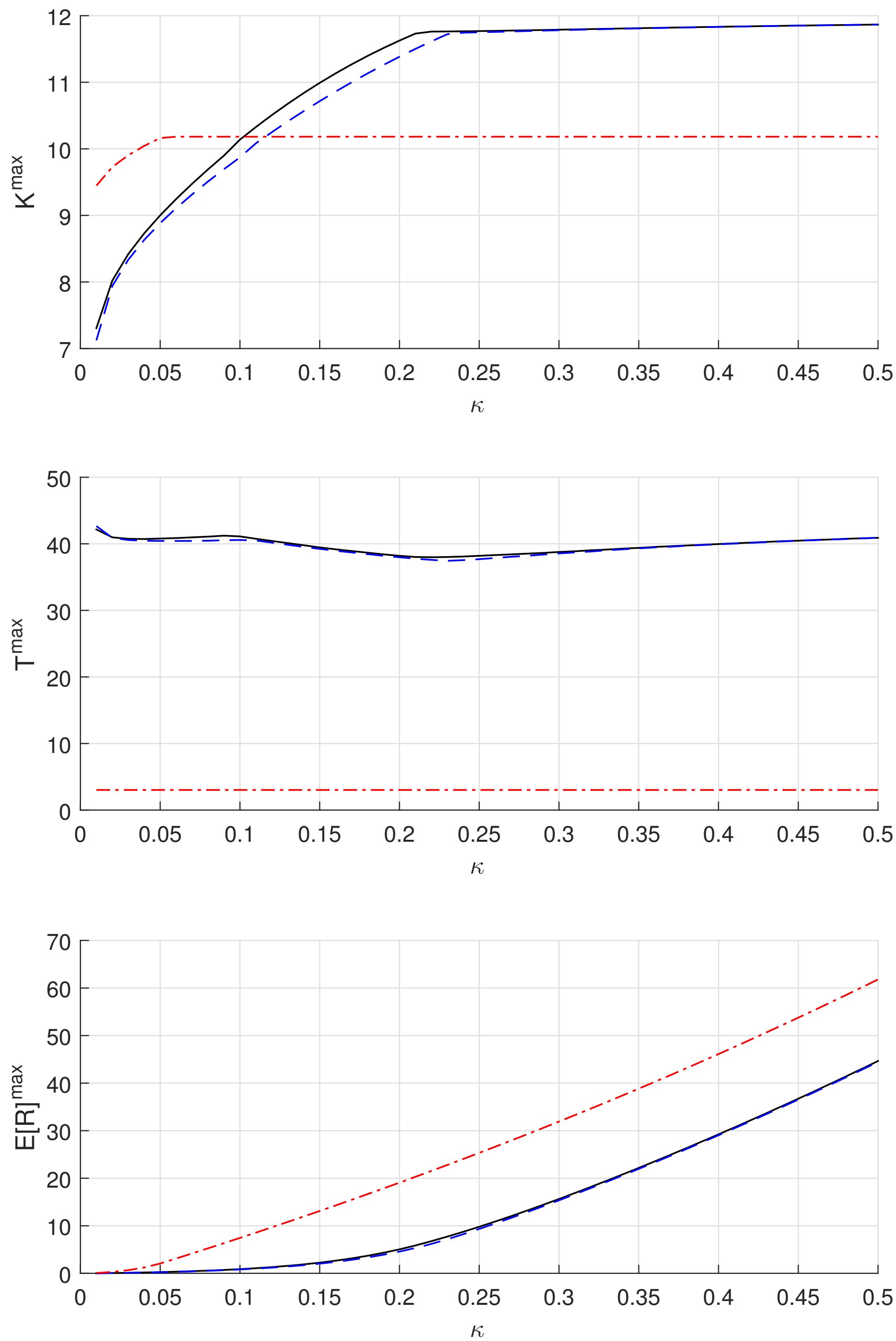


Figure 5: Maximizing Expected Returns to Informed Trading in *Call Options* depending on κ:
The upper two graphs in this figure plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in call options ahead of a positive event as a function of the expected jump in stock prices, κ. The lower graph displays the maximum expected return $E[R]^{max}$. Results are shown for three parameter sets.
(1) black solid line: $\Delta t = 30 days$, $\sigma_{\Delta t} = 5\ days$, $\sigma_\kappa 0.05$
(2) blue dashed line: $\Delta t = 30 days$, $\sigma_{\Delta t} = 5\ days$, $\sigma_\kappa 0.005$
(3) red dash-dotted line: $\Delta t = 3 days$, $\sigma_{\Delta t} = 0\ days$, $\sigma_\kappa 0.005$
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.

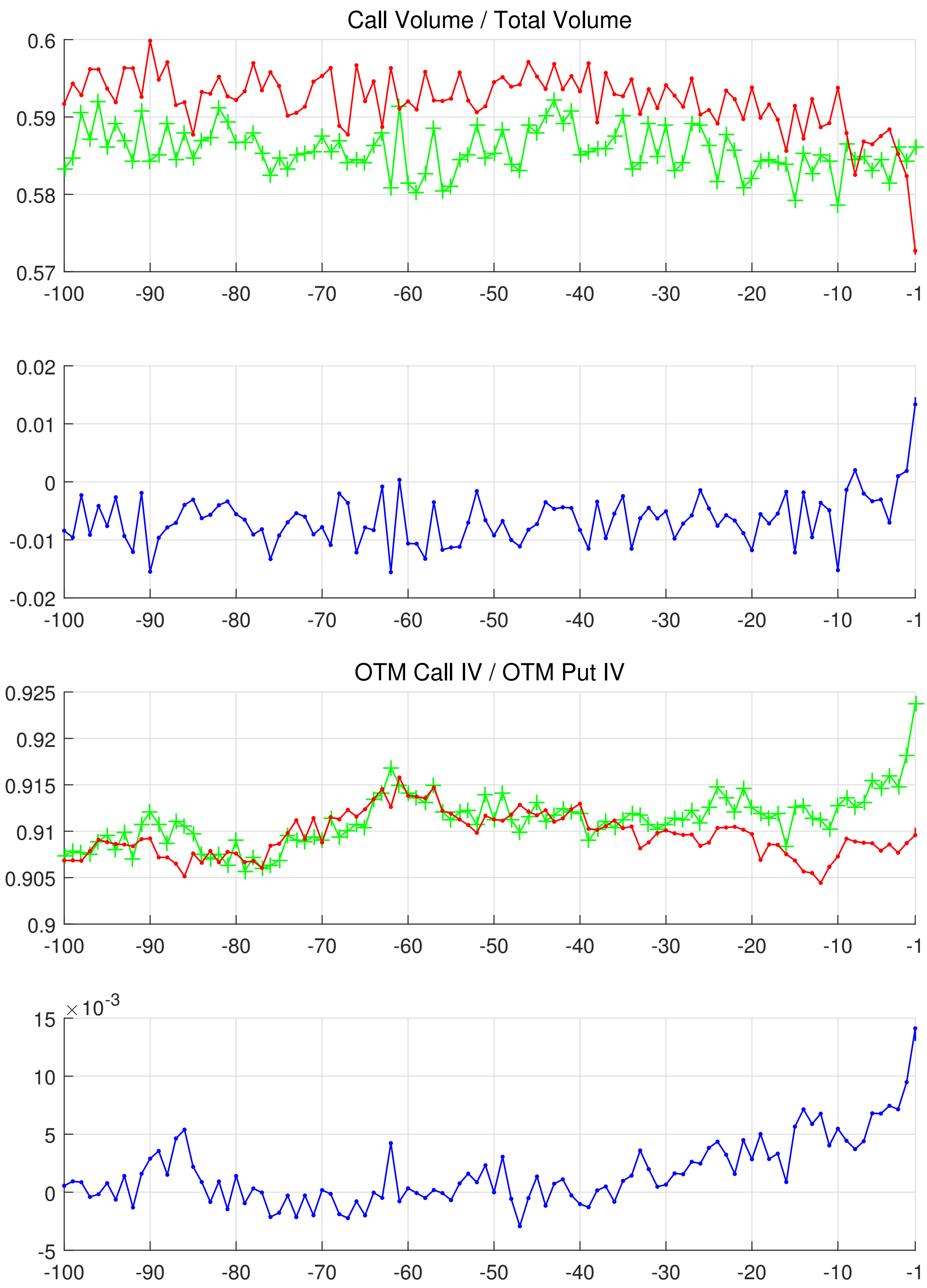


Figure 6: Suspicious Trading Activity ahead of News Events:

This figure plots the average directional trading activity ahead of positive and negative events (first and third graph), as well as the difference between the two (second and fourth graph). The two measures of directional trading activity are the ratio of call volume to total option volume (first two graphs) and the implied volatility of OTM call options to that of OTM put options (last two graphs). The X-axis shows trading days relative to the event and does not include the day of the event itself.

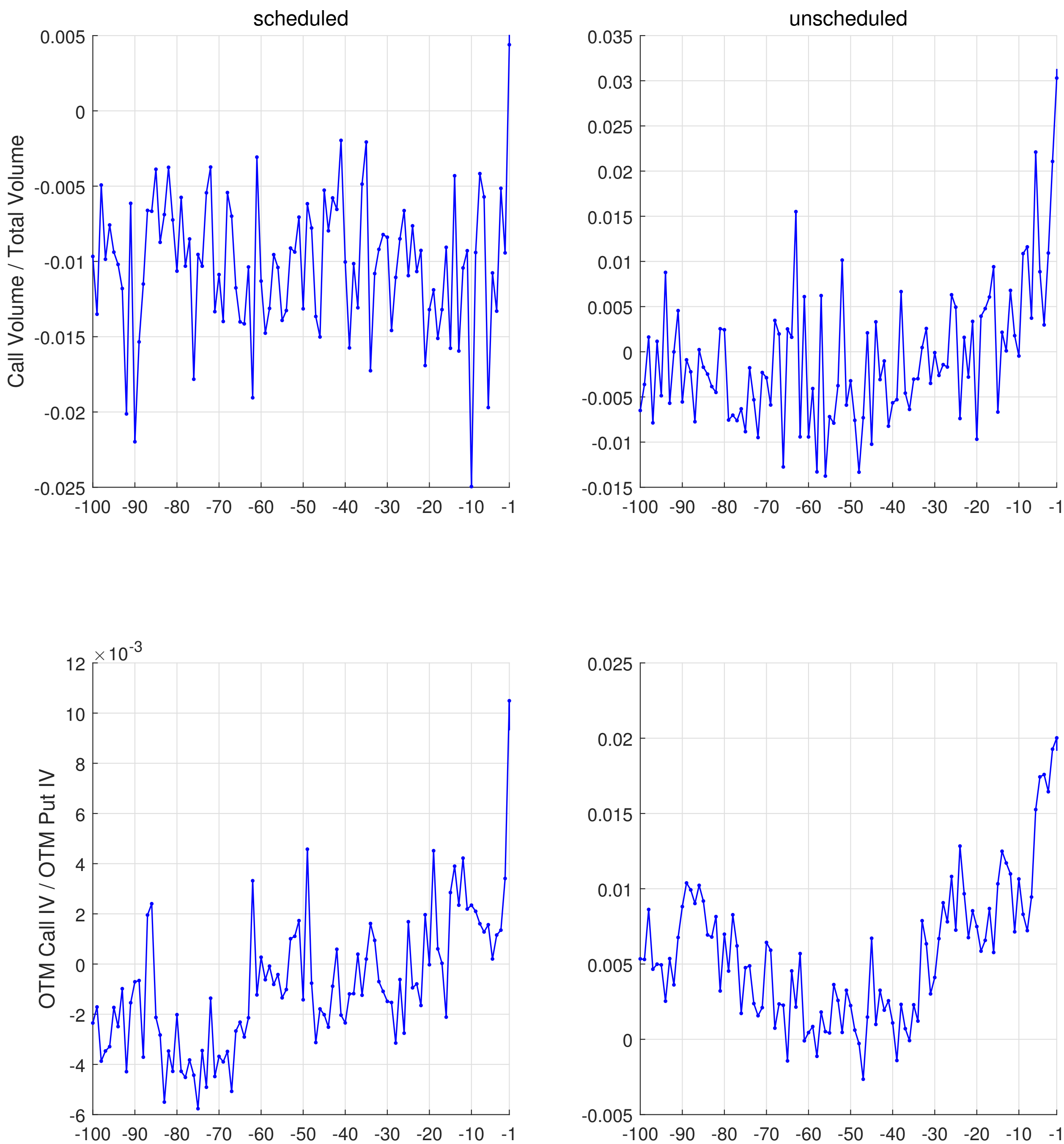


Figure 7: Suspicious Trading Activity ahead of Scheduled and Unscheduled Events:
This figure plots the difference between the average directional trading activity ahead of positive and negative events. The two measures of directional trading activity are the ratio of call volume to total option volume (upper graphs) and the implied volatility of OTM call options to that of OTM put options (lower graphs). The left (right) graphs plot these measures for the subsample of scheduled (unscheduled) news, which we define as any news (not) published at the time of a quarterly earnings announcement. 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 Ravepack 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 date and 4pm of the given day. Of 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 Ravepack 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 date and 4pm of the given day. Of 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
Acquisition (Target)	0	0.00	0.00	0.00	0.00	0.00
Analyst	5,732	53.02	−15.74	−12.54	11.17	94.78
Business Contract	0	0.00	0.00	0.00	0.00	0.00
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
Dividends	0	0.00	0.00	0.00	0.00	0.00
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 medians ("50") and the 90th percentile ("90") of expected returns to informed trading in call (put) options ahead of positive (negative) SCNs for each news category covered in our sample. Expected returns are computed using 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	
	50	90	50	90
Acquisition (Acquirer)	114.72	472.63	92.53	318.60
Acquisition (Target)	293.14	1,289.50	319.90	1,402.91
Analyst	120.15	520.21	103.83	445.07
Business Contract	112.41	574.18	97.78	481.05
Credit Rating	106.90	472.10	141.73	647.44
Drug & Product Development	173.20	1,217.68	124.11	710.38
Dividends	83.71	274.23	67.16	269.00
Earnings	110.95	421.29		
Financing	113.57	506.83	77.25	322.79
Guidance	139.53	557.57	95.17	403.54
Management Change	109.85	666.02	91.08	463.08
Merger	151.56	522.61	99.59	596.22
Others	155.92	619.20	112.79	669.61
ALL	115.86	465.54	110.68	553.15

Negative News	Scheduled		Unscheduled	
	50	90	50	90
Acquisition (Acquirer)	100.39	318.44	60.94	269.77
Analyst	118.96	497.72	95.18	463.94
Credit Rating	83.61	564.13	65.84	396.46
Drug & Product Development	69.27	233.43	88.80	367.66
Earnings	101.63	363.57		
Financing	37.60	152.56	45.99	177.87
Guidance	149.81	688.08	84.24	398.10
Management Change	125.38	481.19	87.82	465.75
Merger	46.88	308.97	105.46	417.90
Others	126.48	920.75	75.25	392.01
ALL	111.29	442.55	86.72	425.46

Table 5: *Predicting Significant News.*
This table reports results from multinomial logistic regressions of an indicator whether (i) no, (ii) a negative, or (iii) a positive news event takes places over the next 1-3 days (columns 1 and 2) or the next 1-10 days (columns 3 and 4) on explanatory variables capturing trading activity in call and put options offering high expected returns to informed traders. The reference case is the one without news, coefficients for negative (positive) events are reported in columns 1 and 3 (2 and 4). 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 10mio with positive trading volume and for which contract specific call and put volume data from are available from the OptionMetrics database. Relative call (put) volume is defined as the volume of 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 price jump of +10% and -10% anticipated for the next day (columns 1 and 2) or in ten days from now (columns 3 and 4). High expected returns returns are expected returns in the highest decile of the pooled distribution. Similarly, the relative call (put) implied volatility (Rel. Call IV or Rel. Put IV) is computed as the average implied volatility of call (put) options with high a expected return divided by that of all other options. On stock-days for which information about implied volatilities is missing even though options were traded, we set the value of Rel. Call IV (Rel. Call IV) equal to the average value of the pooled sample. Standard errors are reported in parentheses.

	Short-Term		Mid-Term	
	Neg.	Pos.	Neg.	Pos.
(Intercept)	-5.46^{a}	-5.76^{a}	-4.31^{a}	-4.97^{a}
	(0.24)	(0.24)	(0.16)	(0.15)
Rel. Call Vlm	0.00	−0.16	0.06	-0.16^{a}
	(0.10)	(0.11)	(0.05)	(0.05)
Rel. Put Vlm	0.33^{a}	0.06	0.19^{a}	0.03
	(0.11)	(0.12)	(0.05)	(0.05)
Rel. Call IV	−0.04	0.34^{b}	0.22	0.68^{a}
	(0.20)	(0.18)	(0.15)	(0.14)
Rel. Put IV	−0.06	−0.04	-0.25^{c}	0.10
	(0.19)	(0.20)	(0.14)	(0.13)

^{a,b,c} Statistically significant at the one, five, or ten percent level, respectively.

Appendix

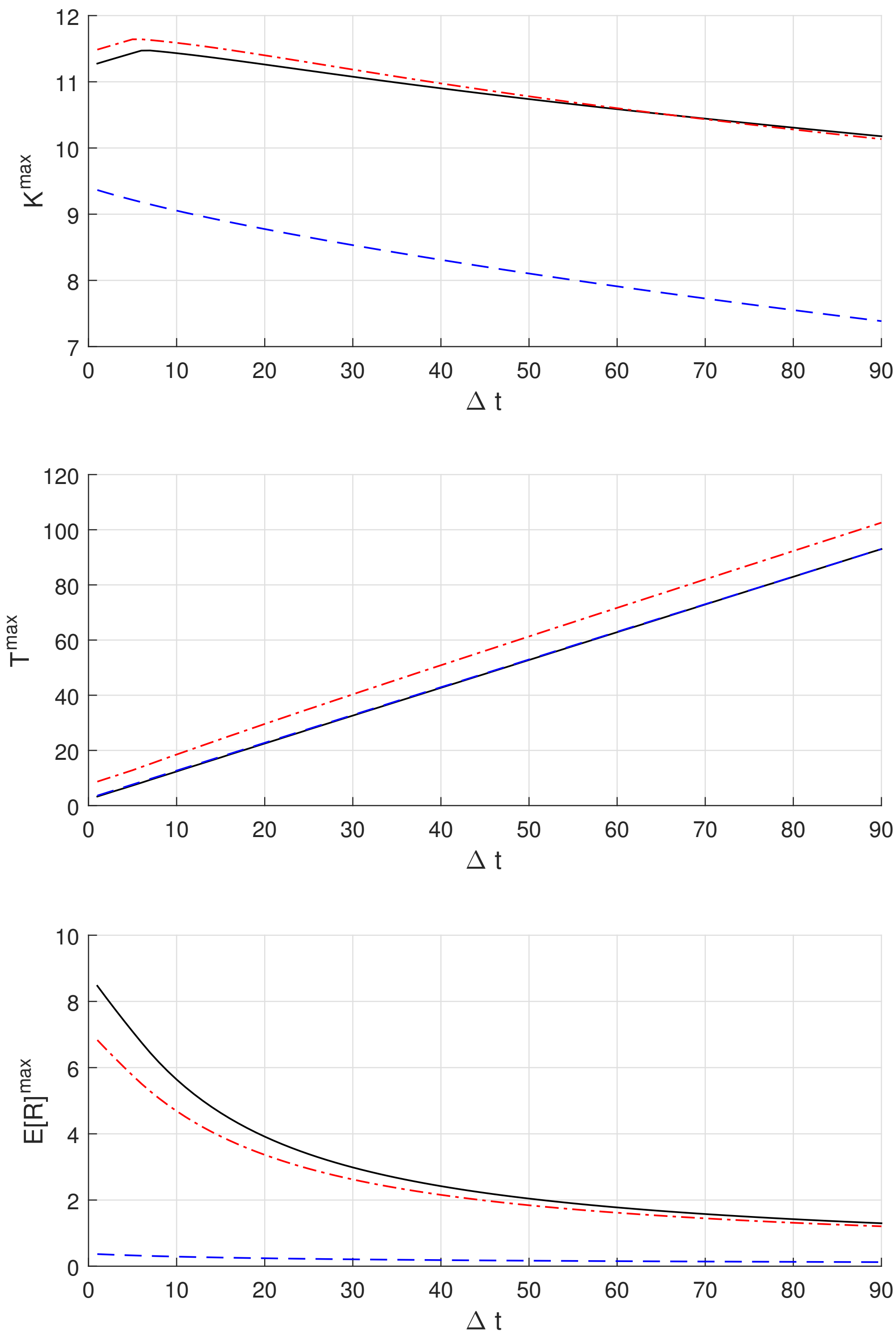


Figure A1: Maximizing Expected Returns to Informed Trading in *Call Options* ahead of Scheduled Events, depending on Δt:
The upper two graphs in this figure plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in call options ahead of a positive event as a function of the time to announcement Δt. 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*, $\kappa = 0.2$, $\sigma_\kappa 0.05$
(2) blue dashed line: $\sigma_{\Delta t} = 1$ *day*, $\kappa = 0.05$, $\sigma_\kappa 0.05$
(3) red dash-dotted line: $\sigma_{\Delta t} = 5$ *days*, $\kappa = 0.2$, $\sigma_\kappa 0.05$
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.

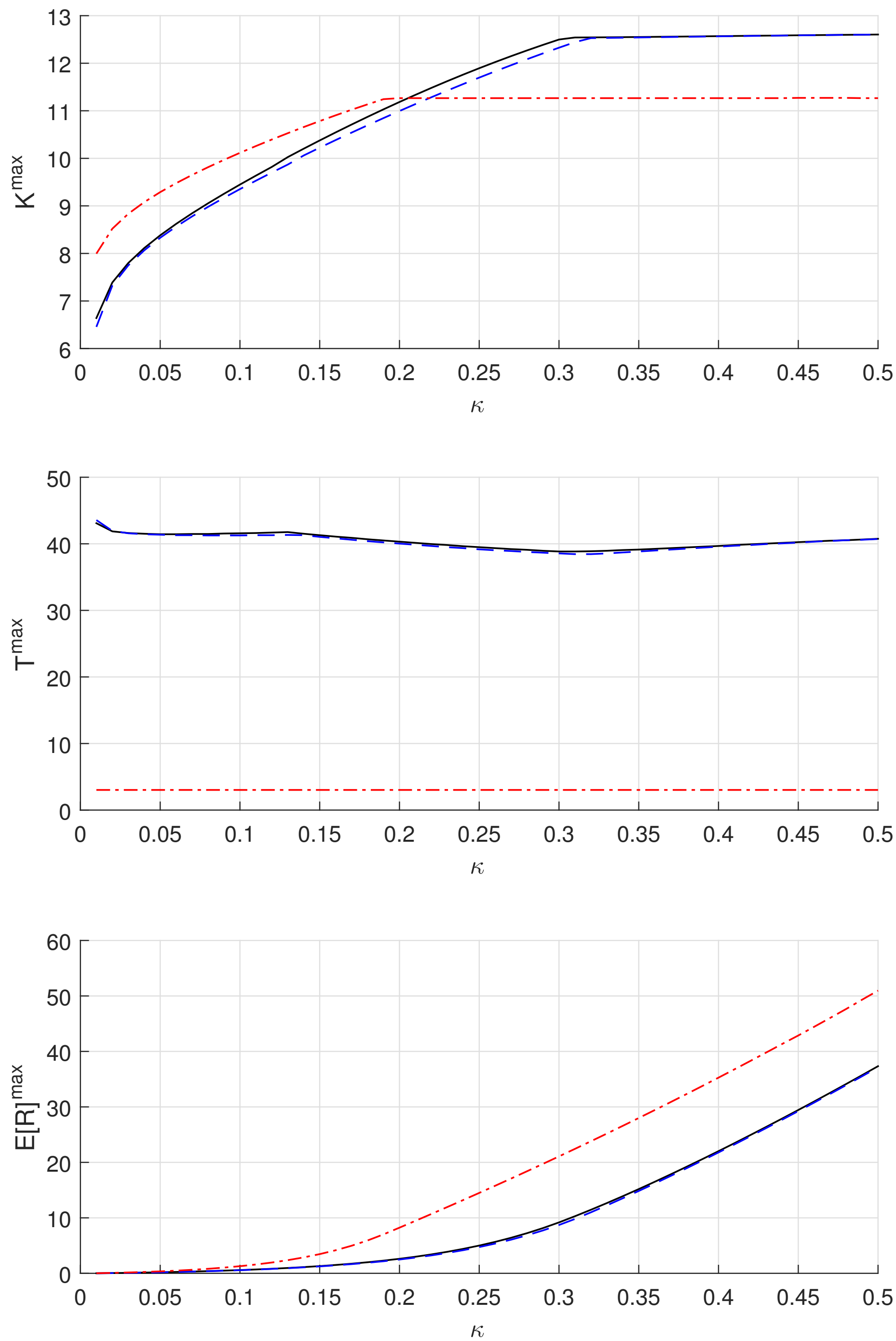


Figure A2: Maximizing Expected Returns to Informed Trading in *Call Options* ahead of Scheduled Events, depending on κ:
The upper two graphs in this figure plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in call options ahead of a positive event as a function of the expected jump in stock prices, κ. The lower graph displays the maximum expected return $E[R]^{max}$. Results are shown for three parameter sets.
(1) black solid line: $\Delta t = 30 days$, $\sigma_{\Delta t} = 5$ *days*, $\sigma_\kappa 0.05$
(2) blue dashed line: $\Delta t = 30 days$, $\sigma_{\Delta t} = 5$ *days*, $\sigma_\kappa 0.005$
(3) red dash-dotted line: $\Delta t = 3 days$, $\sigma_{\Delta t} = 0$ *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.

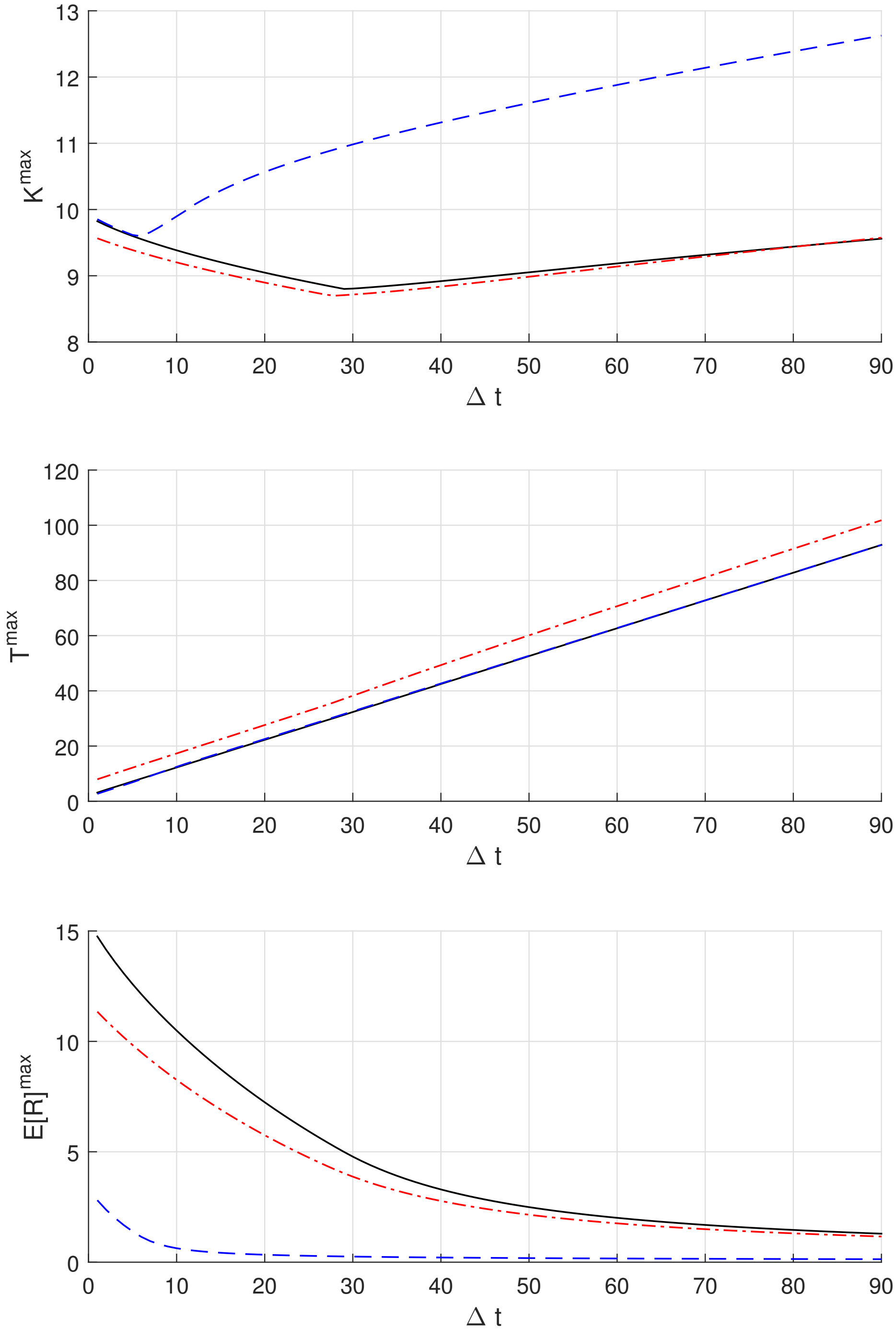


Figure A3: Maximizing Expected Returns to Informed Trading in *Put Options* depending on Δt:
The upper two graphs in this figure plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in put options ahead of a positive event as a function of the time to announcement Δt. The lower graph displays the maximum expected return $E[R]^{max}$. Results are shown for three parameter sets.
(1) black solid line: $\sigma_{\Delta t} = 1\ day$, $\kappa = -0.2$, $\sigma_\kappa 0.05$
(2) blue dashed line: $\sigma_{\Delta t} = 1\ day$, $\kappa = -0.05$, $\sigma_\kappa 0.05$
(3) red dash-dotted line: $\sigma_{\Delta t} = 5\ days$, $\kappa = -0.2$, $\sigma_\kappa 0.05$
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.

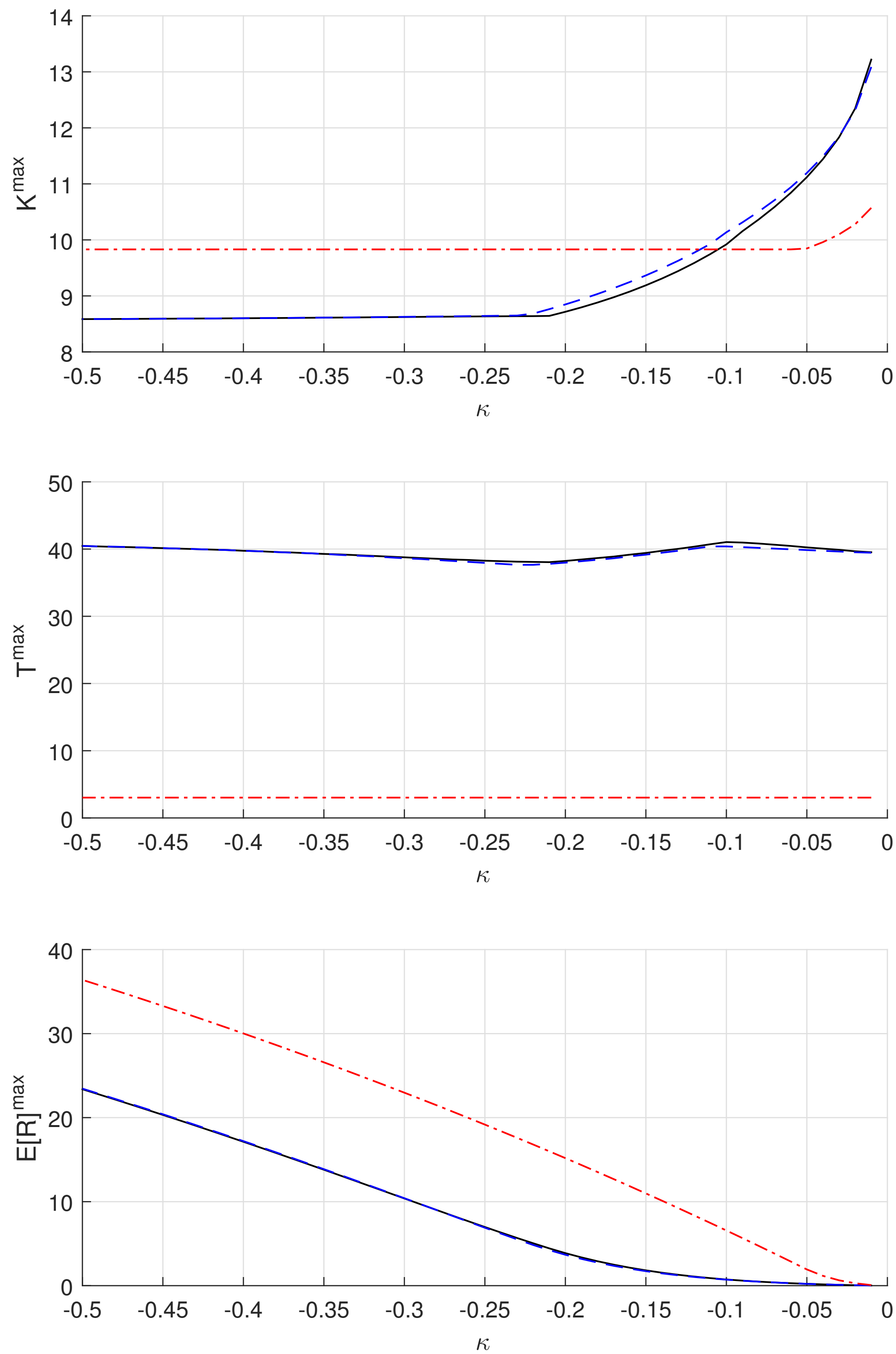


Figure A4: Maximizing Expected Returns to Informed Trading in *Put Options* depending on κ:
The upper two graphs in this figure plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in put options ahead of a positive event as a function of the expected jump in stock prices, κ. The lower graph displays the maximum expected return $E[R]^{max}$. Results are shown for three parameter sets.
(1) black solid line: $\Delta t = 30 days$, $\sigma_{\Delta t} = 5\ days$, $\sigma_{\kappa}0.05$
(2) blue dashed line: $\Delta t = 30 days$, $\sigma_{\Delta t} = 5\ days$, $\sigma_{\kappa}0.005$
(3) red dash-dotted line: $\Delta t = 3 days$, $\sigma_{\Delta t} = 0\ days$, $\sigma_{\kappa}0.005$
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.

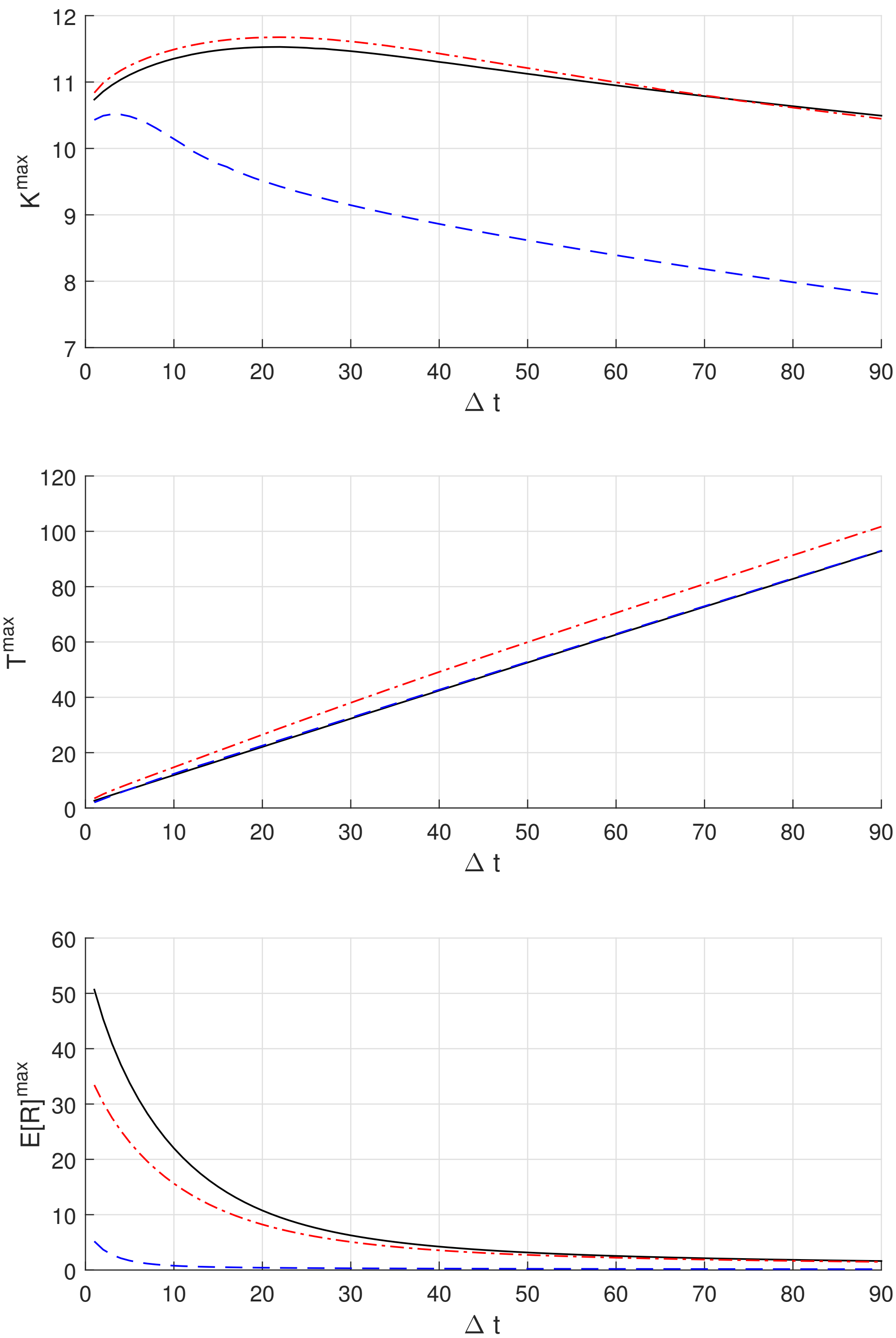


Figure A5: Maximizing Expected Returns to Informed Trading in *Synthetic Call Options* depending on Δt:
The upper two graphs in this figure plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in synthetic call options ahead of a positive event as a function of the time to announcement Δt. The lower graph displays the maximum expected return $E[R]^{max}$. Results are shown for three parameter sets.
(1) black solid line: $\sigma_{\Delta t} = 1\ day$, $\kappa = 0.2$, $\sigma_\kappa 0.05$
(2) blue dashed line: $\sigma_{\Delta t} = 1\ day$, $\kappa = 0.05$, $\sigma_\kappa 0.05$
(3) red dash-dotted line: $\sigma_{\Delta t} = 5\ days$, $\kappa = 0.2$, $\sigma_\kappa 0.05$
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.

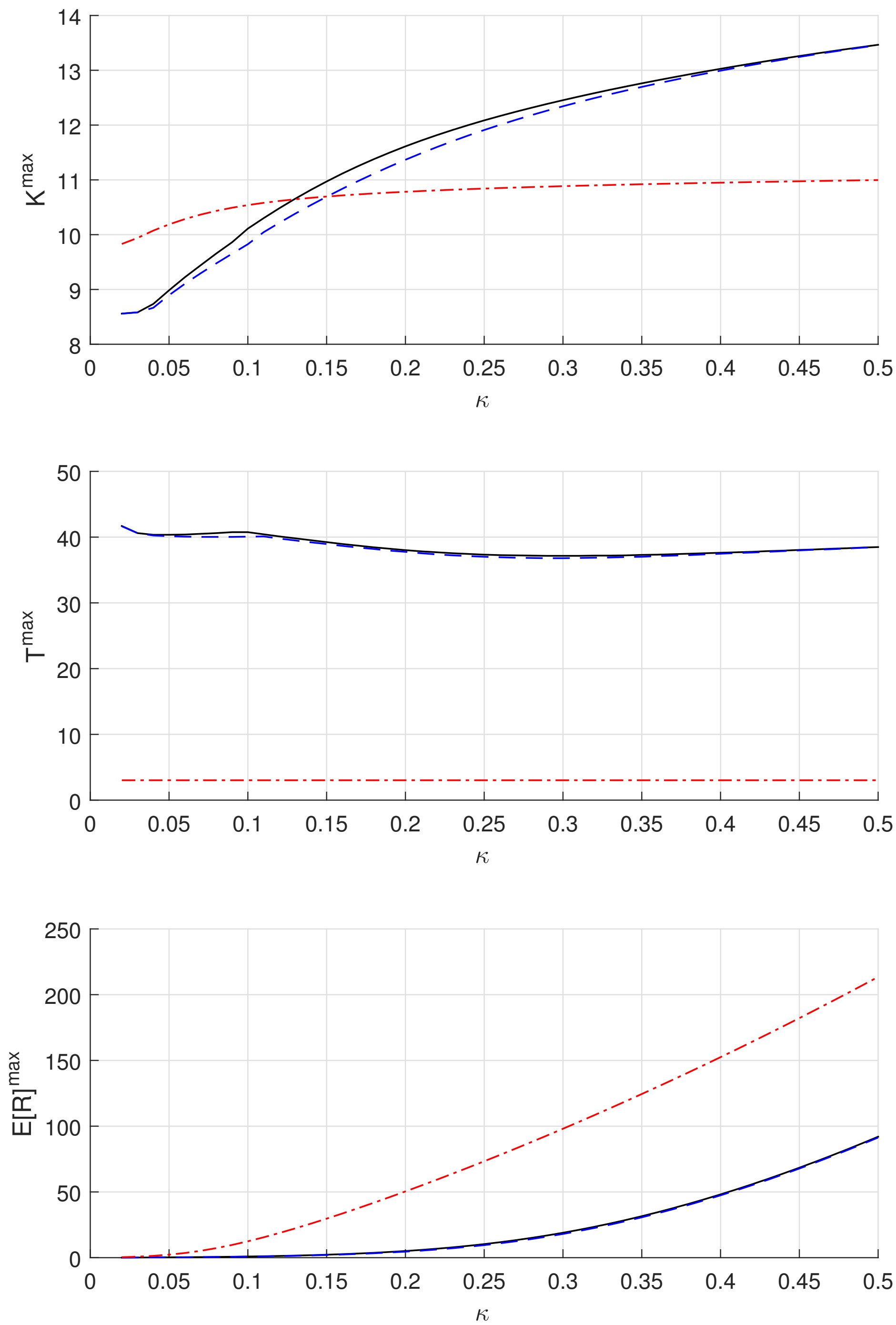


Figure A6: Maximizing Expected Returns to Informed Trading in *Synthetic Call Options* depending on κ:
The upper two graphs in this figure plot the strike price K^{max} and the time to maturity T^{max} that maximize expected returns to informed trading in synthetic call options ahead of a positive event as a function of the expected jump in stock prices, κ. The lower graph displays the maximum expected return $E[R]^{max}$. Results are shown for three parameter sets.
(1) black solid line: $\Delta t = 30 days$, $\sigma_{\Delta t} = 5\ days$, $\sigma_{\kappa}0.05$
(2) blue dashed line: $\Delta t = 30 days$, $\sigma_{\Delta t} = 5\ days$, $\sigma_{\kappa}0.005$
(3) red dash-dotted line: $\Delta t = 3 days$, $\sigma_{\Delta t} = 0\ days$, $\sigma_{\kappa}0.005$
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:

$$\mathcal{L}_t = \frac{R_t}{\hat{\sigma}_t} \tag{5}$$

where volatility is the realized bipower variation:

$$\hat{\sigma}_t^2 = \frac{1}{K-2} \sum_{j=t-k+2}^{t-1} \left|R_j\right| * \left|R_{j-1}\right| \tag{6}$$

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

$$\frac{\max_{t \in \bar{A}_n} |\mathcal{L}_t| - C_n}{S_n} \longrightarrow \xi \tag{7}$$

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

$$C_n = \frac{\sqrt{2\log(n)}}{c} - \frac{\log(\pi) + \log(\log(n))}{2c\sqrt{2\log(n)}} \tag{8}$$

$$S_n = \frac{1}{c\sqrt{2\log(n)}} \tag{9}$$

$$c = \sqrt{\frac{2}{\pi}}. \tag{10}$$

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.

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.

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

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