Jumps in option prices and their determinants: Real-time evidence from the E-mini S&P 500 option market*

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Abstract

We study for the first time the existence of jumps in option prices and examine their characteristics and sources. We employ high frequency data from the 24-hours E-mini S&P 500 options market. The use of this dataset is novel and allows identifying the fine structure and real-time determinants of jumps. We find that option prices do not jump simultaneously across strikes and maturities and are uncorrelated with underlying price jumps. 14% to 28% of detected option price jumps occur around scheduled news releases. However, it is illiquidity rather than the news content that drives jumps.

Keywords: Co-Jumps, Jumps, Informed traders, Liquidity, Option Markets, Scheduled News Announcements

JEL Classification: C58, G10, G12, G13

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1 Introduction

Discontinuities (jumps hereafter) in asset prices constitute a major source of risk and return for investors. A number of studies document the presence of price jumps in various asset classes such as equities (Merton (1976), Chernov et al. (2003), Eraker (2004), Broadie et al. (2007), Lee and Mykland (2008), Ait-Sahalia and Jacod (2009)), bonds (Jiang et al. (2011)), stock index futures, bond futures and exchange rates (Lahaye et al. (2011)). Surprisingly though, to the best of our knowledge, there has been no research on whether option prices jump. We fill this void by providing first-time evidence that jumps in the S&P 500 E-mini futures option prices exist and we study their characteristics and sources.

Exploring the presence of jumps in option prices is of importance to both academics and practitioners for three reasons. First, options have emerged as an important asset class per se and a number of studies examine their risk-return profile (e.g., Coval and Shumway (2001), Driessen and Maenhout (2007), Broadie et al. (2009), Santa-Clara and Saretto (2009)). Hence, the presence of jumps and their determinants is of importance to option investors. Second, in the case where option prices jump, this would constitute an empirical stylized fact that any option pricing model should be able to generate to be consistent with the data. This is of particular importance in the context of no-arbitrage option pricing models built to be consistent with the dynamics of market option prices (for reviews, see Jackwerth (1999) and Skiadopoulos (2001)). Third, the identification of jumps in option prices can shed light on their determinants. This is of importance to understanding the real-time option price formation process. Identifying price jumps first and subsequently searching for their sources allows investigating the distinct determinants of extreme price movements which may differ from the factors that influence more moderate option price changes.

To address our research question, we detect option price jumps using high frequency quote data on the S&P 500 E-mini futures options trading in a nearly 24-hours electronic market at the Chicago Mercantile Exchange (CME). The use of this dataset is novel and enables us to study the fine structure and real-time determinants of jumps thoroughly. In particular, to perform our analysis, we classify traded option contracts in various strike and time-to-maturity categories to study the existence of jumps in option prices across the whole board of traded strikes and maturities. The options' clientele differs across these two dimensions and hence option price dynamics may differ as well. We compute *investable* 10-minutes option returns for any given strike and maturity bucket and we identify price jumps and their exact timings using Lee and Mykland's (2008) (LM, thereafter) jump detection test. Then, we investigate the nature and sources of the detected option price jumps. Regarding the nature of the jumps, we explore whether the identified jumps occur only in the options prices of a certain strike (idiosyncratic jumps) or they occur simultaneously across the board of strikes (co-jumps). In the case where the evidence suggests that option price jumps are idiosyncratic, this will imply that the options market is segmented in terms of the abrupt movements of its prices.

Regarding the sources of the detected option price jumps, we explore their relationship with three classes of determinants being navigated by financial theory and empirical evidence. First, we study whether option price jumps are due to jumps in the underlying asset's price and/or its volatility. Under a complete markets paradigm, the dynamics of option prices are dictated by the dynamics of the price of the underlying asset and by changes in its volatility.

Then, we examine whether the occurrence as well as the content of news releases lead to jumps. In the context of other markets, Maheu and McCurdy (2004), Rangel (2011), Evans (2011), Jiang et al. (2011) and Lahaye et al. (2011) find that jumps in asset prices occur as new information arrives. From a theoretical perspective, the release of news is expected to trigger jumps in option prices too via at least two channels: heterogeneous beliefs (Shefrin (2001), Buraschi and Jiltsov (2006), Friesen et al. (2012)) and market sentiment (Han (2008), Lemmon and Ni (2011)). We relate the detected option price jumps to a set of U.S. scheduled news announcements which are well monitored by academics and practitioners. The investigation of the relationship between jumps and scheduled news announcements is possible thanks to the use of our 24-hours electronic market dataset because this includes periods that would be non-trading intervals for most organized exchanges. Crucially, these periods are the times at which most scheduled U.S. macroeconomic news announcements are released. Moreover, we also employ a comprehensive list of unscheduled news announcements and examine whether these are associated with detected jumps; the previous literature has paid little attention to the effects of unscheduled news to asset prices.

Finally, we investigate whether the detected jumps in option prices may be due to changes in the liquidity of the option market. Christoffersen et al. (2012) find that option illiquidity predicts future option price increases. Hence, rapid changes in liquidity might yield jumps in option prices. Recent evidence further documents that liquidity dry ups result in jumps in bond and equity prices (e.g., Jiang et al. (2011), Boudt and Petitjean (2013)). This is in line with the evidence that liquidity risk is priced for these asset classes, too (Amihud et al. (2005)).

We find that option prices jump. The probability of a jump to occur ranges from 0.22% to 0.56% depending on the option strike and maturity. Jumps are found to be negative on average and they are mostly idiosyncratic, i.e. option prices in one strike and maturity category tend to jump independently from prices in other categories. Moreover, we find that option price jumps are mostly unrelated to jumps in the underlying asset's price. Regarding the economic sources of jumps, we document that 14% to 28% of the identified jumps occur around scheduled macroeconomic news releases depending on the strike and maturity. However, even though a fraction of jumps clusters around news announcements, we find that the *content* of scheduled news announcements does not explain the detected jumps. Instead, we document that jumps related as well as unrelated to the release of scheduled news are preceded by drops in market liquidity. Hence, we conclude that illiquidity rather than news contents drive jumps in option prices. These results are robust to the choice of the sample period (non-crisis versus crisis periods) and to the choice of the set of news releases (scheduled versus unscheduled news items).

Our findings and conclusions on news-related jumps are consistent with the potential existence of informed trading in option markets.[1] Asymmetric information models (e.g., Glosten and Milgrom (1985), Kim and Verrecchia (1994)) predict that

[1]A number of papers document that option markets constitute an attractive venue for informed trading (see e.g., Easley et al. (1998), Pan and Poteshman (2006), and references therein).

market makers quote wider bid-ask spreads and thus they decrease market liquidity just before the news announcement to avoid trading with agents with superior information about the upcoming information event. Thus, these models provide a theoretical underpinning to understanding why the release of news is likely to trigger a jump whereas the news content does not. Informed trading has also been shown to break down the no-arbitrage relationship of the option price with its underlying price (Back (1993)). This is consistent with our finding of non-synchronous reported jumps in the two markets. Finally, our results can also be rationalized in microstructural models of market makers' hedging activities. Huh et al. (2012) show that option market makers increase the bid-ask spreads because of their hedging activities; hedging is expected to be pronounced prior to news announcements as being exposed to unhedged risk is likely to be particularly harmful when new information arrives.

We conclude this introduction by discussing two related strands of literature that our paper also contributes to. First, various studies have examined empirically the time evolution of the S&P 500 implied volatilities (e.g., Skiadopoulos et al. (1999), Gonçalves and Guidolin (2006), Neumann and Skiadopoulos (2013)). However, they do not identify whether the observed changes in implied volatilities are smooth or abrupt. Second, previous studies explore the effect of news announcements on at-the-money equity options implied volatilities (e.g., Ederington and Lee (1996), Fornari and Mele (2001)). However, these papers do not investigate whether the impact of news releases creates discontinuities in option prices and they do not examine the entire spectrum of traded options. Most importantly, they explore the impact of news releases whereas we take the reverse approach by detecting first jumps and then we check their sources in the vicinity of their occurrence.

The remainder of this paper is organized as follows. Section 2 describes the raw dataset and the way we structure it for the purposes of our analysis. Section 3 introduces and applies Lee and Mykland's (2008) test to identify jumps in option prices across different strike and maturity categories. Section 4 investigates the determinants of option price jumps. Section 5 conducts a number of robustness checks and Section 6 concludes and outlines the implications of our research.

2 Data

2.1 Option data

We obtain top-of-book intra-day data for S&P 500 E-mini futures options and the underlying futures (E-mini hereafter) from CME DataMine spanning the period 01/01/2005 to 31/12/2010. The dataset includes the best bid and ask quotes time-stamped down to the second and the sizes quoted at the best bid and ask prices. Both options and futures contracts trade in a nearly 24-hours electronic market termed GLOBEX.[2] The use of this dataset is novel and it is of utmost importance for the purposes of our study because in the subsequent analysis it will allow us to

[2] "E-mini" contracts are sized at one-fifth of the value of the regular contracts, making them more accessible to traders with small margin accounts. They are traded around the clock on an open electronic limit order book system (GLOBEX) that is accessible by off-floor traders. GLOBEX is an international, automated order entry and matching system, which has a network extending to ten financial centers, including New York, Chicago, London, and Tokyo. Trading on GLOBEX starts on Sundays at 5:00 p.m. Central Standard Time (CST) and ends on Fridays at 3:15 p.m. CST. On Mondays through Thursdays, trading stops at 3:15 p.m. CST and restarts at 3:30 p.m. CST. There is also a daily maintenance shut-down from 4:30 p.m. CST to 5:00 p.m. CST on Mondays through Thursdays.

identify any real-time association of detected jumps with the scheduled U.S. news releases. This is because most scheduled U.S. news announcements are released at 7:30 a.m. Central Standard Time (CST) taking place outside of the trading hours of most organized equity derivative exchanges. We sample quotes from 7.00 a.m. to 2.45 p.m. CST to span the occurrence of scheduled news announcements. We do not use quotes beyond 2.45 p.m. to avoid any noise due to a 3.15-3.30 p.m. maintenance shut-down and because the liquidity drops significantly after 3.30 p.m. This is in line with the significant drop in the E-mini and regular futures volume after 2:45 p.m. (see Dungey et al. (2009)).

Three more points are in order regarding the choice of the dataset. First, in line with Birru and Figlewski (2012), we employ best bid and ask quotes rather than transaction prices because only rarely we observe simultaneous transaction prices for a large number of different contracts. Second, we focus on the E-mini S&P 500 futures options instead of the standard sized S&P 500 futures options market because the former is more liquid even when compared to the standard sized contracts trading in the electronic market. In addition, trading in the open outcry S&P 500 futures options market only commences at 8.30 a.m. CST making it infeasible to match any detected jumps with the release of scheduled macroeconomic news in real-time. However, such a real-time analysis is required as news announcement effects have been found to be relatively short-lived, i.e. markets absorb their effect within minutes (see e.g., Andersen et al. (2007) for a similar choice in the context of futures markets). Third, the chosen time period contains both the mid 2007-2010 recent crisis period as well as the previous non-crisis one. Therefore, we will be able to check whether the number as well as the nature of jumps in option market differs over turbulent and non-turbulent periods.

CME offers two kinds of American style E-mini options which differ by their expiration months. Quarterly options expire in March, June, September, and December whereas serial options expire in January, February, and April. The underlying E-mini futures trades on quarterly expiries. The quarterly options are written on the E-mini that expires on the same day as the option. The serial options are written on the futures contract which has a maturity nearest to the option contract's. We match intra day options quotes with the simultaneously recorded underlying futures quotes and we discard observations for which this matching is not possible to avoid problems arising from non-synchronous underlying and option quotes. We also discard in-the-money option quotes because these options are highly illiquid (for a similar approach, see e.g., Neumann and Skiadopoulos (2013)).

We apply a number of filters to minimise the impact of microstructure noise which is likely to contaminate the quotes data. In particular, we apply the Barndorff-Nielsen et al. (2009) filtering criteria commonly used in the market microstructure literature. First, we replace bid and ask quotes with identical time stamps by their median bid and ask quotes for this time stamp. Second, we discard observations for which the bid-ask spread is negative or excessively wide. We implement this by computing the median bid-ask spread for each contract on each day and we discard the contract's observations on that day that have spreads greater than 50 times the daily median spread. Third, we discard quotes that are likely to represent outliers with respect to the midpoint quote. To this end, at any point in time where there is a quote, we compute the median midpoint of bid and ask quotes of the 25 observations preceding and 25 observations following the time t observation. Then, we compute the difference between the t observation and its respective median. Subsequently, we calculate the daily mean of these differences. For any given day, we discard the observations which deviate by more than 10 times from this daily mean.

Next, we group option contracts into buckets based on their strikes and maturities. This classification serves two purposes. First, it provides a sufficient number of observations for each strike and maturity; tracking prices for each single option contract at high frequencies is not feasible because not all strikes are equally actively traded. Second, it allows us to investigate whether option prices behave differently across strikes and maturities. An "idiosyncratic" behavior of the abrupt movements of option prices may be expected given that trading different options serves different purposes and hence they may enjoy a different clientele across the spectrum of strikes and maturities.

To fix ideas, we follow Bollen and Whaley (2004) and group option quotes according to their Black's (1976) model deltas into deep out-of-the-money (DOTM), out-of-the-money (OTM) and at-the-money (ATM) puts and calls; Panel A of Table 1 reports this classification (for a similar approach, see Christoffersen et al. (2012)). The computation of option deltas requires estimates for the risk-free rate, the underlying volatility and the simultaneously recorded underlying price. We assume risk-free rates to be constant throughout the trading day and we proxy them by the daily U.S. LIBOR rates with maturities one week, one month, two months up to 12 months obtained from the website of the St. Louis Fed. Whenever rates with maturities different from the ones covered by the data are required, we linearly interpolate between the rates of the two available adjacent maturities. We use Black's (1976) model to back out the implied volatility for each quote and use this as the volatility input to calculate option's delta.[3] Option prices as well as underlying prices are taken to be the midpoint of the bid and ask quotes. In addition to the delta dimension, we also classify option quotes according to their time to expiration into short-term, medium-term, and long-term options; Panel B of Table 1 reports this classification. These classifications yield 18 distinct groups of option quotes which provide a parsimonious and accurate description of the structure of traded options.

For each one of these groups, we compute a time series of *investable* high frequency returns where each return is measured over a period of length Δt. To this end, we divide each trading day into $n_d = \frac{T_d}{\Delta t}$ subsamples where T_d is the number of observations per day. Then, for each one of these subsamples we select the option quote with delta closest to the midpoint delta of the delta category under scrutiny. Based on this quote and the quote for the *same* contract in the subsequent subinterval, we compute the high frequency log option return for the delta category under scrutiny. This approach ensures that we compute option returns from the same contract. Then, we repeat the same process over the next subintervals. Whenever there has been no quote update for a selected contract from one subinterval to the

[3]Black (1976)'s model prices European style options. Its use to calculate the deltas and implied volatilities of the American style E-mini options is unlikely to introduce any error, though. This is because the early exercise premium is negligible given that we use ATM and OTM options with time-to-maturity less than 100 days (see Barone-Adesi and Whaley (1987)). Hence, there is no loss in accuracy from using the computationally less expensive Black (1976) model. In general, note that the usage of Black (1976)'s model does not assume that this model prices the options accurately. It merely serves as a mapping from option prices as a function of strikes space to option prices as a function of deltas.

next, we set the option return to zero. Applying this procedure to each subinterval, trading day and delta/maturity bucket provides us with a series of high-frequency option returns for all 18 delta/maturity categories.

The empirical implementation of this scheme requires a choice for the subinterval Δt. The jump detection test to be employed assumes Δt to become arbitrarily small. Hence, it is desirable to choose the subinterval as short as possible. However, the more granular the sampling frequency is, the more the data are contaminated by microstructure noise which can distort the subsequent jump detection. Hence, in line with Andersen et al. (2000), we employ volatility signature plots of high-frequency option returns to select the "optimal" subinterval length. Volatility signature plots depict realized volatility as a function of the sampling frequency. In the absence of microstructure noise, realized volatility defined as the squared root of summed squared intraday returns, should be invariant to changes in the sampling frequency provided the data is sampled fine enough. Figures 1, 2 and 3 show the average daily realized volatility as a function of different subinterval lengths for the various delta levels; the figures are depicted for the short, medium and long-term maturity options, respectively. We can see that the realized volatilities diverge as the subinterval length approaches zero and they start converging around the 10 minutes mark. Hence, we choose a subinterval length of $\Delta t = 10$ minutes. This choice overall yields between 52,627 to 62,815 return observations depending on the delta-maturity bucket.

2.2 News announcement data

We employ a list of scheduled U.S. macroeconomic news announcements which includes 11 news items. We obtain the exact timing of the releases and their corresponding survey forecasts from Bloomberg. On Fridays, Bloomberg surveys key market participants for their forecasts regarding the values of economic variables that will be released within the next week. The median of the survey is taken to be the forecast for the respective economic variable. Table 2 reports the announcement items and their timing. All scheduled announcements take place within our daily sampling interval from 7:00 a.m. CST to 14:45 p.m CST with most of them being released at 7:30 a.m. on a monthly basis. The only exception is the FOMC rate announcement on 8/10/2008 which occurred on 6:00 a.m.; we exclude this announcement because it took place outside of our defined trading day. In total, our sample contains 888 announcements and 751 days on which at least one scheduled announcement has been released.

We follow Balduzzi et al. (2001) and consider news surprises to assess the impact of news announcements on option markets; in an efficient market, prices should not respond to information that has already been anticipated by market practitioners. In particular, let $A_{i,t}$ denote the i^{th} news item's actual figure released at time t and let $F_{i,t}$ denote the forecast for this figure. Then, the surprise measure $SUR_{i,t}$ is defined as

$$SUR_{i,t} := \frac{A_{i,t} - F_{i,t}}{\sigma_i} \tag{1}$$

where σ_i denotes the sample standard deviation of the surprise components $A_{i,t} - F_{i,t}$ for the i^{th} news item. Surprise components are standardized to facilitate comparison across different news items. As news surprises measure the information content unanticipated by the market, we will also refer to them as *information shocks* in what follows.

2.3 Liquidity Measures

We compute two liquidity measures to proxy two important dimensions of the definition of market liquidity: the bid-ask spread and the option sizes ordered at the bid and ask prices. The bid-ask spread measures the cost of doing a trade for a given size whereas the size variable measures the depth of the market (i.e. how many contracts are offered) at the best bid and ask price.[4]

To fix ideas, first, in line with Christoffersen et al. (2012), for each option delta and maturity category we compute the time t relative bid-ask spread BA_t

$$BA_t = \frac{Ask_t - Bid_t}{(Ask_t + Bid_t)/2}, \tag{2}$$

where Ask_t (Bid_t) denotes the bid (ask) quote of the contract used to compute the 10-minute option returns in Section 2.1. We compute a relative bid-ask spread because the bid-ask magnitude depends on the option's strike and maturity.

Second, we obtain the time t quoted sizes ($AskSize_t$) and ($BidSize_t$) at the best ask and bid quotes, respectively, for each delta/maturity category. To this

[4]In general, liquidity is defined as the ability to buy or sell significant quantities of securities quickly at a low cost with little price impact.

end, we retain the ask and bid sizes of each one of the quotes used to compute the option returns in Section 2.1. In case multiple simultaneous quotes have been used to compute option returns, we employ the median quote sizes computed from the simultaneous quotes.

3 Jumps in Option prices

3.1 Jump Test

In line with Lahaye et al. (2011) and Bandi and Reno (2012), we employ Lee and Mykland's (LM, 2008) jump detection test to statistically test whether there are any jumps in option prices. Compared to competing approaches, the LM test has the advantage that it detects both the occurrence and the timing of jumps (for a review of jump detection tests, see Dumitru and Urga (2012)). It does so by checking each recorded change in the asset price to conclude whether this is a jump or not. It relies on the idea that large movements in an asset price can either be caused by jumps or they could be realisations of a continuous but highly volatile process. Hence, it adjusts the observed movements by the volatility of the continuous part of the stochastic price process. If a given adjusted movement is "too large," then this change is labeled a jump.

To fix ideas, let $S(t)$ denote the time t asset price. In the absence of jumps, the stochastic evolution of $S(t)$ is represented by

$$d \log S(t) = \mu(t)dt + \sigma(t)dW(t) \tag{3}$$

where $W(t)$ is a Brownian Motion. $\mu(t)$ and $\sigma(t)$ are the (possibly-time varying) drift and volatility such that $d\log S(t)$ is an Itô process with continuous sample paths. In contrast, if jumps are present $S(t)$ is assumed to follow

$$d\log S(t) = \mu(t)dt + \sigma(t)dW(t) + Y(t)dJ(t) \tag{4}$$

where $J(t)$ denotes a counting process that controls the arrival of jumps and $Y(t)$ denotes the jump size.

Assume there are n (equidistant) observations of $S(t)$ available and that $t \in [0, T]$ where T denotes the total number of observations of any given time series of option returns. Then, the distance between observations Δt is given by $\Delta t = \frac{T}{n}$. We want to test whether there was a jump at a particular time $t_i \in [0, T]$. The idea of the LM test is to standardise the log-return from t_{i-1} to t_i by the *instantaneous volatility* of the stochastic price process to account for its diffusive component. Thus, LM propose the following test statistic

$$\mathcal{L}(i) \equiv \frac{\log(S(t_i)) - \log(S(t_{i-1}))}{\widehat{\sigma(t_i)}} \tag{5}$$

where $\widehat{\sigma(t_i)}$ is estimated by the *realized bipower variation* (RBPV) using the past K observations of $S(t)$. The RBPV estimator is given by

$$\widehat{\sigma(t_i)}^2 \equiv \frac{1}{K-2} \sum_{j=i-K+2}^{i-1} |\log(S(t)) - \log(S(t_{j-1}))| \, |\log(S(t_{j-1})) - \log(S(t_{j-2}))| \tag{6}$$

The use of RBPV ensures that the estimator consistently estimates the instantaneous volatility even in the presence of jumps in the past K observations. LM show that under the null of no jumps and as $\Delta t \to 0$, the distribution of $\mathcal{L}(i)$ approximately follows the distribution of a normally distributed random variable with mean 0 and variance $\frac{1}{c^2}$ with $c = \sqrt{2}/\sqrt{\pi}$. In contrast to this, in the presence of jumps as $\Delta t \to 0$, LM show that $\mathcal{L}(i)$ becomes very large. Hence, observing large values of the test statistic gives rise to the presence of jumps.

To assess how big the test statistic must be to indicate the presence of a jump at a certain significance level, LM employ the distribution of the maximum of the test statistic under the null of no jumps; the maximum of the test statistic is Gumbel-distributed. If the test statistic is greater than its maximum under the null of no jumps, it is highly unlikely that the observation in question was generated by a continuous process. As a consequence, one can base rejection of the null of no jumps on the rescaled and centred test statistic $\frac{|\mathcal{L}(i)|-C_n}{S_n}$ with $C_n = \frac{(2\log(n))^{1/2}}{c} - \frac{\log(\pi)+\log(\log(n))}{2c(2\log(n))^{1/2}}$, $S_n = \frac{1}{c(2\log(n))^{(1/2)}}$, and sample size n. The null hypothesis of no jumps is rejected whenever $\frac{|\mathcal{L}(i)|-C_n}{S_n}$ exceeds the critical value β^* obtained from a standard Gumbel cumulative distribution for a given confidence level α with β^* such that $\exp(-\exp^{-\beta^*}) = 1-\alpha$, i.e. $\beta^* = -\log(\log(1-\alpha))$.

For the empirical implementation of the test one has to select a window size K for the purpose of estimating instantaneous volatility. In line with LM, we choose K to be the smallest integer in the interval between $\sqrt{252 \times nobs}$ and $252 \times nobs$, where $nobs$ denotes the number of observations per day. We determine the critical values by setting the Gumbel cumulative distribution function to a confidence level of 0.1%. We choose such a conservative significance level so that to minimise the impact of spuriously detected jumps; under the null hypothesis that there is no jump in any given subinterval, we expect to find a spuriously detected number of jumps equal to the number of observations times the chosen significance level.[5]

3.2 Results

We separately apply the LM test to each option return and to the underlying futures returns time series. Table 3 reports the summary statistics (number of jumps, probability of a jump to occur, number of jump days, probability of a jump day to occur, average jump size, and percentage of negative jumps as a fraction of total jumps) for each one of the delta categories and for the short, medium and long-term maturities.[6] It also reports the same summary statistics for the underlying futures.

We can see that option prices jump. The number of jumps varies substantially across the delta and maturity buckets. With respect to the delta dimension, the DOTM calls and puts exhibit the greatest number of price jumps. With respect to the options maturity dimension, we can see that short maturity options exhibit more jumps than the longer maturity ones for all moneyness levels but OTM and DOTM calls. Regarding the option returns' jump size, we can see that this is negative on average and large with short-term options exhibiting substantially larger jump sizes than longer-term ones. The findings also suggest that negative option price jumps

[5] We have checked the robustness of the results with respect to changes in the significance level. We find that the results are qualitatively the same for different choices of the significance level ranging from 0.1% to 10%. Results are not reported due to space limitations.

[6] Jump sizes are defined to be the realized returns that have been identified as a jump. Note that strictly defined, these returns are the sum of the drift, diffusive, and jump component. Measuring the exact jump size would require disentangling the drift and diffusive component from the realized return. This is beyond the scope of this paper.

occur more often than positive jumps for almost all moneyness levels and maturities. Moreover, exact binomial tests reveal that the probability of observing a negative jump is significantly greater than 50% at the 5% significance level for most delta and maturity categories.

Finally, we compare the number of identified jumps in the price of the underlying asset to the number of identified option price jumps. We can see that the number of identified jumps in the underlying's price remains fairly constant across maturities; this is in contrast to the option price jump case. Furthermore, we can see that in most cases, the number of underlying jumps is less than the number of option price jumps. This finding has implications with respect to the question how jumps are transmitted to option prices. It indicates that option price jumps cannot be solely attributed to simultaneous jumps in the price of the underlying asset. We investigate this relationship further in the next section.

4 Sources of option price jumps

4.1 Jumps in the underlying factors: Assessment of co-jumps

In a complete market, option prices are determined by the price of the underlying asset and its volatility by a no-arbitrage argument. In this section, we explore whether the detected jumps in option prices are due to jumps in the price of the underlying asset and/or its volatility. If jumps in option prices were due to jumps in the price of the underlying asset, one would expect the underlying asset price to jump simultaneously with option prices (co-jump) across various strikes. In particular, one expects an underlying price jump to be accompanied by a price jump in ATM options because their (absolute) deltas are high. Moreover, in the case where the underlying co-jumps with DOTM options, options closer to-the-money should jump as well because their deltas are greater than the DOTM options' ones. Similarly, if option price jumps are due to volatility jumps, any jump in DOTM option prices should be accompanied by a a simultaneous jump in OTM and ATM option prices. This is because OTM/ATM options are more sensitive to changes in the underlying volatility than DOTM options.

To identify whether option prices co-jump, Figure 4 reports the frequency of different co-jump events for the short, medium and long-term maturity buckets, respectively. A co-jump event is characterized by the number of concurrent jumps across options of different delta levels and the underlying. The figures depict for each maturity bucket how often options of one, two, three,..., six delta categories and/or the underlying have jumped simultaneously. In particular, the case where the number of concurrent jumps is one refers to an idiosyncratic option price jump in one of the delta categories or in the underlying price. We can see that co-jumps are rare. The vast majority of option price jumps are not accompanied by simultaneous jumps in option prices of other delta buckets or by a simultaneous jumps in the underlying asset.

Yet, the mere evidence that most option price jumps are idiosyncratic does not rule out the possibility that the detected option price co-jumps are still due to price and/or volatility jumps. For instance, a jump in the underlying price may yield a jump in the ATM option price but not necessarily in OTM and DOTM option prices. Similarly, cases where only ATM calls and puts jump simultaneously might be attributed to volatility jumps as these moneyness categories are more sensitive to changes in volatility than OTM/DOTM options. To investigate this further, we examine *which* delta categories and/or the underlying asset jump simultaneously (termed composition of co-jump events). Figure 5 shows the composition of co-jumps for the short, medium, and long-term maturities, respectively. We can see that the already small number of detected co-jumps is spread across various delta and delta/underlying combinations. Therefore, co-jumps do not cluster in a particular combination.

Our findings suggest that option price jumps are not due to jumps in the underlying price and its volatility. This implies that the no-arbitrage relationship between the option price and the underlying's price and its volatility does not hold. Moreover, the presence of idiosyncratic jumps in option prices implies that there is not a common factor that explains the variability of the cross-section of jump induced option returns. Note that this is not at odds with the literature which finds that there are common factors in the cross-section of *total* (defined to be the sum of diffusive and discontinuous) option returns though (e.g., Christoffersen et al. (2012)).

4.2 Information events as sources of option price jumps

We explore further the sources of jumps in option prices. A number of studies document that a fraction of identified jumps in spot markets can be attributed to the release of scheduled macroeconomic announcements (see e.g., Lahaye et al. (2011), Jiang et al. (2011)) and references therein). Regarding the option market, from a theoretical perspective news announcements can also make option prices jump. This is because heterogeneous beliefs (Shefrin (2001), Buraschi and Jiltsov (2006), Friesen et al. (2012)) and market sentiment ((Han (2008), Lemmon and Ni (2011)) are related to the slope of the implied volatility curve.[7] Given that certain news may affect these factors drastically, one might expect these news effects to be transmitted to the slope of the implied volatility skew in a jump-like fashion. This will be manifested as jumps in option prices. Motivated by these considerations, we investigate whether jumps in option prices can also be related to macroeconomic news announcements.

To investigate to what extent detected option price jumps are related to scheduled macroeconomic news announcements, we match the detected jumps with the the release of scheduled news announcements events presented in Section 2.2. We define that an identified jump is related to a specific news announcement if the jump has occurred within ±10 minutes of the respective announcement. Panel A of Table 4 reports the conditional probabilities $P(News|Jump)$ and $P(Jump|News)$ to detect the relationship between the detected jumps and *all* considered macroeconomic news. $P(News|Jump)$ shows the fraction of detected jumps associated with news announcements whereas $P(Jump|News)$ shows the fraction of news associated with jumps, i.e. it denotes the probability that a news announcement triggers a jump.

Regarding $P(News|Jump)$, we can see that 14.35% and 28.50% of detected jumps are linked to the scheduled release of macroeconomic news depending on the delta and maturity category. In addition, the number of news related jumps in the

[7]On any given point in time and for any given option expiry, the implied volatility curve is defined to be the relationship between the options implied volatilities and their respective strikes.

underlying asset differs substantially from the options ones. This indicates that the previously documented segmentation of option and underlying price jumps prevails around scheduled news announcements as well. Regarding $P(Jump|News)$, we can see that the probability of news yielding jumps is greater for DOTM calls and puts and it is greatest for short-term options. Hence, it is more probable that a news release will yield an option price jump for shorter term options than for longer term ones.

To shed more light on the relative importance of the *individual* news items reported in Section 2.2, we report the probabilities $P(News|Jump)$ and $P(Jump|News)$ for each news item separately in Table 4, Panels B and C, respectively. Regarding $P(News|Jump)$, the nonfarm payrolls (NFP) report and the initial jobless claims (IJC) explain most of the detected jumps. In particular, the NFP report explains up to 10% of the detected jumps whereas IJC explains up to 11.51% of the detected option price jumps.

Regarding the probability $P(Jump|News)$ that a specific news release will cause a jump, we can see that the NFP Report is the news item among all individual news items that is most likely to trigger an option price jump. For certain delta categories of short-term options, a NFP release results in a jump in more than 20% of all cases. This is in line with the existing literature on jumps and news announcements effects in financial markets which documents that the NFP report is the most influential scheduled news announcement (e.g., Andersen and Bollerslev (1998)).

4.3 Information shocks as sources of option price jumps

The analysis in Section 4.2 has revealed that a fraction of option price jumps is related to information events. However, one may hypothesize that not only the fact that new information is released but also the content of the released information itself explains the occurrence of jumps.

Hence, we examine this hypothesis by statistically linking the content of the released scheduled macroeconomic news to the occurrence of detected option price jumps. To this end, we employ a logistic regression methodology (for a similar approach, see Jiang et al. (2011)). Lee (2012) shows that following this approach using discrete time data (option returns and jump determinants) allows drawing inference on the determinants of the unobservable stochastic jump intensity of the continuous time jump process. In particular, we are interested in estimating the following specification

$$P(Jump_t|News) = \frac{1}{1 + \exp(-c - \sum_{j=1}^{11} \theta_j |SUR_{j,t}|)} \tag{7}$$

where $j \in \{\mathrm{NFP, CCI, CPI, DGO, FOMC, GDP, IJC, LI, NHS, PPI, RSA}\}$ and $P(Jump_t|News)$ denotes the probability of an option price jump to occur conditional on a scheduled macroeconomic announcement taking place. This conditioning is necessary because the values of the macroeconomic surprises variables are only available at announcement times which implies that equation (7) can only be estimated for observations coincident with announcement times.

A few remarks are in order at this point. For any given delta and maturity category, the number of option price jumps that can be linked to the concurrent release of scheduled news is too small to accurately estimate equation (7) separately for each delta/maturity category. To increase the statistical accuracy of our estimates, we pool observations across different delta levels and estimate equation (7) once for each maturity category. We also only incorporate announcement items which exhibit at least one non-zero surprise matched with a concurrent option price jump. Pooling across different delta categories is not expected to affect our results for two reasons. First, the results of the analysis in Section 4.2 do not reveal any major differences across deltas with regards to the question which news items are most important in explaining option price jumps. Second, we use absolute surprises and a binary jump indicator variable so that the expected sign of the θ_j is the same (positive) for all delta categories.

Panel A of Table 5 reports the estimation results for equation (7). In line with the evidence from Section 4.2, NFP surprises have a significant positive impact on the probability of a jump to occur in short and medium-term options. Surprisingly, there is no significant effect of NFP on the probability of a jump to occur in long-term options, though. For these options instead, GDP as well as Retail Sales Less Auto surprises have a positive impact on the jump probability. However, in general the evidence for a strong relationship between news surprises and option price jumps appears to be rather weak; only a small number of coefficients in equation (7) turns out to be significant. The results from the logistic regression approach suggest that the option price jumps clustering around news announcements reported in Section 4.2 is not due to the news content, i.e. due to the fact that new information is being impounded into prices. This implies that option price jumps are primarily driven by other determinants. We explore this further in the next section.

4.4 Illiquidity as a source of option price jumps

As a final source of option price jumps, we investigate the role of illiquidity in option markets. Jiang et al. (2011) and Boudt and Petitjean (2013) find that illiquidity predicts jumps in bond and equity prices beyond information shocks induced by macroeconomic news announcements. In addition, Christoffersen et al. (2012) find that option illiquidity reduces current option prices and predicts future option price increases. Hence, rapid movements in liquidity might result in jumps in option prices.

We study whether illiquidity affects the probability of an option price jump to occur. To this end, we re-estimate equation (7) by augmenting the set of covariates by the liquidity variables introduced in Section 2.3 (relative bid-ask spread, quoted size at the best bid price and quoted size at the best ask price). In particular, we estimate

$$P(Jump_t|News) = \frac{1}{1 + \exp(-c - \sum_{j=1}^{11} \theta_j |SUR_{j,t}| - \sum_{k=1}^{3} \gamma_k IL_{k,t-1})} \tag{8}$$

where $IL_{k,t-1}$ denotes the time $t-1$ value of the k^{th} liquidity variable. The liquidity variables are taken at their first lags to avoid any endogeneity problems.

Panel B of Table 5 reports the estimation results for the model shown in equation (8). We can see that even though the bid and ask size variables are not significant, the coefficients of the lagged relative bid-ask spread are positive and highly significant for all maturity categories. This shows that option price jumps tend to be preceded by option market liquidity dry ups. Most importantly, almost all news surprise variables become insignificant after adding the liquidity variables to the model. Hence, after controlling for liquidity in the option market, the content of the considered news announcements has almost no power in explaining option price jumps.

Our findings suggest that it is liquidity and not the news surprises, that drive the occurrence of option price jumps around announcements. This finding can be explained by asymmetric information among option traders and the hedging activities of market makers in option markets. In particular, market makers widen the bid-ask spreads they quote and thus they decrease market liquidity just before the news announcement. They do so to avoid the risk of trading with traders with superior information about the upcoming information event. This practice is in line with the predictions of the models in Glosten and Milgrom (1985) and Kim and Verrecchia (1994) and it is highly relevant to options markets since these are commonly considered to be a natural setting for informed traders (see e.g., Easley et al. (1998), Pan and Poteshman (2006) and references therein). Interestingly, the informed option traders explanation also explains our findings on the detected asynchronous news-related jumps in the option and E-mini futures prices. Back (1993)'s model predicts that the presence of informed trading in options will impede the dynamic replication of options via trading the underlying asset and hence it will break down the no-arbitrage relationship of the option price with its underlying price. Our results are also in line with the predictions of the Huh et al. (2012) model where option market makers increase bid-ask spreads because of their hedging activities; hedging is expected to be particularly pronounced prior to news announcements.

To robustify the evidence on the link between illiquidity and option price jumps, we explore the determinants of option price jumps outside scheduled news announcement times. We estimate the following logistic regression based on a pooled (across delta categories) sample of non-news related observations

$$P(Jump_t|No\ News) = \frac{1}{1 + \exp(-c - \sum_{k=1}^{3} \gamma_k IL_{k,t-1})}. \quad (9)$$

Panel C of Table 5 reports the estimation results. We can see that non-news related jumps are strongly related to lagged liquidity dry ups in option markets. This result holds for all liquidity measures considered. Hence, our findings suggest that option market illiquidity is by far the most important driver of option price jumps.

5 Further robustness analysis

We provide further robustness analyses by conducting a subsample analysis and by also considering the relationship of detected jumps with unscheduled news announcements.

5.1 Subsample analysis

We investigate the existence of option price jumps over two non-overlapping subsamples. In particular, we divide the entire sample period from 1/5/2005 to 31/12/2010 into a non-crisis and a crisis period spanning the period 1/5/2005 to 31/7/2007 and 1/8/2007 to 31/12/2010, respectively; typically, August 2007 is considered to mark the eruption of the global credit crisis. We then recompute the jump and jump-news statistics as in Section 4.2 separately for the non-crisis and crisis subsamples.

Panels A and B of Table 6 report summary statistics for the detected option price jumps for the non-crisis and crisis period, respectively. Comparing the jump frequencies in the non-crisis to the ones in the crisis subsample, we can see that these are of similar magnitude. This finding is consistent across all investigated maturity levels. Hence, we conclude that jumps in option prices exist regardless of the general market conditions contradicting conventional perception that jumps are mainly a crisis phenomenon.

Panels A and B of Table 7 report the summary statistics on the relationship between jumps and all scheduled macroeconomic news announcements for the non-crisis and the crisis periods, respectively. The comparison of the non-crisis figures to the crisis figures reveals an interesting pattern. The association of jumps and news is stronger in the crisis than in the non-crisis subsample. Both the probability of news to cause a jump as well as the fraction of jumps related to news announcements are substantially greater in the crisis than in the non-crisis subsample for almost all delta and maturity categories. In the most pronounced case (short-term DOTM calls), the probability of a news announcement triggering a jump is almost three times higher in the crisis than in the non-crisis subsample. This suggests that option markets have been more sensitive to the release of macroeconomic news announcements during the crisis than the non-crisis periods.

Finally, Panels A and B (C and D) of Table 8 report $P(News|Jump)$ ($P(Jump|News)$) disaggregated by news items for the non-crisis and crisis periods, respectively. We can see that the results are in line with the results aggregated over all announcements as well as with the results over the full sample (Section 4.2). The NFP report as well as the IJC turn out to be the news items most commonly associated with jumps both in the non-crisis and crisis subsample. Also, the jump-news relationship appears to be stronger in the crisis than in the non-crisis subsample. Hence, our results suggest that the timing of news release is more important in explaining option price jumps in the crisis subsample than over both the non-crisis subsample and the full sample.

The more pronounced clustering of option price jumps around the release of scheduled news in the crisis subsample also raises the question whether the news content is more powerful in explaining the occurrence of option price jumps in the crisis subsample. In fact, the empirical evidence in the context of spot markets suggests that macroeconomic news surprises affect equity prices differently depending on the state of the business cycle (e.g., Andersen et al. (2007)). This diverse response of jumps to news surprises depending on the general state of the economy might also carry over to option markets.

To shed more light on this question, we re-estimate the logistic regression equations (7) and (8) on the crisis subsample. Panels A and B of Table 9 report the respective estimation results. Surprisingly, even though the association between news events and option price jumps has been found to be stronger in the crisis subsample, the explanatory power of news surprises for option price jumps turn out to be low. In the logistic model which includes only the news surprise variables (Panel A), only three news surprise coefficients turn out to be significant. After controlling for the option market's liquidity, this result becomes even weaker with only the NFP in the short-term and the GDP in the long-term maturity category remaining significant (Panel B).

As a further robustness check, we examine the dynamics of option market illiquidity over the non-crisis and crisis subsamples. Given that the likelihood of option price jumps has been found to be similar across the crisis and non-crisis subsample, one would expect the dynamics of option market illiquidity not to be different, too. This is because our results over the full sample period suggest that the arrival of option price jumps is mostly driven by option market's illiquidity. Figures 6, 7, and 8 depict the evolution of the daily average relative bid-ask spread for short-term, medium-term, and long-term options of the various delta categories, separately. We can see that option market illiquidity dynamics are comparable in the non-crisis and crisis subsample. In particular, the dynamics of illiquidity do not appear to be any more erratic in the crisis subsample than in the non-crisis subsample. This is in line with the previous finding that option price jumps are equally likely in the non-crisis and crisis subsample provided option price jumps are driven by option market illiquidity. Hence, we conclude that the results from the subsample analysis further confirm that it is liquidity and not news shocks that drive jumps in option prices.

5.2 Unscheduled news announcements

As a second robustness check, we extend the set of information shocks considered in our analysis. The vast majority of papers studying news announcement effects on financial markets have focussed on the analysis of scheduled news announcements (e.g., Andersen et al. (2007), Lahaye et al. (2011)). Our list of scheduled macroeconomic news described in Section 2.2 includes the news items most commonly used in the existing literature and it can be regarded as a comprehensive list of the universe of scheduled information shocks. However, information shocks might also arise from the release of unscheduled news.

Hence, we match detected option price jumps with a set of unscheduled news announcements. The list of announcements considered is taken from Jiang et al. (2012) and includes a total of 137 unscheduled announcement items. The selection of these items has been based on the chronology of significant events of the California Department of Finance, the crisis time line provided by the Federal Reserve Bank of St. Louis, and the European crisis time line provided by Bloomberg (for a detailed description, see Jiang et al. (2012)).

Tracing the exact intraday timing of an unscheduled news announcement is not feasible because different data sources provide a different timing. Hence, we match detected option price jumps with unscheduled news announcements on a daily level. In particular, we define an unscheduled news day to be the day on which at least one unscheduled news announcement has been released and we compute the fraction of jump days that are equal to unscheduled news days. A remark is in order at this point. 72 of the unscheduled news days in our sample coincide with scheduled news days as well. Consequently, it is not possible to unambiguously attribute a jump day to either unscheduled or scheduled news on these dates. Therefore, we only retain unscheduled news days on which there has been no release of scheduled news.

Table 10 reports the results of the resulting jump day-unscheduled news day matching. We can see that unscheduled news appear to play a minor role in explaining option price jump days. Only up to 6% of the detected option price jump days might be attributed to the release of unscheduled news across all delta/maturity categories . Hence, we can conclude that by focussing on the set of scheduled news announcements from Section 2.2, we do not ignore any relevant effect arising from unscheduled news announcements. Furthermore, the unimportance of unscheduled news for explaining option price jumps is consistent with liquidity being the most important jump determinant. This is because unscheduled news announcements occur unexpectedly by definition and thus they cannot adversely affect market liquidity through the informed trading channel described in Section 4.4.

6 Conclusions

We provide first-time evidence that jumps in the S&P 500 E-mini futures options prices exist and we investigate the characteristics and sources of the detected jumps. To address our research question in real-time, we employ high frequency options data from the 24-hours electronic Chicago Mercantile Exchange GLOBEX trading platform. We examine the joint jump dynamics across the cross-section of traded options and we explore whether they are driven by jumps in the underlying option pricing factors, information shocks or the liquidity level. We find that option price jumps do not occur simultaneously across strikes and maturities and they are uncorrelated with jumps in the underlying futures price. On the other hand, 14% to 28% of the detected option price jumps are associated with scheduled releases. However, even though the occurrence of news announcements explains a fraction of option price jumps, the specific news *content* does not. Instead, we find that the option market's liquidity drives option price jumps.

Our findings have three implications. First, jumps in option prices are idiosyncratic. This implies that there is not a common factor that explains the *abrupt* variability of the cross-section of option returns. This may be attributed to the fact that options with different strikes and maturities may have a different clientele resulting in a heterogeneous asset class. This is expected because different types of option strategies exploiting different type of expectations use different strikes and maturities. Second, the option market is segmented from the underlying market in terms of abrupt changes in asset prices. This may be due to the presence of informed option traders and asymmetric information effects (Back (1993)). Third, the fact that liquidity rather than the content of information shocks drive jumps in option markets may also be explained by typical asymmetric information models as well as market microstructure models that consider the hedging activities of option market markers. These models predict that illiquidity measured by the bid-ask spread increases prior to news announcements.

Our findings open three avenues for future research. Our analysis can be extended to other option markets to check whether our findings carry through there as well. It would also be worth exploring whether existing option pricing model can generate the documented jump patterns in option prices. In the case they do not, one should look into developing an asset pricing model that generates idiosyncratic jumps in the cross-section of option prices. Finally, our results further support the call for incorporating option market liquidity risk into option pricing theory (Christoffersen et al. (2012)).

References

Ait-Sahalia, Y. and J. Jacod (2009): "Estimating the degree of activity of jumps in high frequency data," *Annals of Statistics*, 37, 2202–2244.

Amihud, Y., H. Mendelson, and L. H. Pedersen (2005): "Liquidity and asset prices," *Foundations and Trends in Finance*, 4, 269 – 364.

Andersen, T. G. and T. Bollerslev (1998): "Deutsche Mark-Dollar volatility: Intraday activity patterns, macroeconomic announcements, and longer run dependencies," *The Journal of Finance*, 53, 219–265.

Andersen, T. G., T. Bollerslev, F. X. Diebold, and P. Labys (2000): "Great realisations," *Risk*, March 2000, 105 – 108.

Andersen, T. G., T. Bollerslev, F. X. Diebold, and C. Vega (2007): "Real-time price discovery in global stock, bond and foreign exchange markets," *Journal of International Economics*, 73, 251 – 277.

Back, K. (1993): "Asymmetric information and options," *Review of Financial Studies*, 6, 435–472.

Balduzzi, P., E. J. Elton, and T. C. Green (2001): "Economic news and bond prices: Evidence from the U.S. treasury market," *Journal of Financial and Quantitative Analysis*, 36, 523–543.

Bandi, F. M. and R. Reno (2012): "Price and volatility co-jumps," *Working Paper, Johns Hopkins University.*

Barndorff-Nielsen, O. E., P. R. Hansen, A. Lunde, and N. Shephard (2009): "Realized kernels in practice: trades and quotes," *Econometrics Journal*, 12, C1–C32.

Barone-Adesi, G. and R. Whaley (1987): "Efficient analytical approximation of American option values," *Journal of Finance*, 42, 301–320.

Birru, J. and S. Figlewski (2012): "Anatomy of a meltdown: The risk neutral density for the S&P 500 in the fall of 2008," *Journal of Financial Markets*, 15, 151 – 180.

Black, F. (1976): "The pricing of commodity contracts," *Journal of Financial Economics*, 3, 167 – 179.

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

Boudt, K. and M. Petitjean (2013): "Intraday liquidity dynamics and news releases around price jumps: Evidence from the DJIA stocks," *Journal of Financial Markets, in Press.*

Broadie, M., M. Chernov, and M. Johannes (2007): "Model specification and risk premia: Evidence from futures options," *Journal of Finance*, 62, 1453–1490.

——— (2009): "Understanding index option returns," *Review of Financial Studies*, 22, 4493–4529.

Buraschi, A. and A. Jiltsov (2006): "Model uncertainty and option markets with heterogeneous beliefs," *Journal of Finance*, 61, 2841–2897.

Chernov, M., A. R. Gallant, E. Ghysels, and G. Tauchen (2003): "Alternative models for stock price dynamics," *Journal of Econometrics*, 116, 225 – 257.

Christoffersen, P., R. Goyenko, K. Jacobs, and M. Karoui (2012): "Illiquidity premia in the equity options market," *Working Paper, University of Toronto.*

Coval, J. D. and T. Shumway (2001): "Expected option returns," *Journal of Finance*, 56, 983–1009.

Driessen, J. and P. Maenhout (2007): "An empirical portfolio perspective on option pricing anomalies," *Review of Finance*, 11, 561–603.

Dumitru, A.-M. and G. Urga (2012): "Identifying jumps in financial assets: A comparison between nonparametric jump tests," *Journal of Business & Economic Statistics*, 30, 242–255.

Dungey, M., L. Fakhrutdinova, and C. Goodhart (2009): "After-hours trading in equity futures markets," *Journal of Futures Markets*, 29, 114–136.

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

Ederington, L. H. and J. H. Lee (1996): "The creation and resolution of market uncertainty: The impact of information releases on implied volatility," *Journal of Financial and Quantitative Analysis*, 31, 513–539.

Eraker, B. (2004): "Do stock prices and volatility jump? Reconciling evidence from spot and option prices," *Journal of Finance*, 59, 1367–1404.

Evans, K. P. (2011): "Intraday jumps and US macroeconomic news announcements," *Journal of Banking and Finance*, 35, 2511 – 2527.

Fornari, F. and A. Mele (2001): "Volatility smiles and the information content of news," *Applied Financial Economics*, 11, 179–186.

Friesen, G. C., Y. Zhang, and T. S. Zorn (2012): "Heterogeneous beliefs and risk neutral skewness," *Journal of Financial and Quantitative Analysis*, 47, 851–872.

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

Gonçalves, S. and M. Guidolin (2006): "Predictable dynamics in the S&P 500 index options implied volatility surface," *Journal of Business*, 79, 1591–1635.

Han, B. (2008): "Investor sentiment and option prices," *Review of Financial Studies*, 21, 387–414.

Huh, S.-W., H. Lin, and A. S. Mello (2012): "Hedging by option market makers: Theory and evidence," *Working Paper, University of Wisconsin at Madison.*

Jackwerth, J. C. (1999): "Option implied risk-neutral distributions and implied binomial trees: A literature review," *Journal of Derivatives*, 7, 66–82.

Jiang, G. J., E. Konstantinidi, and G. Skiadopoulos (2012): "Volatility spillovers and the effect of news announcements," *Journal of Banking and Finance*, 36, 2260–2273.

Jiang, G. J., I. Lo, and A. Verdelhan (2011): "Information shocks, liquidity shocks, jumps, and price discovery: Evidence from the U.S. treasury market," *Journal of Financial and Quantitative Analysis*, 46, 527–551.

Kim, O. and R. E. Verrecchia (1994): "Market liquidity and volume around earnings announcements," *Journal of Accounting and Economics*, 17, 41 – 67.

Lahaye, J., S. Laurent, and C. J. Neely (2011): "Jumps, cojumps and macro announcements," *Journal of Applied Econometrics*, 26, 893–921.

Lee, S. S. (2012): "Jumps and information flow in financial markets," *Review of Financial Studies*, 25, 439–479.

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

Lemmon, M. L. and S. X. Ni (2011): "The effects of investor sentiment on speculative trading and prices of stock and index options," *Working Paper, University of Utah*.

Maheu, J. M. and T. H. McCurdy (2004): "News arrival, jump dynamics, and volatility components for individual stock returns," *Journal of Finance*, 59, 755–793.

Merton, R. C. (1976): "Option pricing when underlying stock returns are discontinuous," *Journal of Financial Economics*, 3, 125 – 144.

Neumann, M. and G. Skiadopoulos (2013): "Predictable dynamics in higher order risk-neutral moments: Evidence from the S&P 500 options," *Journal of Financial and Quantitative Analysis*, 48, 947–977.

Pan, J. and A. Poteshman (2006): "The information in options volume for future stock prices," *Review of Financial Studies*, 19, 871–908.

Rangel, J. G. (2011): "Macroeconomic news, announcements, and stock market jump intensity dynamics," *Journal of Banking and Finance*, 35, 1263 – 1276.

Santa-Clara, P. and A. Saretto (2009): "Option strategies: Good deals and margin calls," *Journal of Financial Markets*, 12, 391 – 417.

Shefrin, H. M. (2001): "On kernels and sentiment," *Working Paper, Santa Clara University.*

Skiadopoulos, G., S. Hodges, and L. Clewlow (1999): "The dynamics of the S&P 500 implied volatility surface," *Review of Derivatives Research*, 3, 263–282.

Skiadopoulos, G. S. (2001): "Volatility smile consistent option models: A survey," *International Journal of Theoretical and Applied Finance*, 4, 403–437.

Tables

Table 1: Option Categories

Category	Name	Delta Interval/ Time to Expiration T (in days)
Panel A: Delta Categories		
1	Deep out-of-the-money (DOTM) put	$-0.125 < \Delta \leq -0.02$
2	Out-of-the-money (OTM) put	$-0.375 < \Delta \leq -0.125$
3	At-the-money (ATM) put	$-0.625 < \Delta \leq -0.375$
4	At-the-money (ATM) call	$0.375 < \Delta \leq 0.625$
5	Out-of-the-money (OTM) call	$0.125 < \Delta \leq 0.375$
6	Deep out-of-the-money (DOTM) call	$0.02 < \Delta \leq 0.125$
Panel B: Maturity Categories		
1	Short-term options	$10 \leq T \leq 40$
2	Medium-term options	$10 < T \leq 70$
3	Long-term options	$70 < T \leq 100$

Entries report the different option delta categories and their definitions in terms of their Black (1976) options delta (Panel A) and the different option expiration categories and their definitions in terms of their number of days to expiration (Panel B).

Table 2: Scheduled News Announcements

News Announcement Item		Frequency	Source	N	Announcement Time
1	Non-Farm Payroll Employment (NFP)	Monthly	Bureau of Labor Statistics	72	7:30 a.m. (CST)
2	Consumer Confidence Index (CCI)	Monthly	Conference Board	72	9:00 a.m. (CST)
3	Consumer Price Index (CPI)	Monthly	Bureau of Labor Statistics	72	7:30 a.m. (CDT)
4	Durable Goods Orders (DGO)	Monthly	US Census Bureau	72	7:30 a.m. (CST)
5	Target Federal Funds Rate (FOMC)	Eight times per year	Federal Reserve Bank	50	1:15 p.m. (CST)
6	Gross Domestic Product (GDP)	Monthly	Bureau of Economic Analysis	72	7:30 a.m. (CST)
7	Initial Jobless Claims (IJC)	Weekly	Department of Labor	313	7:30 a.m. (CST)
8	Leading Indicators (LI)	Monthly	Conference Board	72	9:00 a.m. (CST)
9	New Home Sales (NHS)	Monthly	US Census Bureau	72	9:00 a.m. (CST)
10	Producer Price Index (PPI)	Monthly	Bureau of Labor Statistics	72	7:30 a.m. (CST)
11	Retails Sales Less Automotive (RSLA)	Monthly	US Census Bureau	72	7:30 a.m. (CST)

Entries report the scheduled U.S. news announcements considered in the analysis. The name of the respective items, their source as well as their timing and the number of occurrences in the sample (N) are provided. **Notes:** 1) The Federal Reserve Board can meet more than eight times per year. 2) In our sample, the FOMC announcement has been released twice at times deviating from the figure given in the table (at 7:30 a.m. on 22/01/2008 (CST) and at 6:00 a.m. (CST) on 8/10/2008; the latter is excluded from analysis as it falls outside of the trading hours considered in our analysis.

Table 3: Summary Statistics of Detected Jumps

	DOTM Puts	OTM Puts	ATM Puts	ATM Calls	OTM Calls	DOTM Calls	Futures
Short-Term Options							
# Observations	62,142	63,142	62,734	62,815	63,074	61,549	64,665
# Jumps	289	169	171	200	139	297	95
# Jump Days	231	134	128	161	111	246	72
$P(Jump\ Day)$	16.08%	9.32%	8.91%	11.20%	7.72%	17.12%	5.01%
P(Jump)	0.47%	0.27%	0.27%	0.32%	0.22%	0.48%	0.15%
Avg. Jump Size	-23.84%	-25.35%	-14.85%	-16.12%	-28.15%	-63.35%	-0.07%
% Negative Jumps	57.79%	69.82%	78.95%	80.00%	60.43%	72.05%	54.74%
Medium-Term Options							
# Observations	60,814	62,234	61,958	62,062	62,124	60,540	64,755
# Jumps	228	129	159	106	150	263	92
# Jump Days	181	100	111	80	125	218	70
$P(Jump\ Day)$	12.58%	6.95%	7.71%	5.56%	8.69%	15.15%	4.86%
$P(Jump)$	0.37%	0.21%	0.26%	0.17%	0.24%	0.43%	0.14%
Avg. Jump Size	-5.93%	-7.80%	-5.06%	-12.97%	-7.35%	-29.60%	-0.07%
% Negative Jumps	45.18%	58.14%	76.73%	84.91%	53.33%	60.84%	55.43%
Long-Term Options							
# Observations	52,770	54,088	53,716	53,902	54,034	52,627	56,970
# Jumps	223	106	145	72	118	296	86
# Jump Days	159	80	112	62	97	222	67
$P(Jump\ Day)$	12.57%	6.32%	8.85%	4.90%	7.66%	17.54%	5.29%
$P(Jump)$	0.42%	0.20%	0.27%	0.13%	0.22%	0.56%	0.15%
Average Jump Size	-8.95%	-9.78%	-5.98%	-10.24%	-27.73%	-21.76%	-0.08%
% Negative Jumps	56.50%	55.66%	85.52%	83.33%	57.63%	60.81%	55.81%

Entries report summary statistics for the detected jumps for all investigated moneyness and maturity categories. The number of detected jumps, the number of jump days (days with at least one jump), the probability of a jump day to occur $P(Jump\ Day)$, the probability of a jump to occur $P(Jump)$ and the number of negative jumps as a fraction of all jumps are reported. Jumps have been detected using the Lee and Mykland (2008) jump detection methodology based on a significance level $\alpha = 0.1\%$. The sample period is 1/1/2005 to 31/12/2010.

Table 4: **Relationship between Jumps and Scheduled Announcements**

	DOTM Puts	OTM Puts	ATM Puts	ATM Calls	OTM Calls	DOTM Calls	Futures
Panel A: Aggregated over all News Items							
Short-Term Options							
# Jumps within 10 mins of News	60	42	40	57	39	61	23
$P(News \mid Jump)$	20.76%	24.85%	23.39%	28.50%	28.06%	20.54%	24.21%
$P(Jump \mid News)$	6.75%	4.72%	4.50%	6.41%	4.39%	6.86%	2.59%
Medium-Term Options							
# Jumps within 10 mins of News	34	35	25	19	35	43	25
$P(News \mid Jump)$	14.91%	27.13%	15.72%	17.92%	23.33%	16.35%	27.17%
$P(Jump \mid News)$	3.82%	3.94%	2.81%	2.14%	3.94%	4.84%	2.81%
Long-Term Options							
# Jumps within 10 mins of News	32	21	21	12	33	44	23
$P(News \mid Jump)$	14.35%	19.81%	14.48%	16.67%	27.97%	14.86%	26.74%
$P(Jump \mid News)$	3.60%	2.36%	2.36%	1.35%	3.71%	4.95%	2.59%

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Table 4: Relationship between Jumps and Scheduled Announcements

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	DOTM Puts	OTM Puts	ATM Puts	ATM Calls	OTM Calls	DOTM Calls	Futures
Panel B: $P(News\|Jump)$ ***Disaggregated by News Items***							
Short-Term							
NFP	5.19%	8.88%	6.43%	6.00%	5.04%	4.38%	11.58%
CCI	0.35%	0.00%	1.75%	1.50%	0.00%	1.35%	0.00%
CPI	2.42%	2.37%	2.92%	3.50%	4.32%	0.67%	0.00%
DGO	2.08%	0.59%	2.92%	2.00%	1.44%	2.02%	0.00%
FOMC	0.69%	1.18%	2.34%	1.50%	2.16%	0.67%	9.47%
GDP	2.08%	1.78%	1.75%	3.50%	2.88%	2.69%	1.05%
IJC	7.96%	5.92%	7.60%	9.50%	11.51%	8.75%	1.05%
LI	0.35%	0.00%	0.58%	0.50%	0.00%	0.34%	0.00%
NHS	0.35%	0.59%	0.00%	1.00%	0.00%	0.67%	1.05%
PPI	1.73%	4.14%	0.00%	1.50%	1.44%	1.68%	0.00%
RSA	1.04%	3.55%	0.00%	1.00%	2.88%	1.01%	0.00%
Medium-Term							
NFP	6.14%	8.53%	5.66%	5.66%	10.00%	2.28%	14.13%
CCI	0.00%	0.78%	1.89%	1.89%	0.67%	0.38%	0.00%
CPI	0.88%	0.78%	1.89%	0.94%	1.33%	2.28%	0.00%
DGO	0.44%	1.55%	0.63%	0.00%	2.67%	1.52%	0.00%
FOMC	1.75%	3.10%	2.52%	1.89%	1.33%	0.76%	9.78%
GDP	0.44%	3.88%	0.00%	1.89%	1.33%	0.76%	1.09%
IJC	3.07%	10.08%	1.89%	4.72%	5.33%	6.08%	1.09%
LI	0.44%	0.78%	0.00%	0.00%	0.67%	1.14%	0.00%
NHS	0.00%	0.00%	0.63%	1.89%	0.67%	0.76%	1.09%
PPI	1.32%	0.78%	0.63%	0.00%	0.00%	0.76%	0.00%
RSA	0.44%	1.55%	0.00%	0.94%	0.67%	0.76%	0.00%
Long-Term							
NFP	3.14%	6.60%	4.14%	5.56%	7.63%	3.04%	10.47%
CCI	1.35%	1.89%	2.07%	0.00%	3.39%	0.00%	2.33%
CPI	0.90%	0.00%	1.38%	0.00%	5.93%	1.01%	0.00%
DGO	2.69%	0.00%	0.69%	0.00%	0.85%	1.69%	0.00%
FOMC	0.45%	3.77%	3.45%	1.39%	1.69%	1.35%	10.47%
GDP	0.90%	0.94%	0.00%	1.39%	3.39%	1.69%	1.16%
IJC	4.04%	5.66%	0.69%	2.78%	8.47%	3.72%	1.16%
LI	1.35%	0.00%	0.00%	0.00%	0.00%	0.68%	0.00%
NHS	0.90%	0.94%	2.07%	1.39%	0.00%	0.34%	1.16%
PPI	0.45%	0.94%	0.00%	0.00%	0.85%	1.35%	0.00%
RSA	0.45%	0.94%	0.00%	5.56%	0.00%	2.36%	0.00%

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Table 4: Relationship between Jumps and Scheduled Announcements

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	DOTM Puts	OTM Puts	ATM Puts	ATM Calls	OTM Calls	DOTM Calls	Futures
Panel C: $P(Jump\|News)$ ***Disaggregated by News Items***							
Short-Term							
NFP	20.83%	20.83%	15.28%	16.67%	9.72%	18.06%	15.28%
CCI	1.39%	0.00%	4.17%	4.17%	0.00%	5.56%	0.00%
CPI	9.72%	5.56%	6.94%	9.72%	8.33%	2.78%	0.00%
DGO	8.33%	1.39%	6.94%	5.56%	2.78%	8.33%	0.00%
FOMC	4.00%	4.00%	8.00%	6.00%	6.00%	4.00%	18.00%
GDP	8.33%	4.17%	4.17%	9.72%	5.56%	11.11%	1.39%
IJC	7.35%	3.19%	4.15%	6.07%	5.11%	8.31%	0.32%
LI	1.39%	0.00%	1.39%	1.39%	0.00%	1.39%	0.00%
NHS	1.39%	1.39%	0.00%	2.78%	0.00%	2.78%	1.39%
PPI	6.94%	9.72%	0.00%	4.17%	2.78%	6.94%	0.00%
RSA	4.17%	8.33%	0.00%	2.78%	5.56%	4.17%	0.00%
Medium-Term							
NFP	19.44%	15.28%	12.50%	8.33%	20.83%	8.33%	18.06%
CCI	0.00%	1.39%	4.17%	2.78%	1.39%	1.39%	0.00%
CPI	2.78%	1.39%	4.17%	1.39%	2.78%	8.33%	0.00%
DGO	1.39%	2.78%	1.39%	0.00%	5.56%	5.56%	0.00%
FOMC	8.00%	8.00%	8.00%	4.00%	4.00%	4.00%	18.00%
GDP	1.39%	6.94%	0.00%	2.78%	2.78%	2.78%	1.39%
IJC	2.24%	4.15%	0.96%	1.60%	2.56%	5.11%	0.32%
LI	1.39%	1.39%	0.00%	0.00%	1.39%	4.17%	0.00%
NHS	0.00%	0.00%	1.39%	2.78%	1.39%	2.78%	1.39%
PPI	4.17%	1.39%	1.39%	0.00%	0.00%	2.78%	0.00%
RSA	1.39%	2.78%	0.00%	1.39%	1.39%	2.78%	0.00%
Long-Term							
NFP	9.72%	9.72%	8.33%	5.56%	12.50%	12.50%	12.50%
CCI	4.17%	2.78%	4.17%	0.00%	5.56%	0.00%	2.78%
CPI	2.78%	0.00%	2.78%	0.00%	9.72%	4.17%	0.00%
DGO	8.33%	0.00%	1.39%	0.00%	1.39%	6.94%	0.00%
FOMC	2.00%	8.00%	10.00%	2.00%	4.00%	8.00%	18.00%
GDP	2.78%	1.39%	0.00%	1.39%	5.56%	6.94%	1.39%
IJC	2.88%	1.92%	0.32%	0.64%	3.19%	3.51%	0.32%
LI	4.17%	0.00%	0.00%	0.00%	0.00%	2.78%	0.00%
NHS	2.78%	1.39%	4.17%	1.39%	0.00%	1.39%	1.39%
PPI	1.39%	1.39%	0.00%	0.00%	1.39%	5.56%	0.00%
RSA	1.39%	1.39%	0.00%	5.56%	0.00%	9.72%	0.00%

Entries report summary statistics on the relationship between detected jumps and scheduled macroeconomic news announcement items for all investigated moneyness and maturity categories. The probability of a jump being related to a specific news announcement $P(News|Jump)$ and the probability of a news announcement leading to a jump $P(Jump|News)$ are reported. Panel A reports these statistics aggregated over all considered news announcement items and Panel B and C report them disaggregated by individal announcement items. Jumps have been detected using the Lee and Mykland (2008) jump detection methodology based on a significance level $\alpha = 0.1\%$. A jump is defined to be related to news if it occurred within ± 10 minutes of a scheduled news announcement

Table 5: Information Shocks and Illiquidity as Jump Determinants

	Short-Term	Medium-Term	Long-Term
Panel A: News Covariates			
c	-3.858***	-4.158***	-4.808***
NFP_t	0.751***	0.632**	-0.06
CCI_t	-1.001	-0.61	-0.09
CPI_t	0.237	-0.28	0.25
DGO_t	0.132	-0.98	-1.11
$FOMC_t$	-	-	-
GDP_t	0.157	-0.11	0.724***
IJC_t	0.287*	-0.07	0.13
LI_t	-0.980	-0.69	-
NHS_t	-	-6.66	-
PPI_t	-0.045	-0.14	-0.09
RSA_t	-0.141	-1.08	0.779**
Panel B: News and Liquidity Covariates			
c	-3.760***	-3.803***	-4.257***
BA_{t-1}	1.385***	1.318***	2.003***
$BidSize_{t-1}$	-0.002*	-0.002	-0.002
$AskSize_{t-1}$	-0.001	-0.002	-0.003
NFP_t	0.568***	0.504	-0.302
CCI_t	-0.442	-0.212	0.329
CPI_t	0.172	-0.297	0.085
DGO_t	0.071	-1.110	-1.411
$FOMC_t$	-	-	-
GDP_t	0.018	-0.309	0.581**
IJC_t	0.185	-0.212	-0.151
LI_t	-0.430	-0.334	-
NHS_t	-	-5.025	-
PPI_t	-0.136	-0.170	-0.285
RSA_t	-0.204	-1.004	0.324
Panel C: Liquidity Covariates for no-news related jumps			
c	-6.040***	-6.001***	-5.781***
BA_{t-1}	3.138***	3.288***	3.230***
$BidSize_{t-1}$	-0.002***	-0.001***	-0.001***
$AskSize_{t-1}$	-0.001***	-0.002***	-0.002***

Entries report the estimation results for the logistic regression models in equation (7), (8), and (9) in Panel A, B, and C, respectively. The estimation is performed separately for short, medium, and long-term options on a sample pooled across all delta categories. Panels A and B consider only news-related observations and Panel C considers only non-news-related observations. The estimation is performed via Maximum Likelihood and ***, **, * report statistical significance on a 1%, 5%, and 10% significance level, respectively. The sample period is 1/1/2005 to 31/12/2010.

Table 6: Summary Statistics of Detected Jumps (Non-Crisis and Crisis Subsample)

	DOTM Puts	OTM Puts	ATM Puts	ATM Calls	OTM Calls	DOTM Calls	Futures
Panel A: Non-Crisis Subsample							
Short-Term							
# Observations	25,501	26,419	26,044	26,122	26,359	24,912	27,720
# Jumps	149	98	54	101	88	115	40
# Jump Days	124	78	46	85	68	95	32
$P(Jump\ Day)$	20.13%	12.66%	7.47%	13.80%	11.04%	15.42%	5.19%
$P(Jump)$	0.58%	0.37%	0.21%	0.39%	0.33%	0.46%	0.14%
Avg. Jump Size	-31.44%	-30.79%	-19.93%	-21.31%	-36.98%	-35.99%	0.00%
% Negative Jumps	59.73%	71.43%	85.19%	83.17%	62.50%	66.96%	50.00%
Medium-Term							
# Observations	24,237	25,356	25,092	25,204	25,262	23,937	27,540
# Jumps	120	55	47	54	89	98	39
# Jump Days	97	45	36	44	75	83	31
$P(Jump\ Day)$	15.85%	7.35%	5.88%	7.19%	12.25%	13.56%	5.07%
$P(Jump)$	0.50%	0.22%	0.19%	0.21%	0.35%	0.41%	0.14%
Avg. Jump Size	-5.49%	-11.71%	-14.79%	-10.78%	-4.17%	-16.26%	0.00%
% Negative Jumps	46.67%	65.45%	95.74%	87.04%	47.19%	50.00%	51.28%
Long-Term							
# Observations	17,569	18,427	18,082	18,252	18,369	17,431	20,700
# Jumps	116	38	43	37	44	103	36
# Jump Days	77	28	36	35	36	79	30
$P(Jump\ Day)$	16.74%	6.09%	7.83%	7.63%	7.83%	17.17%	6.52%
$P(Jump)$	0.66%	0.21%	0.24%	0.20%	0.24%	0.59%	0.17%
Avg. Jump Size	-3.60%	-2.04%	-9.34%	-7.08%	-5.81%	-21.31%	-0.02%
% Negative Jumps	48.28%	55.26%	93.02%	86.49%	61.36%	53.40%	52.78%

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Table 6: **Summary Statistics of Detected Jumps (Non-Crisis and Crisis Subsample)**

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	DOTM Puts	**OTM Puts**	**ATM Puts**	**ATM Calls**	**OTM Calls**	**DOTM Calls**	**Futures**
Panel B: Crisis Subsample							
Short-Term							
# Observations	36,596	36,678	36,645	36,648	36,670	36,592	36,900
# Jumps	140	71	117	99	51	182	55
# Jump Days	107	56	82	76	43	151	40
$P(Jump\ Day)$	13.05%	6.83%	10.00%	9.27%	5.24%	18.41%	4.88%
$P(Jump)$	0.38%	0.19%	0.32%	0.27%	0.14%	0.50%	0.15%
Avg. Jump Size	-32.31%	-30.03%	-17.59%	-21.40%	-56.32%	-50.81%	0.06%
% Negative Jumps	60.71%	71.83%	82.91%	82.83%	72.55%	70.88%	47.27%
Medium-Term							
# Observations	36,532	36,833	36,821	36,813	36,817	36,558	37,170
# Jumps	107	74	112	52	61	165	53
# Jump Days	83	55	75	36	50	135	39
$P(Jump\ Day)$	10.05%	6.66%	9.08%	4.36%	6.05%	16.34%	4.72%
$P(Jump)$	0.29%	0.20%	0.30%	0.14%	0.17%	0.45%	0.14%
Avg. Jump Size	-3.13%	-9.71%	-5.89%	-12.40%	-12.36%	-29.17%	0.06%
% Negative Jumps	45.79%	66.22%	80.36%	90.38%	57.38%	60.61%	49.06%
Long-Term							
# Observations	35,156	35,616	35,590	35,606	35,620	35,151	36,225
# Jumps	107	68	102	35	74	193	50
# Jump Days	82	52	76	27	61	143	37
$P(Jump\ Day)$	10.20%	6.46%	9.44%	3.35%	7.58%	17.76%	4.60%
$P(Jump)$	0.30%	0.19%	0.29%	0.10%	0.21%	0.55%	0.14%
Avg. Jump Size	-3.87%	-7.75%	-5.59%	-7.77%	-17.44%	-28.65%	0.01%
% Negative Jumps	48.60%	61.76%	87.25%	88.57%	54.05%	62.69%	50.00%

Entries report summary statistics for the detected jumps for all investigated moneyness and maturity categories over the non-crisis subsample (Panel A) and crisis subsample (Panel B). The number of detected jumps, the number of jump days (days with at least one jump), the probability of a jump day to occur $P(Jump\ Day)$, the probability of a jump to occur $P(Jump)$ and the number of negative jumps as a fraction of all jumps are reported. Jumps have been detected using the Lee and Mykland (2008) jump detection methodology based on a significance level $\alpha = 0.1\%$. The sample period is 1/1/2005 to 31/7/2007 for the non-crisis subsample and 1/8/2007 to 31/12/2010 for the crisis subsample.

Table 7: Relationship between Jumps and Scheduled Announcements (Non-Crisis and Crisis Subsample)

	DOTM Puts	OTM Puts	ATM Puts	ATM Calls	OTM Calls	DOTM Calls	Futures
Panel A: Non-Crisis Subsample							
Short-Term							
# Jumps within 10 mins of News	19	20	9	26	18	14	11
$P(News\|Jump)$	12.75%	20.41%	16.67%	25.74%	20.45%	12.17%	27.50%
$P(Jump\|News)$	4.95%	5.21%	2.34%	6.77%	4.69%	3.65%	2.86%
Medium-Term							
# Jumps within 10 mins of News	11	11	6	5	15	10	12
$P(News\|Jump)$	9.17%	20.00%	12.77%	9.26%	16.85%	10.20%	30.77%
$P(Jump\|News)$	2.86%	2.86%	1.56%	1.30%	3.91%	2.60%	3.13%
Long-Term							
# Jumps within 10 mins of News	9	5	7	1	9	9	12
$P(News\|Jump)$	7.76%	13.16%	16.28%	2.70%	20.45%	8.74%	33.33%
$P(Jump\|News)$	2.34%	1.30%	1.82%	0.26%	2.34%	2.34%	3.13%
Panel B: Crisis Subsample							
Short-Term							
# Jumps within 10 mins of News	41	22	31	31	21	47	12
$P(News\|Jump)$	29.29%	30.99%	26.50%	31.31%	41.18%	25.82%	21.82%
$P(Jump\|News)$	8.13%	4.37%	6.15%	6.15%	4.17%	9.33%	2.38%
Medium-Term							
# Jumps within 10 mins of News	23	24	19	14	20	33	13
$P(News\|Jump)$	21.50%	32.43%	16.96%	26.92%	32.79%	20.00%	24.53%
$P(Jump\|News)$	4.56%	4.76%	3.77%	2.78%	3.97%	6.55%	2.58%
Long-Term							
# Jumps within 10 mins of News	23	16	14	11	24	35	11
$P(News\|Jump)$	21.50%	23.53%	13.73%	31.43%	32.43%	18.13%	22.00%
$P(Jump\|News)$	4.56%	3.17%	2.78%	2.18%	4.76%	6.94%	2.18%

Entries report summary statistics on the relationship between detected jumps and macroeconomic news announcements for all investigated moneyness and maturity categories over the non-crisis subsample (Panel A) and crisis subsample (Panel B). The number of jumps that occurred within ±10 minutes of a scheduled news announcement, the probability of a news announcement leading to a jump $P(Jump|News)$ as well as the probability of a jump being related to a news announcement $P(News|Jump)$ are reported. Jumps have been detected using the Lee and Mykland (2008) jump detection methodology based on a significance level $\alpha = 0.1\%$. The sample period is 1/1/2005 to 31/7/2007 for the non-crisis and 1/8/2007 to 31/12/2010 for the crisis subsample.

Table 8: **Relationship between Jumps and Scheduled Announcements Disaggregated by Announcement Items (Non-Crisis and Crisis Subsample)**

	DOTM Puts	OTM Puts	ATM Puts	ATM Calls	OTM Calls	DOTM Calls	Futures
Panel A: $P(News \mid Jump)$ ***over the Non-Crisis Subsample***							
Short-Term Options							
NFP	1.34%	4.08%	5.56%	1.98%	2.27%	1.74%	10.00%
CCI	0.67%	0.00%	1.85%	0.00%	0.00%	2.61%	0.00%
CPI	2.68%	3.06%	3.70%	4.95%	2.27%	0.87%	0.00%
DGO	2.01%	0.00%	1.85%	0.00%	2.27%	0.87%	0.00%
FOMC	0.00%	0.00%	1.85%	0.99%	0.00%	0.00%	12.50%
GDP	2.68%	0.00%	1.85%	2.97%	1.14%	0.00%	0.00%
IJC	3.36%	8.16%	0.00%	11.88%	10.23%	3.48%	2.50%
LI	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
NHS	0.00%	0.00%	0.00%	0.99%	0.00%	0.00%	2.50%
PPI	0.67%	6.12%	0.00%	1.98%	2.27%	2.61%	0.00%
RSA	0.00%	5.10%	0.00%	1.98%	1.14%	0.87%	0.00%
Medium-Term Options							
NFP	3.33%	7.27%	2.13%	0.00%	7.87%	2.04%	12.82%
CCI	0.00%	0.00%	2.13%	1.85%	1.12%	0.00%	0.00%
CPI	0.83%	1.82%	4.26%	1.85%	2.25%	2.04%	0.00%
DGO	0.83%	0.00%	0.00%	0.00%	0.00%	1.02%	0.00%
FOMC	0.83%	1.82%	2.13%	0.00%	0.00%	1.02%	12.82%
GDP	0.83%	5.45%	0.00%	1.85%	1.12%	1.02%	0.00%
IJC	0.83%	3.64%	2.13%	1.85%	3.37%	0.00%	2.56%
LI	0.00%	0.00%	0.00%	0.00%	1.12%	1.02%	0.00%
NHS	0.00%	0.00%	0.00%	1.85%	0.00%	1.02%	2.56%
PPI	1.67%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
RSA	0.00%	0.00%	0.00%	0.00%	1.12%	1.02%	0.00%
Long-Term Options							
NFP	0.86%	2.63%	2.33%	0.00%	4.55%	2.91%	8.33%
CCI	2.59%	2.63%	2.33%	0.00%	6.82%	0.00%	5.56%
CPI	0.00%	0.00%	2.33%	0.00%	4.55%	0.00%	0.00%
DGO	1.72%	0.00%	0.00%	0.00%	0.00%	0.97%	0.00%
FOMC	0.00%	5.26%	4.65%	0.00%	0.00%	2.91%	13.89%
GDP	0.00%	0.00%	0.00%	0.00%	0.00%	0.91%	0.00%
IJC	0.86%	0.00%	0.00%	0.00%	4.55%	0.00%	2.78%
LI	0.86%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
NHS	1.72%	0.00%	4.65%	2.70%	0.00%	0.00%	2.78%
PPI	0.00%	2.63%	0.00%	0.00%	0.00%	0.00%	0.00%
RSA	0.00%	0.00%	0.00%	0.00%	0.00%	0.97%	0.00%

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Table 8: Relationship between Jumps and Scheduled Announcements Disaggregated by Announcement Items (Non-Crisis and Crisis Subsample)

Continued from previous page

	DOTM Puts	OTM Puts	ATM Puts	ATM Calls	OTM Calls	DOTM Calls	Futures
Panel B: $P(News \mid Jump)$ ***over the Crisis Subsample***							
Short-Term Options							
NFP	9.29%	15.49%	6.84%	10.10%	9.80%	6.04%	12.73%
CCI	0.00%	0.00%	1.71%	3.03%	0.00%	0.55%	0.00%
CPI	2.14%	1.41%	2.56%	2.02%	7.84%	0.55%	0.00%
DGO	2.14%	1.41%	3.42%	4.04%	0.00%	2.75%	0.00%
FOMC	1.43%	2.82%	2.56%	2.02%	5.88%	1.10%	7.27%
GDP	1.43%	4.23%	1.71%	4.04%	5.88%	4.40%	1.82%
IJC	12.86%	2.82%	11.11%	7.07%	13.73%	12.09%	0.00%
LI	0.71%	0.00%	0.85%	1.01%	0.00%	0.55%	0.00%
NHS	0.71%	1.41%	0.00%	1.01%	0.00%	1.10%	0.00%
PPI	2.86%	1.41%	0.00%	1.01%	0.00%	1.10%	0.00%
RSA	2.14%	1.41%	0.00%	0.00%	5.88%	1.10%	0.00%
Medium-Term Options							
NFP	9.35%	9.46%	7.14%	11.54%	13.11%	2.42%	15.09%
CCI	0.00%	1.35%	1.79%	1.92%	0.00%	0.61%	0.00%
CPI	0.93%	0.00%	0.89%	0.00%	0.00%	2.42%	0.00%
DGO	0.00%	2.70%	0.89%	0.00%	6.56%	1.82%	0.00%
FOMC	2.80%	4.05%	2.68%	3.85%	3.28%	0.61%	7.55%
GDP	0.00%	2.70%	0.00%	1.92%	1.64%	0.61%	1.89%
IJC	5.61%	14.86%	1.79%	7.69%	8.20%	9.70%	0.00%
LI	0.93%	1.35%	0.00%	0.00%	0.00%	1.21%	0.00%
NHS	0.00%	0.00%	0.89%	1.92%	1.64%	0.61%	0.00%
PPI	0.93%	1.35%	0.89%	0.00%	0.00%	1.21%	0.00%
RSA	0.93%	2.70%	0.00%	1.92%	0.00%	0.61%	0.00%
Long-Term Options							
NFP	5.61%	8.82%	4.90%	11.43%	9.46%	3.11%	12.00%
CCI	0.00%	1.47%	1.96%	0.00%	1.35%	0.00%	0.00%
CPI	1.87%	0.00%	0.98%	0.00%	6.76%	1.55%	0.00%
DGO	3.74%	0.00%	0.98%	0.00%	1.35%	2.07%	0.00%
FOMC	0.94%	2.94%	2.94%	2.86%	2.70%	0.52%	8.00%
GDP	1.87%	1.47%	0.00%	2.86%	5.41%	2.07%	2.00%
IJC	7.48%	8.82%	0.98%	5.71%	10.82%	5.70%	0.00%
LI	1.87%	0.00%	0.00%	0.00%	0.00%	1.03%	0.00%
NHS	0.00%	1.47%	0.98%	0.00%	0.00%	0.52%	0.00%
PPI	0.94%	0.00%	0.00%	0.00%	1.35%	2.07%	0.00%
RSA	0.94%	1.47%	0.00%	11.43%	0.00%	3.11%	0.00%

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Table 8: Relationship between Jumps and Scheduled Announcements Disaggregated by Announcement Items (Non-Crisis and Crisis Subsample)

Continued from previous page

	DOTM Puts	OTM Puts	ATM Puts	ATM Calls	OTM Calls	DOTM Calls	Futures
Panel C: $P(Jump \mid News)$ ***over the Non-Crisis Subsample***							
Short-Term Options							
NFP	6.45%	12.90%	9.68%	6.45%	6.45%	6.45%	12.90%
CCI	3.33%	0.00%	3.33%	0.00%	0.00%	10.00%	0.00%
CPI	12.90%	9.68%	6.45%	16.13%	6.45%	3.23%	0.00%
DGO	9.68%	0.00%	3.23%	0.00%	6.45%	3.23%	0.00%
FOMC	0.00%	0.00%	5.00%	5.00%	0.00%	0.00%	25.00%
GDP	12.90%	0.00%	3.23%	9.68%	3.23%	0.00%	0.00%
IJC	3.73%	5.97%	0.00%	8.96%	6.72%	2.99%	0.75%
LI	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
NHS	0.00%	0.00%	0.00%	3.23%	0.00%	0.00%	3.23%
PPI	3.23%	19.35%	0.00%	6.45%	6.45%	9.68%	0.00%
RSA	0.00%	16.13%	0.00%	6.45%	3.23%	3.23%	0.00%
Medium-Term Options							
NFP	12.90%	12.90%	3.23%	0.00%	22.58%	6.45%	16.13%
CCI	0.00%	0.00%	3.33%	3.33%	3.33%	0.00%	0.00%
CPI	3.23%	3.23%	6.45%	3.23%	6.45%	6.45%	0.00%
DGO	3.23%	0.00%	0.00%	0.00%	0.00%	3.23%	0.00%
FOMC	5.00%	5.00%	5.00%	0.00%	0.00%	5.00%	25.00%
GDP	3.23%	9.68%	0.00%	3.23%	3.23%	3.23%	0.00%
IJC	0.75%	1.49%	0.75%	0.75%	2.24%	0.00%	0.75%
LI	0.00%	0.00%	0.00%	0.00%	3.23%	3.23%	0.00%
NHS	0.00%	0.00%	0.00%	3.23%	0.00%	3.23%	3.23%
PPI	6.45%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
RSA	0.00%	0.00%	0.00%	0.00%	3.23%	3.23%	0.00%
Long-Term Options							
NFP	3.23%	3.23%	3.23%	0.00%	6.45%	9.68%	9.68%
CCI	10.00%	3.33%	3.33%	0.00%	10.00%	0.00%	6.67%
CPI	0.00%	0.00%	3.23%	0.00%	6.45%	0.00%	0.00%
DGO	6.45%	0.00%	0.00%	0.00%	0.00%	3.23%	0.00%
FOMC	0.00%	10.00%	10.00%	0.00%	0.00%	15.00%	25.00%
GDP	0.00%	0.00%	0.00%	0.00%	0.00%	3.23%	0.00%
IJC	0.75%	0.00%	0.00%	0.00%	1.49%	0.00%	0.75%
LI	3.23%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
NHS	6.45%	0.00%	6.45%	3.23%	0.00%	0.00%	3.23%
PPI	0.00%	3.23%	0.00%	0.00%	0.00%	0.00%	0.00%
RSA	0.00%	0.00%	0.00%	0.00%	0.00%	3.23%	0.00%

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Table 8: Relationship between Jumps and Scheduled Announcements Disaggregated by Announcement Items (Non-Crisis and Crisis Subsample)

Continued from previous page

	DOTM Puts	OTM Puts	ATM Puts	ATM Calls	OTM Calls	DOTM Calls	Futures
Panel D: $P(Jump\|News)$ ***over the Crisis Subsample***							
Short-Term Options							
NFP	31.71%	26.83%	19.51%	24.39%	12.20%	26.83%	17.07%
CCI	0.00%	0.00%	4.88%	7.32%	0.00%	2.44%	0.00%
CPI	7.32%	2.44%	7.32%	4.88%	9.76%	2.44%	0.00%
DGO	7.32%	2.44%	9.76%	9.76%	0.00%	12.20%	0.00%
FOMC	6.67%	6.67%	10.00%	6.67%	10.00%	6.67%	13.33%
GDP	4.88%	7.32%	4.88%	9.76%	7.32%	19.51%	2.44%
IJC	10.06%	1.12%	7.26%	3.91%	3.91%	12.29%	0.00%
LI	2.44%	0.00%	2.44%	2.44%	0.00%	2.44%	0.00%
NHS	2.44%	2.44%	0.00%	2.44%	0.00%	4.88%	0.00%
PPI	9.76%	2.44%	0.00%	2.44%	0.00%	4.88%	0.00%
RSA	7.32%	2.44%	0.00%	0.00%	7.32%	4.88%	0.00%
Medium-Term Options							
NFP	24.39%	17.07%	19.51%	14.63%	19.51%	9.76%	19.51%
CCI	0.00%	2.44%	4.88%	2.44%	0.00%	2.44%	0.00%
CPI	2.44%	0.00%	2.44%	0.00%	0.00%	9.76%	0.00%
DGO	0.00%	4.88%	2.44%	0.00%	9.76%	7.32%	0.00%
FOMC	10.00%	10.00%	10.00%	6.67%	6.67%	3.33%	13.33%
GDP	0.00%	4.88%	0.00%	2.44%	2.44%	2.44%	2.44%
IJC	3.35%	6.15%	1.12%	2.23%	2.79%	8.94%	0.00%
LI	2.44%	2.44%	0.00%	0.00%	0.00%	4.88%	0.00%
NHS	0.00%	0.00%	2.44%	2.44%	2.44%	2.44%	0.00%
PPI	2.44%	2.44%	2.44%	0.00%	0.00%	4.88%	0.00%
RSA	2.44%	4.88%	0.00%	2.44%	0.00%	2.44%	0.00%
Long-Term Options							
NFP	14.63%	14.63%	12.20%	9.76%	17.07%	14.63%	14.63%
CCI	0.00%	2.44%	4.88%	0.00%	2.44%	0.00%	0.00%
CPI	4.88%	0.00%	2.44%	0.00%	12.20%	7.32%	0.00%
DGO	9.76%	0.00%	2.44%	0.00%	2.44%	9.76%	0.00%
FOMC	3.33%	6.67%	10.00%	3.33%	6.67%	3.33%	13.33%
GDP	4.88%	2.44%	0.00%	2.44%	9.76%	9.76%	2.44%
IJC	4.47%	3.35%	0.56%	1.12%	4.47%	6.15%	0.00%
LI	4.88%	0.00%	0.00%	0.00%	0.00%	4.88%	0.00%
NHS	0.00%	2.44%	2.44%	0.00%	0.00%	2.44%	0.00%
PPI	2.44%	0.00%	0.00%	0.00%	2.44%	9.76%	0.00%
RSA	2.44%	2.44%	0.00%	9.76%	0.00%	14.63%	0.00%

Entries report summary statistics on the relationship between detected jumps and macroeconomic news announcements disaggregated by news items for all investigated moneyness and maturity categories over the non-crisis subsample (Panels A and C) and the crisis subsample (Panels B and D). The probability of a jump to be related to a specific news announcement $P(News|Jump)$ (Panels A and B) and the probability of a specific news announcement leading to a jump $P(Jump|News)$ (Panels C and D) are reported. Jumps have been detected using the Lee and Mykland (2008) jump detection methodology based on a significance level $\alpha = 0.1\%$. Jumps are defined to be related to a news announcement if they occurred within ± 10 minutes of an announcement. The sample period is 1/1/2005 to 31/7/2007 for the non-crisis subsample and 1/8/2007 to 31/12/2010 for the crisis subsample.

Table 9: Information Shocks and Illiquidity as jump determinants (Crisis Subsample)

	Short-Term	Medium-Term	Long-Term
Panel A: News Covariates			
c	-3.599***	-3.794***	-4.869***
NFP_t	0.713***	0.444	0.075
CCI_t	-2.989	-12.931	-
CPI_t	-0.020	-0.896	0.324
DGO_t	-0.068	-0.775	-0.964
$FOMC_t$	-	-	-
GDP_t	0.154	-1.354	0.756***
IJC_t	0.044	-0.044	0.203
LI_t	-0.705	-0.788	-
NHS_t	-	-6.498	-
PPI_t	-0.151	-1.567	-0.055
RSA_t	-0.232	-0.644	0.803**
Panel B: News and Liquidity Covariates			
c	-3.756***	-3.541***	-4.316***
BA_{t-1}	1.382***	1.105***	1.995***
$BidSize_{t-1}$	-0.001	-0.001	-0.002
$AskSize_{t-1}$	0.000	-0.003	-0.004
NFP_t	0.604***	0.311	-0.249
CCI_t	-2.111	-8.614	-
CPI_t	-0.119	-0.934	0.148
DGO_t	-0.137	-0.896	-1.344
$FOMC_t$	-	-	-
GDP_t	0.077	-1.510	0.610**
IJC_t	-0.065	-0.161	-0.109
LI_t	-0.287	-0.196	-
NHS_t	-	-3.922	-
PPI_t	-0.303	-1.680	-0.239
RSA_t	-0.312	-0.706	0.354

Entries report the estimation results for the logistic regression models in equation (7) and (8) over the crisis subsample in Panels A and B, respectively. The estimation is performed separately for short, medium, and long-term options on a sample pooled across all delta categories. Only news-related observations are considered. The estimation is performed via Maximum Likelihood and ***, **, or * report statistical significance on a 1%, 5%, or 10% significance level. The sample period is 1/8/2007 to 31/12/2010.

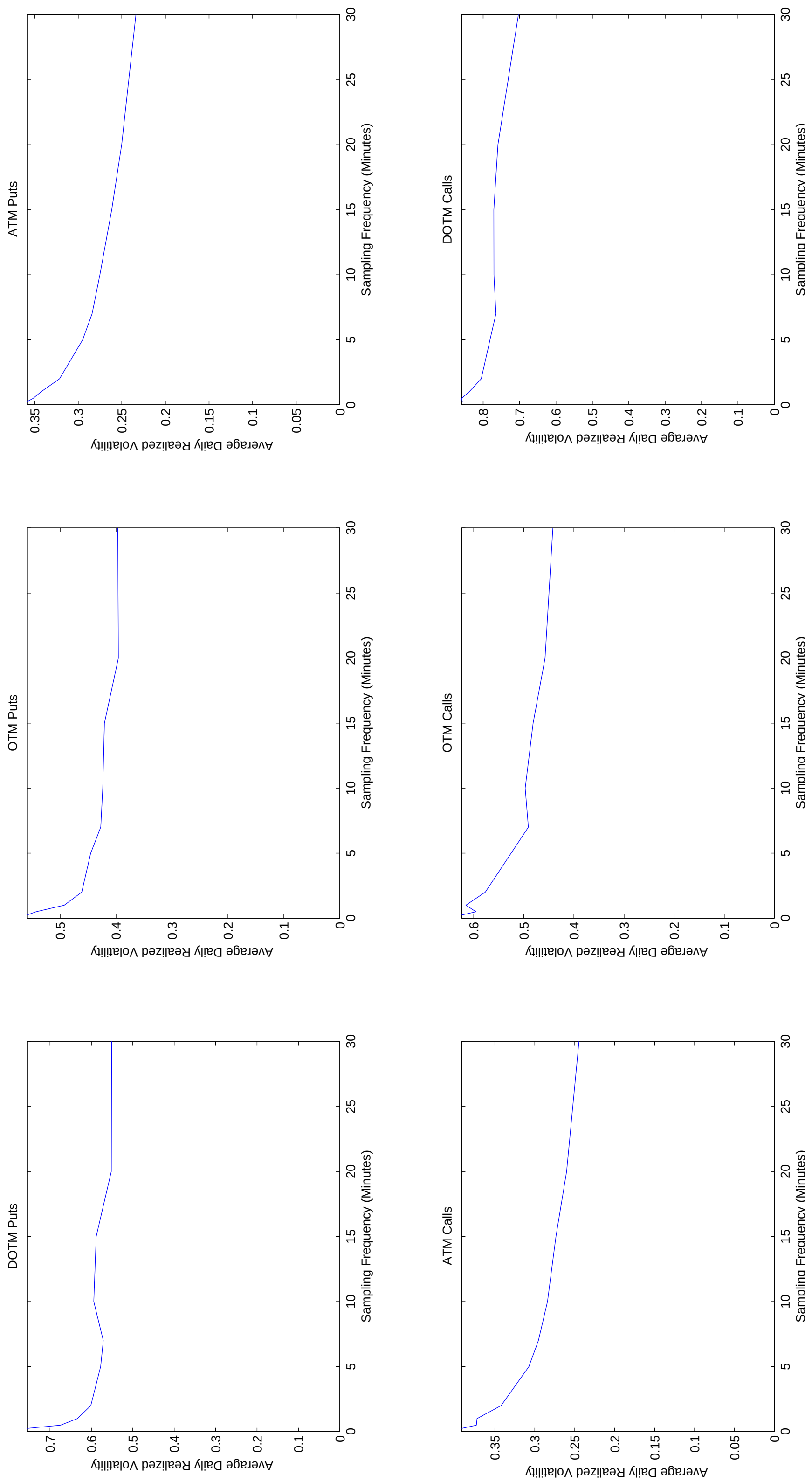
Table 10: Relationship between Jumps and Unscheduled News Announcements

	DOTM Puts	OTM Puts	ATM Puts	ATM Calls	OTM Calls	DOTM Calls	Futures
Short-Term Options							
# Jump Days equal to Unsched. News Day	5	4	3	2	0	10	3
% Jump Days equal to % Unsched. News Day	2.16%	2.99%	2.34%	1.24%	0.00%	4.07%	4.17%
Medium-Term Options							
# Jump Days equal to Unsched. News Day	3	4	7	3	3	7	3
% Jump Days equal to Unsched. News Day	1.66%	4.00%	6.31%	3.75%	2.40%	3.21%	4.29%
Long-Term Options							
# Jump Days equal to Unsched. News Day	4	4	7	1	1	9	3
% Jump Days equal to Unsched. News Day	2.52%	5.00%	6.25%	1.61%	1.03%	4.05%	4.48%

Entries report summary statistics on the relationship between detected jumps and unscheduled news announcements for all investigated moneyness and maturity categories (Panels A to C). The number of jump days that are equal to a day on which unscheduled news has been released and this number as a fraction of all jump days is reported. Jumps have been detected using the Lee and Mykland (2008) jump detection methodology based on a significance level $\alpha = 0.1\%$. The sample period is 1/1/2005 to 31/12/2010.

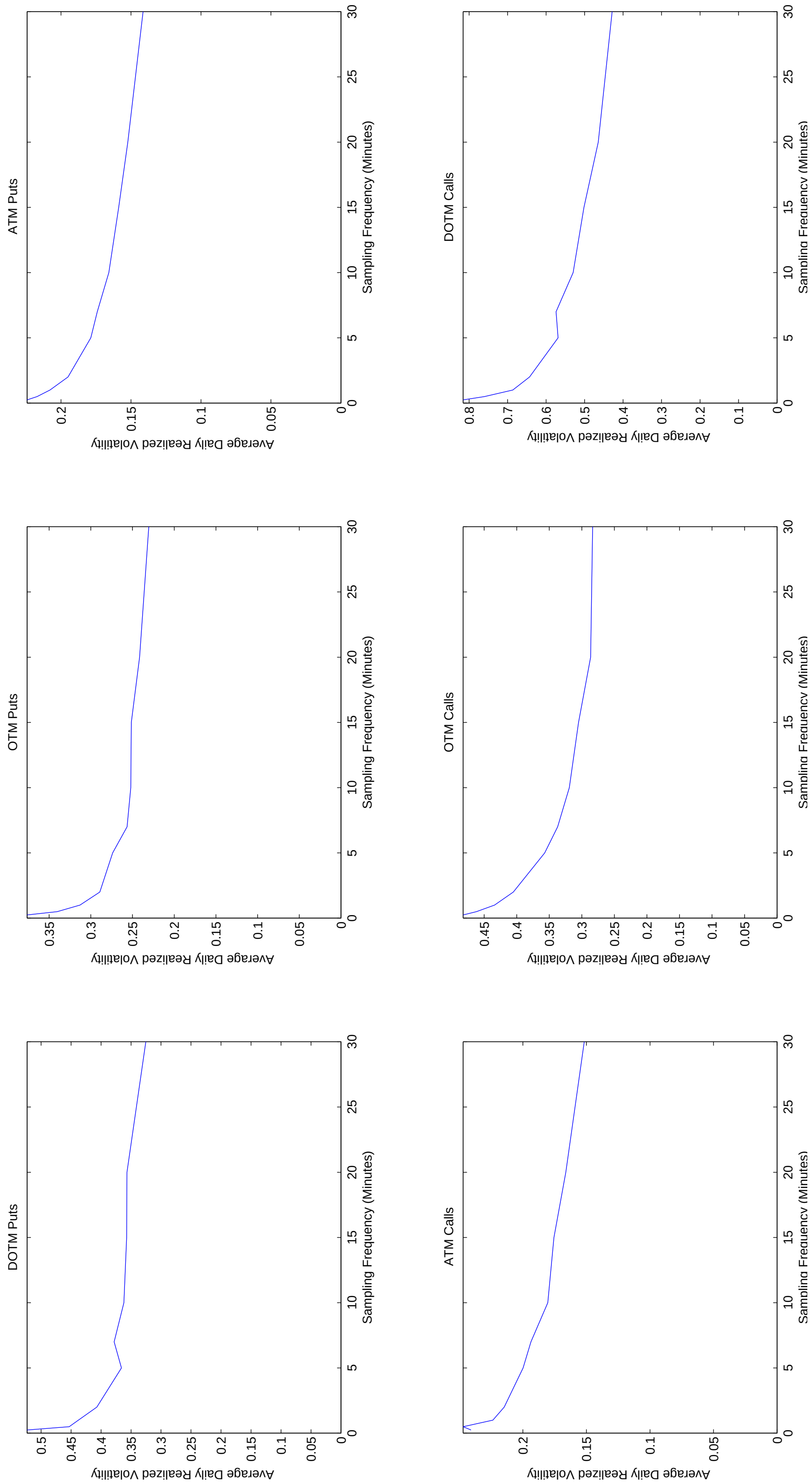
Figures

Figure 1: Volatility Signature Plots of Short-Term Options Returns



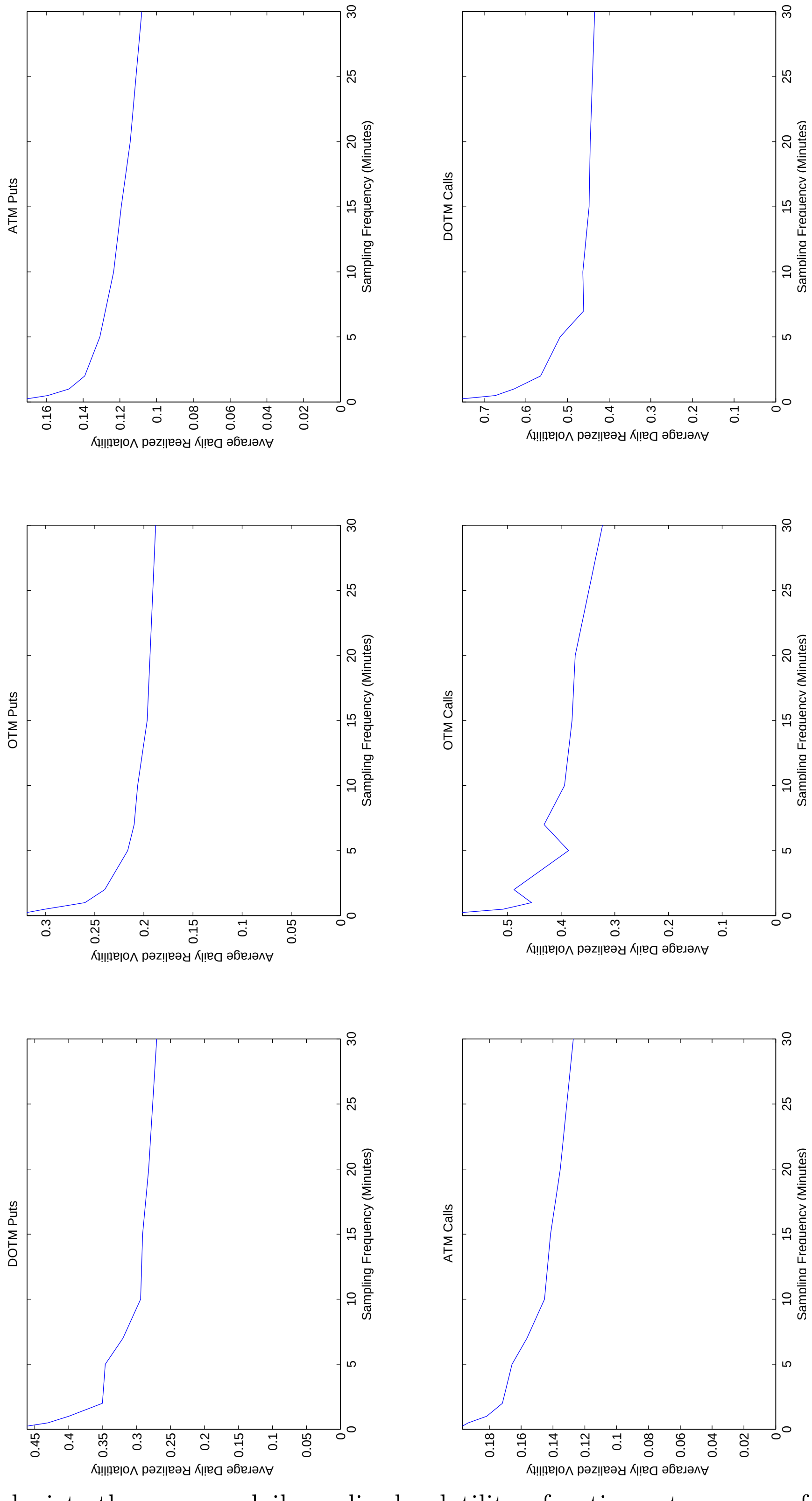
The figure depicts the average daily realized volatility of option returns as a function of the sampling frequency for short-term options of different delta categories.

Figure 2: Volatility Signature Plots of Medium-Term Options Returns



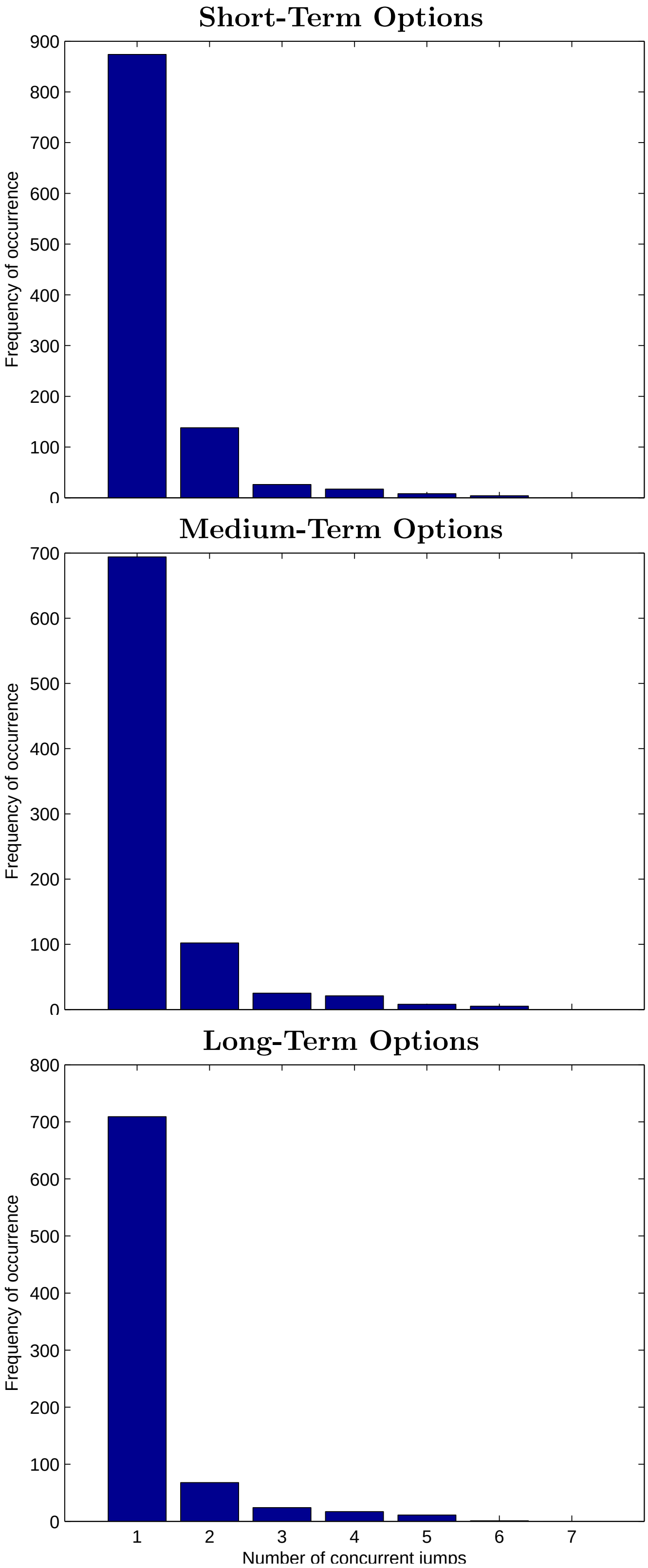
The figure depicts the average daily realized volatility of option returns as a function of the sampling frequency for medium-term options of different delta categories.

Figure 3: Volatility Signature Plots of Long-Term Options Returns



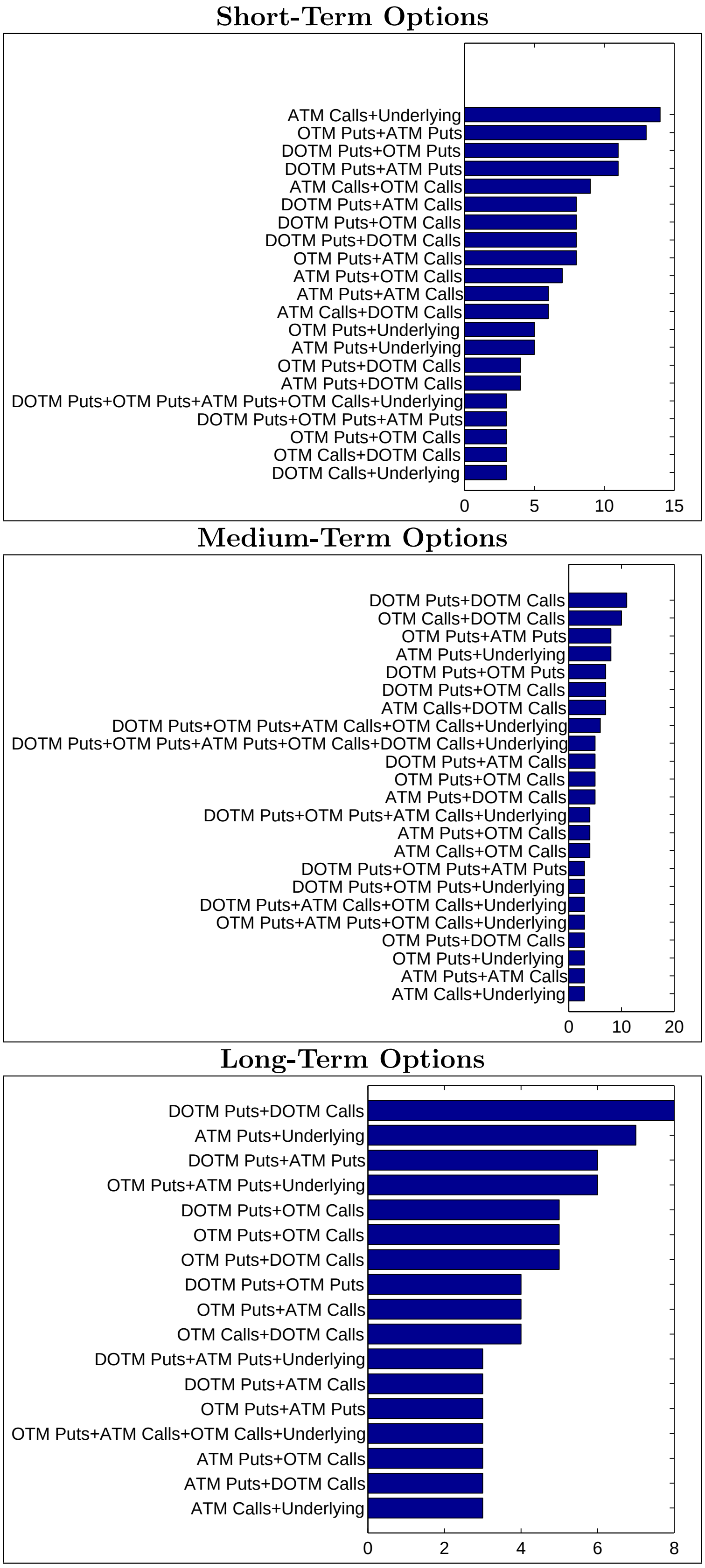
The figure depicts the average daily realized volatility of option returns as a function of the sampling frequency for long-term options of different delta categories.

Figure 4: Distribution of Co-Jumps



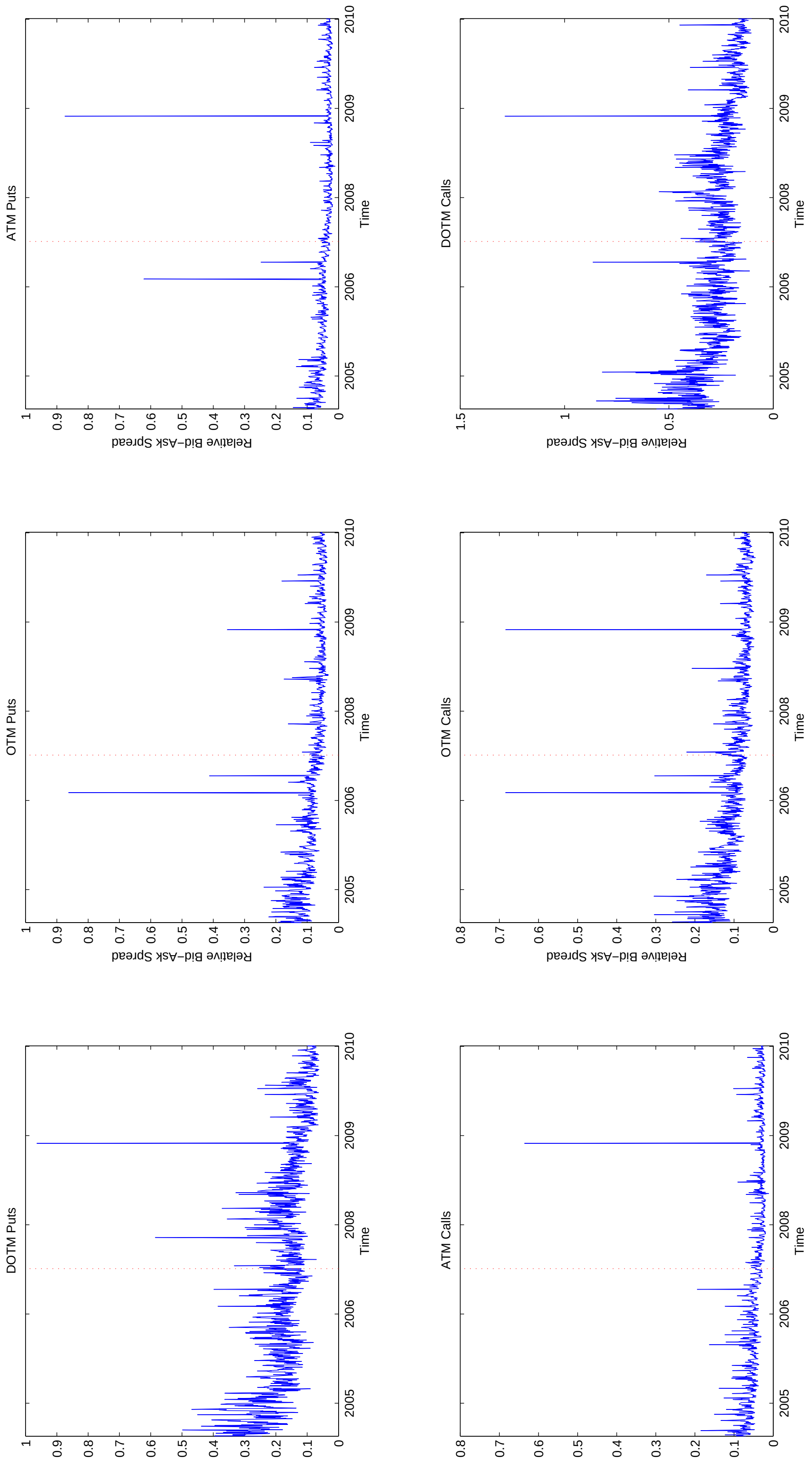
The figure illustrates the distribution of co-jump events for short, medium, and long-term options, separately. Co-jump events are defined by the number of concurrent jumps across different delta levels and the underlying asset. The event of only one concurrent jump corresponds to an idiosyncratic jump in only one of the delta categories or the underlying asset. The frequency of occurrence is reported for each possible co-jump event.

Figure 5: Composition of Co-Jumps



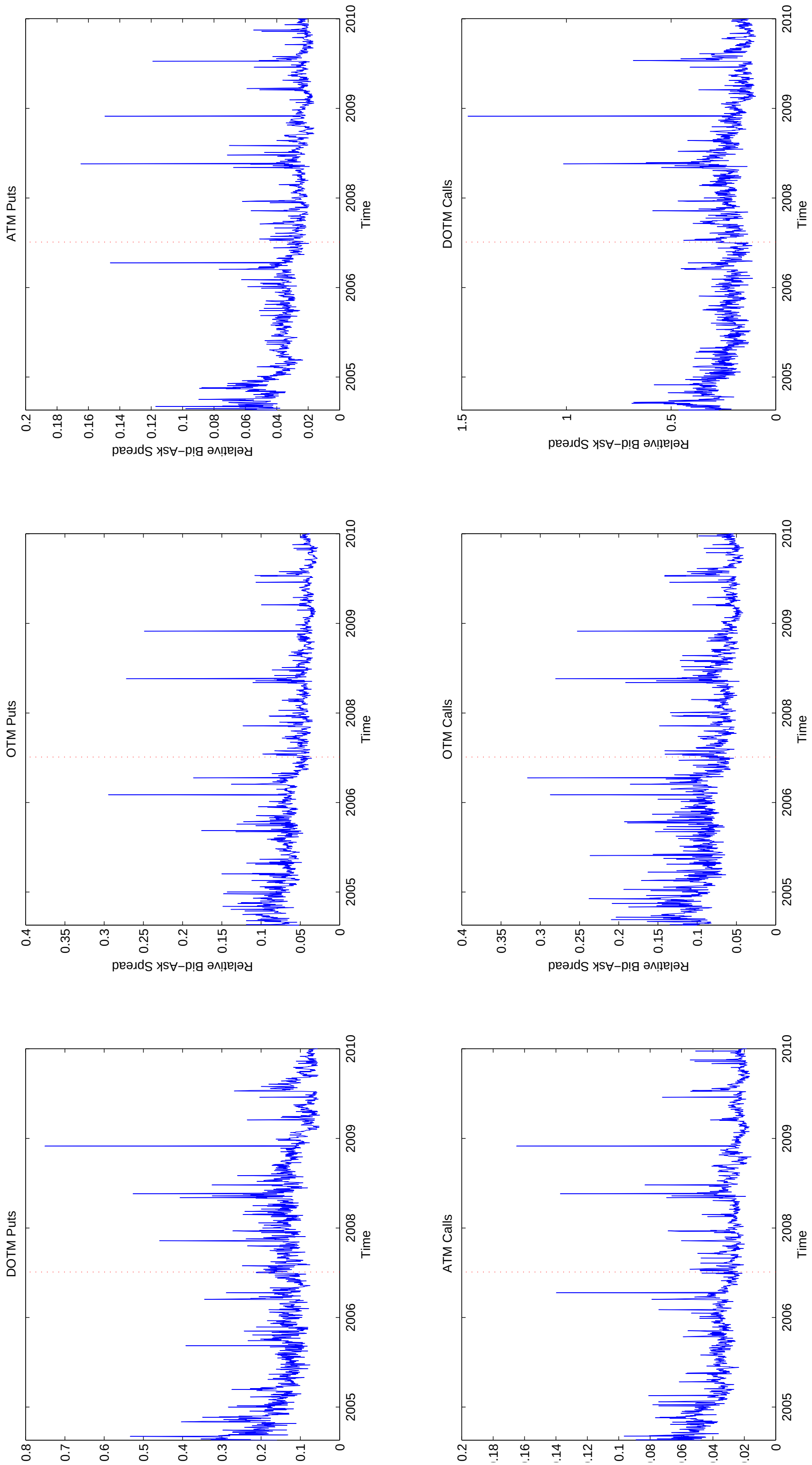
The figure illustrates the composition of the most frequent co-jump events for short-term, medium-term, and long-term options. The composition of a co-jump event is characterized by the delta categories of the options and/or the underlying asset that simultaneously exhibit a jump.

Figure 6: Dynamics of Short-Term Options Bid-Ask Spreads



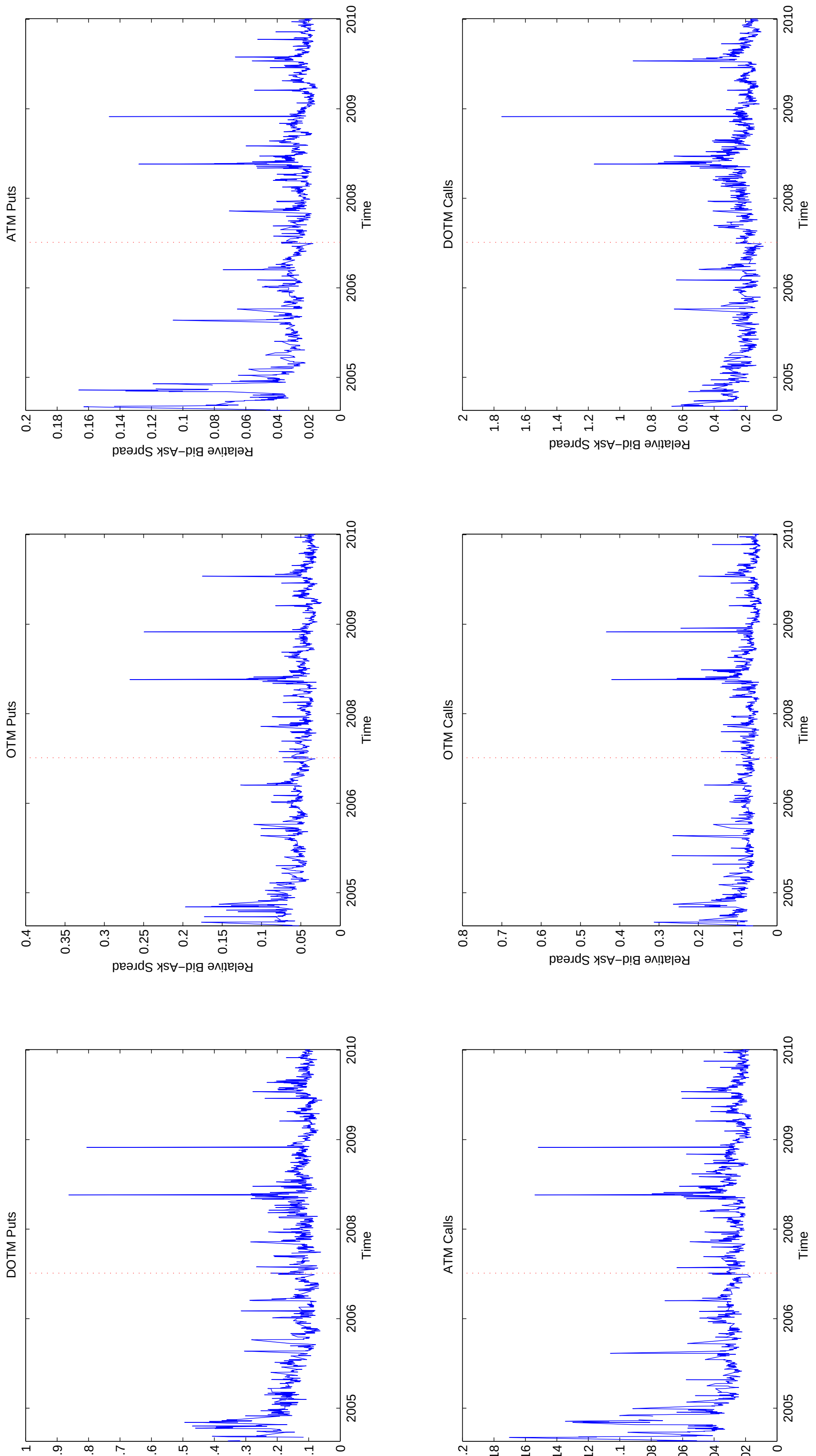
The figure illustrates the time evolution of the relative bid-ask spread of short-term options of different delta categories over the non-crisis and crisis subsample. The daily average relative-bid ask spread is depicted. The dashed line illustrates the non-crisis/crisis split point.

Figure 7: Dynamics of Medium-Term Options Bid-Ask Spreads



The figure illustrates the time evolution of the relative bid-ask spread of medium-term options of different delta categories over the non-crisis and crisis subsample. The daily average relative-bid ask spread is depicted. The dashed line illustrates the non-crisis/crisis split point.

Figure 8: Dynamics of Long-Term Options Bid-Ask Spreads



The figure illustrates the time evolution of the relative bid-ask spread of long-term options of different delta categories over the non-crisis and crisis subsample. The daily average relative-bid ask spread is depicted. The dashed line illustrates the non-crisis/crisis split point.