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Detecting abnormal trading activities in option markets

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ABSTRACT

We develop an econometric method to detect "abnormal trades" in option markets, i.e., trades which are not driven by liquidity motives. Abnormal trades are characterized by unusually large increments in open interest, trading volume, and option returns, and are not used for option hedging purposes. We use a multiple hypothesis testing technique to control for false discoveries in abnormal trades. We apply the method to 9.6 million of daily option prices.

1. Introduction

An important distinction of option trades is between liquidity and non-liquidity trades. The former is solely driven by liquidity shocks to option traders. The latter can be driven by various motives, including private information and hedging needs. Disentangling these option trades can potentially improve our understanding of the functioning of option markets.

This paper develops an econometric approach to detect certain non-liquidity option trades that we call *abnormal trades*. We define abnormal trades as unusual trades in option contracts which generate large gains, are not used for option hedging purposes, and are made a few days before the occurrence of a specific event.

We develop two statistical methods to detect abnormal trades. The first method uses only ex-ante information and aims to detect abnormal trades as soon as they take place. We look for option trades characterized by unusually large increments in open interest, i.e., number of outstanding contracts, which are close to daily trading volumes. In those cases the originator of such transactions is not interested in intraday speculations but has reasons for keeping her position for a longer period. As it turns out in our empirical study, the higher the increment in open interest and volume the higher the future return of the corresponding option. We refine the first method using a nonparametric test to check whether those option trades are hedged with the underlying asset or used for option hedging purposes. The second method uses also ex-post information and encompasses the first method by adding an additional criterion. An option trade is identified as abnormal when the increment in open interest and volume is unusual, not hedged (as in the first method), and generates large option gains.

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Our approach to detect option abnormal trading has two distinctive features: it controls for false discoveries in abnormal trades and accounts for option hedging. Addressing these issues is a challenging task. In any statistical method, the probability that any liquidity trade will appear to be abnormal simply by chance is not zero. This misclassification is induced by the Type I error in hypothesis testing, as the test of abnormal trade is repeated each day. However, this misclassification error can be formally quantified using multiple hypothesis testing techniques. Intuitively, liquidity trades should have zero return on average, while abnormal trades should have statistically large returns. Under the null hypothesis that all trades are liquidity trades, the proportion of lucky liquidity trades depends on the size of the test and can be calculated using option returns. When the difference between the actual fraction of large returns (due to abnormal and lucky trades) and the expected fraction of large returns due to lucky liquidity trades is statistically large, the test rejects the null hypothesis that all trades are liquidity trades.

We develop a nonparametric test to assess whether option hedging takes place or not. For example, when studying long positions in call options, the idea is to decompose the underlying stock seller-initiated trading volume in the hedging and non-hedging components. This decomposition is achieved using the theoretical amount of stock trading which would have been generated if no abnormal trading would have occurred. Then the test rejects the null hypothesis of absence of hedging when the hedging component is statistically large.

An obvious question at this stage is who originates abnormal trades. Although information on traders' identity is not available, it is conceivable that mainly informed traders are behind abnormal trades in call options. This conjecture would be consistent with the large returns generated by call option abnormal trades. For abnormal trades in put options the situation is different. Informed traders and/or corporate insiders hedging their human capital are most probably behind those trades.[1] Without knowing trader identities, it is not possible to disentangle whether put option abnormal trades are due to informed traders or corporate insiders hedging their human capital. We describe this situation as saying that we are testing a *joint hypothesis*.

We apply the two statistical methods to 9.6 million of daily option prices of 31 selected companies mainly from airline, banking and insurance sectors. Several millions of intraday stock price and volume data are also analyzed to assess whether an option trade is hedged or not. The sample period spans 14 years, from January 1996 to September 2009 (part of our sample ends in April 2006), and our analysis is at the level of individual option, rather than on the cross-section of stock returns.[2]

Our empirical findings can be summarized as follows. First, abnormal trades tend to cluster prior to certain events such as merger and acquisition (M&A) announcements, quarterly financial or earning related statements, the terrorist attacks of September 11th, and first announcements of financial disruptions of banking and insurance companies during the Subprime financial crisis 2007–2009. Second, prior to a particular event which will impact a particular company, abnormal trades can involve more than one option but rarely the cheapest option, i.e., deep out-of-the-money and with shortest maturity. Third, the majority of abnormal trades take place in put rather than call options. Fourth, estimated option gains of abnormal trades easily exceed several millions for a single event. Finally, the underlying stock price does not display any particular behavior on the day of the detected abnormal trade. Only some days later, for example when a negative company news is released, the stock price drops generating large gains in long put positions.

The paper is organized as follows. Section 2 reviews the related literature. Section 3 presents our method to detect abnormal trades. Section 4 describes the dataset. Section 5 summarizes the empirical results. Section 6 quantifies false discoveries in abnormal trades. Section 7 discusses various robustness checks. Section 8 concludes.

2. Related literature

Although we are testing a *joint hypothesis* for put options, abnormal trades can be related to informed trades which have been the subject of an extensive literature; see, e.g., Hasbrouck (1991), Easley and O'Hara (1992), Easley et al. (1998), Poteshman (2006), and Boulatov et al. (2013). As discussed in Grossman (1977), Diamond and Verrechia (1987), and others, option markets offer significant advantages to informed traders. Options provide potential downside protection, an alternative way of short selling when shorting stocks is expensive or forbidden, additional leverage which might not be possible in stock or bond markets (Biais and Hillion, 1994), and possibly more discreetness for trading on private signals. Indeed, Cao et al. (2005) show that call–volume imbalances prior to unscheduled takeover announcements are strongly related to stock returns on the announcement day. Pan and Poteshman (2006) report clear evidence that option trading volumes predict future price changes. Bali and Hovakimian (2009) show that the difference between realized and implied volatilities of individual stocks predicts the cross-sectional variation of expected returns. Cremers and Weibaum (2010) find that deviations from put–call parity contain information about future stock returns. Yan (2011) documents a negative relation between the slope of implied volatility smile and stock return. In these studies (and others), the analysis is systematically conducted at an aggregate level, e.g., extracting information from *all* current option prices, while we conduct the analysis at *individual* option contracts.

Stephan and Whaley (1990), Chan et al. (1993), Manaster and Rendleman (1982), and Lee and Yi (2001), among others, discuss why informed traders may consider options as superior trading vehicles. Our results show that option markets can offer significant

[1] Human capital can be defined as the sum of the present value of the future cash income, shares, stock options, etc., and it represents the most significant risk faced by corporate insiders especially senior managers. To the extent that it is legal, a long put option is probably the only liquid instrument that can be used by corporate insiders to hedge the risk attached to their human capital.

[2] As mentioned above, we rely on statistical methods to detect abnormal trades. Therefore, those trades will be abnormal only with a certain probability. For brevity, we refer to those trades simply as abnormal trades. Moreover, detected abnormal trades might or might not be legal. From a legal viewpoint this study does not constitute proof per se of illegal activities. Legal proof would require trader identities and their motivations, information which is not contained in our dataset.

profits to informed traders, lending empirical support to these studies. Chen et al. (2001) show that asset crashes can be predicted using shares trading volume. We complement this work by showing that certain increments in open interest and trading volume have predictive power for future movements in the underlying stock. Blume et al. (1994) and Vijh (1990) provide related studies on trading volume and information-related trading.

3. Detecting option abnormal trades

We propose two methods to detect option abnormal trades. The first method relies on a broad definition of an option abnormal trade, based on open interest and volume, and makes use only of ex-ante information. The second method is based on a more stringent definition of abnormal trades and uses ex-post information as well.

We now describe the second method with the first method being a special case. We define an option abnormal trade as follows: C_1) an unusual trade in an option contract, C_2) which is made a few days before the occurrence of a specific event and generates large gains in the following days, and C_3) the position is not hedged in the stock market and not used for option hedging purposes. These three characteristics, C_i, $i = 1, 2, 3$, lead to the following method to detect abnormal trading activities in option markets: first on each day the option contract with largest increment in open interest (i.e., number of outstanding contracts) and volume is identified, then the rate of return and dollar gain generated by this transaction are calculated, and finally it is studied whether option hedging occurs. Option trades which are delta hedged or used for option hedging purposes are not regarded as abnormal trades. The first method relies only on characteristics C_1 and C_3, and their practical implementation. Importantly, both methods require only commonly available data and thus can be easily used to detect abnormal trades in various option markets.

We now explain how to detect abnormal trades in call options. The application to put options can easily be deduced. In the empirical section, we apply both methods to a large dataset of call and put options.

3.1. First criterion: increment in open interest relative to volume

For every call option k available at day t we compute the difference $\Delta OI_t^k := OI_t^k - OI_{t-1}^k$, where OI_t^k is its open interest at day t, and $:=$ means defined as. When the option does not exist at time $t-1$, its open interest is set to zero. Since we are interested in unusual transactions, only the option with the largest increment in open interest is considered

$$X_t := \max_{k \in K_t} \Delta OI_t^k \tag{1}$$

where K_t is the set of all call options available at day t. The motivation for using open interest is the following. Large trading volumes can emerge under various scenarios for example when the same call option is traded several times during the day or large sell orders are executed. In contrast large increments in open interest are usually originated by large buy orders. These increments also imply that other long investors are unwilling to close their positions forcing the dealer or market maker to issue new call options. Consequently, we use large increment in open interest as a proxy for large buy orders.

We focus on transactions for which the corresponding volume almost coincides with the increment in open interest. Let V_t denote the daily trading volume corresponding to the call option selected in Eq. (1). The positive difference $Z_t := (V_t - X_t)$ provides a measure of how often the newly issued options are exchanged: the smaller the Z_t, the less the new options are traded during the day on which they are created. In that case the originator of such transactions is not interested in intraday speculations but has reasons for keeping her position for a longer period possibly waiting for the realization of future events.

This first criterion already allows us to identify single transactions as potential candidates for abnormal trades. Let q_t denote the time-t ex-ante joint historical probability of observing an unusual large increment in open interest close to the trading volume

$$q_t := \mathbb{P}[X \geq X_t, Z \leq Z_t] = \frac{1}{N} \sum_{i=1}^{N} 1_{\{X_i \geq X_t, Z_i \leq Z_t\}} \tag{2}$$

where $\mathbb{P}$ denotes the empirical probability, N the length of the estimation window, e.g., $N = 500$ trading days, and $1_{\{A\}} = 1$ when event A occurs, and zero otherwise. By construction, low values of q_t suggest that these transactions were unusual. For example when $q_t = 1 / N$, it means that what occurred on day t has no precedents in the previous two years.

3.2. Second criterion: relative return and realized gain

The second criterion takes into consideration ex-post option returns and realized gains. For each day t the option trade with the lowest ex-ante probability q_t is considered. Let $r_t^{\max}$ denote the maximum option return generated in the following two trading weeks

$$r_t^{\max} := \max_{j=1,\ldots,10} \frac{P_{t+j} - P_t}{P_t} \tag{3}$$

where P_t denotes the mid-quote price of the selected call option at day t. When $r_t^{\max}$ is unusually high, an unusual event occurs during the following two trading weeks.

For the computation of realized gains, we consider decrements in open interest, ΔOI_t^k, which occur when exercising or selling to the market maker the call option.[3] Then we set the American call option value to its exercise value, which is true in most cases. Given our definition of abnormal trade, it is quite likely that on the event day the rise in the stock price is large enough to reach the exercise region. If options are sold rather than exercised, our calculation of realized gains may underestimate the actual gains. Hence reported gains should be interpreted as conservative estimates. For brevity, we refer to decrement in open interest as option exercise. Also, we omit the superscript k and whenever we refer to a specific option we mean the one which was selected because of its largest increment in open interest close to trading volume, i.e., lowest ex-ante probability q_t.

Let G_t denote the corresponding cumulative gains achieved through the exercise of options

$$G_t := \sum_{\tilde{t}=t+1^{\tau_t}} \left((S_{\tilde{t}-K})^+ - P_t \right) \ (-\Delta OI_{\tilde{t}}) 1_{\{\Delta OI_{\tilde{t}} < 0\}} \tag{4}$$

where τ_t is such that $t < \tau_t \le T$, with T being the maturity of the selected option. If the call options were optimally exercised (i.e., as soon as the underlying asset $S_{\tilde{t}}$ touches the exercise region), the payoff $(S_{\tilde{t}-K})^+$ corresponds to the price of the option at time $\tilde{t}$.

The cumulative gains G_t could be easily calculated for every $\tau_t \le T$. This has however the disadvantage that G_t could include gains which are realized through the exercise of options which were issued before time t.[4] To avoid this inconsistency, the time τ_t is defined as follows

$$\tau_t^* := \arg\max_{l \in \{t+1,\dots,T\}} \left(\sum_{\tilde{t}=t+1}^{l} (-\Delta OI_{\tilde{t}}) 1_{\{\Delta OI_{\tilde{t}} < 0\}} \le X_t \right) \tau_t := \min(\tau_t^*, 30)$$

giving the option trader no more than 30 days to collect her gains. In general the sum of negative decrements in open interest till time τ_t will be smaller than the observed increment in open interest X_t. In that case, we will add to G_t the gains realized through the fraction of the next decrement in open interest. Hence the sum of all negative decrements in open interest will be equal to the increment X_t.

Calculating G_t for each day t and each option in our dataset provides information on whether or not option trades with a low ex-ante probability q_t generate large gains through exercise. Using the maximal return $r_t^{\max}$ in Eq. (3), we can calculate the time-t ex-post joint historical probability p_t of the event $\{X_t, Z_t, r_t^{\max}\}$

$$p_t := \mathbb{P}\left[X \ge X_t, Z \le Z_t, r^{\max} \ge r_t^{\max}\right] = \frac{1}{N} \sum_{i=1}^{N} 1_{\{X_i \ge X_t, Z_i \le Z_t, r_i^{\max} \ge r_t^{\max}\}}. \tag{5}$$

The higher the $(1 - p_t)$ the larger the option return and the more unusual the increment in open interest close to trading volume.

3.3. Third criterion: hedging option position

Option trades for which the first two criteria show abnormal behavior cannot be immediately classified as abnormal trades. It could be the case that such transactions were hedged by traders using the underlying asset. Without knowing the exact composition of each trader's portfolio, it is not possible to assess directly whether each option trade was hedged or not.

We attempt to assess indirectly whether unusual trades in call options are actually delta hedged using the underlying asset. The idea is to compare the *theoretical* total amount of shares sold for non-hedging purposes and the *actual* total volume of seller-initiated transactions in the underlying stock. If the latter is significantly larger than the former, then it is likely that some of the seller-initiated trades occur for hedging purposes. In the opposite case we conclude that the new option positions are not hedged.

One difficulty is that the volume due to hedging is typically a small component of the total seller-initiated volume. Usually, when hedging occurs, newly issued options are hedged on the same day which is our working assumption. Hedging analyses at the level of single option are not possible using our OptionMetrics dataset. We therefore check whether all the newly issued options are hedged on a specific day t. Given our definition of abnormal trades, such trades certainly account for a large fraction of the newly issued options.

For each day t, the total trading volume of the underlying stock is divided into seller- and buyer-initiated using intraday volumes and transaction prices according to the Lee and Ready (1991) algorithm.[5] Then the seller-initiated volume of underlying stock, V_t^{sell}, is

[3] On a given day, opening new positions (which increases open interest) and closing existing positions (which decreases open interest) can off-set each other. Hence the observed decrement in open interest is a lower bound for actual exercised or sold options.

[4] Consider for example an option which exhibits an unusually high increment in open interest at time t, say $OI_{t-1} = 1000$ and $OI_t = 3000$ resulting in $X_t := OI_t - OI_{t-1} = 2000$. Suppose that in the days following this transaction the level of open interest decreases and after h days reaches the level $OI_{t+h} = 500$. One should only consider the gains realized through exercise till time $\tau_t \le t + h$, where τ_t is such that the sum of negative decrements in open interest during $[t + 1, \tau_t]$ equals $X_t = 2000$.

[5] The algorithm states that a trade with a transaction price above (below) the prevailing quote midpoint is classified as a buyer- (seller-) initiated trade. A trade at the quote midpoint is classified as seller-initiated if the midpoint moved down from the previous trade (down-tick), and buyer-initiated if the midpoint moved up (up-tick). If there was no movement from the previous price, the previous rule is successively applied to several lags to determine whether a trade was buyer- or seller-initiated.

divided into trading volume due to hedging and to non-hedging purposes, $V_t^{\text{sell,hedge}}$ and $V_t^{\text{sell,non}-\text{hedge}}$, respectively. Let $\Delta_t^{C,k}$ be the delta of call option k and K_t^C be the set of call options (newly issued or already existing) on day t. Similarly for $\Delta_t^{P,k}$ and K_t^P. Let

$$\alpha_t := \sum_{k\in K_t^C} |OI_t^{C,k} - OI_{t-1}^{C,k}|\,|\Delta_t^{C,k}|, \gamma_t := \sum_{k\in K_t^P} |OI_t^{P,k} - OI_{t-1}^{P,k}|\Delta_t^{P,k}, \beta_t := \sum_{k\in K_t^C} |\Delta_t^{C,k} - \Delta_{t-1}^{C,k}|OI_{t-1}^{C,k}, \delta_t := \sum_{k\in K_t^P} |\Delta_t^{P,k} - \Delta_{t-1}^{P,k}|OI_{t-1}^{P,k}.$$

The α_t and γ_t represent the theoretical number of shares to sell for hedging the new call options issued at day t, whereas β_t and δ_t are the theoretical number of shares to sell to rebalance the portfolio of existing options at day t. Absolute changes in open interests and deltas account for the fact that each option contract has a long and short side that follow opposite trading strategies if hedging occurs. The theoretical seller-initiated volume of stock at day t for hedging purposes is $V_t^{\text{sell,hedge - theory}} := \alpha_t + \beta_t + \gamma_t + \delta_t$.

When the first two criteria of our method do not signal any abnormal trade, we approximate $V_t^{\text{sell,hedge}}$ by $V_t^{\text{sell,hedge - theory}}$. Then the amount of stock sold for non-hedging purposes is calculated as $V_t^{\text{sell,non - hedge}} = V_t^{\text{sell}} - V_t^{\text{sell,hedge - theory}}$.

When abnormal trades take place on day i, $V_i^{\text{sell,non - hedge}}$ cannot be computed as in the last equation because $V_i^{\text{sell,hedge - theory}}$ would be distorted by the unhedged option abnormal trades. We circumvent this issue by forecasting the volume $V_i^{\text{sell,non - hedge}}$ on day i using historical data on $V_t^{\text{sell,non - hedge}}$. The conditional distribution of $V_i^{\text{sell,non - hedge}}$ is estimated using the adjusted Nadaraya–Watson estimator and the bootstrap method proposed by Hall et al. (1999)

$$\widetilde{F}(y|\mathrm{x}) = \frac{\sum_{t=1}^{T} 1_{\{Y_t \le y\}} w_t(\mathrm{x}) K_{\mathbf{H}}(\mathbf{X}_t - \mathrm{x})}{\sum_{t=1}^{T} w_t(\mathrm{x}) K_{\mathbf{H}}(\mathbf{X}_t - \mathrm{x})} \tag{6}$$

with $Y_t := V_t^{\text{sell,non - hedge}}$, $\mathbf{X}_t := (|r_t|, V_{t-1}^{\text{sell,non - hedge}})$, $K_{\mathbf{H}}(\cdot)$ being a multivariate kernel with bandwidth matrix $\mathbf{H}$, $w_t(\mathrm{x})$ the weighting function, and r_t the stock return at day t; we refer the reader to Fan and Yao (2003) for the implementation of Eq. (6).

We can now formally test the null hypothesis, H_0, that hedging does not take place at day i. Whenever the observed V_i^{sell} is large enough, say above the 95% quantile of the predicted distribution of $V_i^{\text{sell,non - hedge}}$, it is likely that a fraction of V_i^{sell} is due to hedging purposes. Hence we reject H_0 at day i when $V_i^{\text{sell}} > q_{0.95}^{V_i^{\text{sell,non-hedge}}}$, where $q_\alpha^{V_i^{\text{sell,non-hedge}}} = \widetilde{F}^{-1}(\alpha|\mathbf{X}_i)$ is the α-quantile of the predicted distribution of $V_i^{\text{sell,non - hedge}}$ estimated using Eq. (6). The separate appendix shows that the power of the test depends on the conditioning variables $\mathbf{X}_i$ but can be as high as 20% when V_i^{sell} is 20% larger than $V_i^{\text{sell,non - hedge}}$.

We remark that the null hypothesis H_0 of no hedging (when abnormal trades occur) concerns only long positions in newly issued call options. Short positions in the same call options do not affect our hedging detection method. It is so because the total volume of the underlying stock is divided into buyer- and seller-initiated and only the latter matters when hedging long call options.

3.4. Detecting abnormal trades combining the three criteria

Let k_t denote the selected abnormal trade at day t in call option k. The two methods to detect option abnormal trades can be described using the following four sets of events: $\Omega_1 := \{k_t \text{ such that } q_t \le 5\,\%\}$; $\Omega_2 := \{k_t$ such that "H_0: non-hedging" is not rejected at day $t\}$; $\Omega_3 := \{k_t \text{ such that } r_t^{\max} \ge q_{0.90}^{r_t^{\max}}\}$; and $\Omega_4 := \{k_t \text{ such that } G_t \ge q_{0.98}^{G_t}\}$. The first method detects an abnormal trade when it belongs to the first two sets, i.e., $k_t \in \Omega_1 \cap \Omega_2$. According to the second method an option trade is abnormal when it belongs to all four sets, i.e., $k_t \in \Omega_1 \cap \Omega_2 \cap \Omega_3 \cap \Omega_4$.

4. Data

To keep the empirical analysis manageable, we focus on three main sectors, i.e., banking, insurance, and airline, and within each sector we consider some of the main companies. In addition, we also consider a number of randomly selected companies from other sectors, such as Coca Cola and Philip Morris, to broaden our empirical analysis. We organize our dataset in two parts. The first part includes only put options, while the second part put and call options.

The first part of our dataset includes 14 companies from airline, banking and various other sectors. The list of companies includes: American Airlines (AMR), United Airlines (UAL), Delta Air Lines (DAL), Boeing (BA) and KLM for the airline sector; Bank of America (BAC), Citigroup (C), J.P. Morgan (JPM), Merrill Lynch (MER) and Morgan Stanley (MWD) for the banking sector; and AT&T (ATT), Coca Cola (KO), Hewlett Packard (HP), and Philip Morris (MO) for the remaining sectors. Option data are from the Chicago Board Options Exchange (CBOE) as provided by OptionMetrics. The dataset includes the daily cross-section of available put options for each company from January 1996 to April 2006 and amounts to about 2.1 million options. Option data for DAL and KLM were available for somewhat shorter periods. Stock prices are downloaded from OptionMetrics as well to avoid non-synchronicity issues and are adjusted for stock splits and spin-offs using information from the CRSP database. Intraday transaction prices and volumes for each underlying stock price are from NYSE's Trade and Quote (TAQ) database. This dataset consists of several millions of records for each stock and is necessary to classify trading volumes in buyer- and seller-initiated transactions in order to complete the analysis related to the hedging criterion. Discrepancies among datasets have been carefully taken into account when merging databases.[6] Additionally, we analyze put options on 3 European companies, Swiss Re, Munich Re and EADS, using daily data from the EUREX provided by Deutsche Bank.

The second part of our dataset includes 19 companies from the banking and insurance sectors. Put and call options data are from January 1996 to September 2009, covering the recent financial crisis, and amounts to about 7.5 million options. The list of American companies includes: American International Group (AIG), Bank of America Corporation (BAC), Bear Stearns Corporation (BSC), Citigroup (C), Fannie Mae (FNM), Freddie Mac (FRE), Goldman Sachs (GS), J.P. Morgan (JPM), Lehman Brothers (LEH), Merrill Lynch (MER), Morgan Stanley (MS), Wachovia Bank (WB) and Wells Fargo Company (WFC). Most of these companies belong to the list of banks which were bailed out and, in which, the American Treasury Department invested approximately $200 billion through its Capital Purchase Program in an effort to bolster capital and support new lending. Options and stock data are from the same databases as before, namely CBOE, TAQ, and CRSP. Furthermore we analyze 6 European banks: UBS, Credit Suisse Group (CS) and Deutsche Bank (DBK) whose options are traded on EUREX, and Societé Générale (GL), HSBC (HSB) and BNP Paribas (BN) with options listed on Euronext. Option data as well as intraday transaction prices and volumes for the underlying stock are obtained from EUREX provided by Deutsche Bank, and from EURONEXT provided by NYSE Euronext database. All analyzed options are in American style.

5. Empirical results

The two proposed methods to detect option abnormal trades are applied to the companies listed in the previous section. We recall that when testing abnormal trades in put options, we are testing the *joint hypothesis* discussed in the introduction.

The first method, which relies only on ex-ante information, aims at detecting abnormal trades as soon as they take place. On average, less than 0.1% of the total analyzed trades belongs to the set $\Omega_1 \cap \Omega_2$ defined in Section 3.4. As an example for AMR our first method detects 141 abnormal trades, the total number of analyzed options being more than 137,000. This suggests that already the ex-ante method can be quite effective in signaling abnormal trades.

The second method, which relies also on ex-post information, selects a significantly smaller number of abnormal trades. For example, only 5 abnormal trades are detected for AMR. Importantly, the empirical patterns of abnormal trades based on the two methods are roughly the same. For example, both methods suggest that most abnormal trades for AMR occur before an acquisition announcement in May 2000 and the 9/11 terrorist attacks.

Due to space constraints we only discuss abnormal trades selected by the ex-post method. The separate appendix reports a detailed analysis of various abnormal trades.

Analyzing the first part of our dataset, 37 transactions on the CBOE have been identified as belonging to the set $\Omega_1 \cap \Omega_2 \cap \Omega_3 \cap \Omega_4$ defined in Section 3.4. Nearly all the detected abnormal trades can be associated to one of the following three event categories: merger and acquisition (M&A) announcements, six transactions; quarterly financial/earnings related statements, 14 transactions; and the terrorist attacks of September 11th, 13 transactions. Four transactions could not be identified. Tables 1 and 2 summarize abnormal trades for the airline sector. Corresponding tables for the banking sector and the last group of companies are reported in the separate appendix.

The second part of our dataset focuses on the banking and insurance sectors and consists of call and put options. Detailed empirical results are collected in the separate appendix. Although the sample period spans almost 15 years, from January 1996 to September 2009, the vast majority of detected abnormal trades occur during the Subprime crisis 2007–2009. Most abnormal trades involve put options which speaks to the *joint hypothesis* discussed in the introduction. We also detect abnormal trades in call options for every bank and insurance company analyzed. Call option abnormal trades are mainly related to positive quarterly announcements and news about certain companies raising new capital during the financial crisis 2007–2009.

To provide some insights on option abnormal trading, below we discuss in detail the case of an acquisition announcement in the U.S. airline sector in May 2000. Additional cases are discussed in the separate appendix.

The ex-post method detects two put option abnormal trades on May 10th and 11th, 2000. They involved AMR and UAL. On May 10th and 11th, the number of options issued with strike $35 and maturity in June 2000 with underlying AMR is very large: 3374 on May 10th and 5720 the day after (at 99.7% and 99.9% quantile of their two-year empirical distributions, respectively). These transactions correspond to those which exhibit the strongest increments in open interest during a span of five years; see Fig. 1 (upper left graph) and Fig. 2.

On May 10th, the underlying stock had a value of $35.50 and the selected put was traded at $2.25. For UAL 2505 put option contracts (at 98.7% quantile of its two-year empirical distribution) with strike $65 and the same maturity as those of AMR were issued on May 11th at the price of $5.25 when the underlying had a value of $61.50. The market conditions under which such transactions took place are stable. For example the average return of the stock the week before is, in both cases, positive and less than 0.5%.

The days of the drop in the underlying stock price are May 24th and May 25th, 2000, with the first day corresponding to the public announcement of United Airline's regarding a $4.3 billion acquisition of US Airways. As reported in the May 25th, 2000 edition of the New York Times, "shares of UAL and those of its main rivals crashed."[7] The stock price of AMR dropped to $27.13 (−23.59% of value losses when compared to the stock price on May 11th) increasing the value of the put options to $7.88 (resulting in a return of 250% in

[6] For example data for J.P. Morgan from OptionMetrics and TAQ do not match. Whereas the stock volume reported in OptionMetrics for the years 1996–2000 is given by the sum of the volume of Chase Manhattan Corporation and J.P. Morgan & Co. (Chase Manhattan Corporation acquired J.P. Morgan & Co. in 2000); TAQ only reports the volume of J.P. Morgan & Co. Same issue was found for Bank of America Corporation and NationsBank Corporation, whose merger took place in 1998 under the new name of Bank of America Corporation.

[7] The New York Times article reports that AMR was considered the company most threatened by the merger, explaining therefore the 17% drop in its share price in the days after the public announcement. According to James Goodwin, chairman and chief executive of UAL, two major hurdles would challenge UAL: "the first is to get US Airways shareholders to approve this transaction. [The second] is the regulatory work, which revolves around the Department of Transportation, the Department of Justice and the European Union." The skepticism on Wall Street was immediately reflected on UAL share price which declined $7.19 to $53.19 on the announcement day.

Table 1
Abnormal trades in the airline sector. The table shows the day on which the transaction took place, Date; identification number of the put option, *Id*; moneyness, i.e., stock price divided by strike price, S / K; time-to-maturity, τ; level of open interest the day before the abnormal trade, OI_{t-1}; increment in open interest from day $t-1$ to day t, ΔOI_t; its quantile with respect to its empirical distribution computed over the last two years, $q_t^{\Delta OI}$; total increment in open interest, i.e., when considering all the available options at day t and not only the ones which had the highest increment, ΔOI_t^{tot}; corresponding volume, Vol_t; maximum return realized by the selected option during the two-week period following the transaction day, $r_t^{\max}$; number of days between transaction day t and when this maximum return occurs, τ_2; gains realized through the exercise of the option issued at time t as in (4), G_t; minimum between the number of days (starting from the transaction day) needed for the exercise of ΔOI_t and 30 days, τ_3; percentage of ΔOI_t exercised within the first 30 days after the transaction, *%ex.*; ex-ante probability in Eq. (2), q_t; p-value of the hypothesis that delta hedging does not take place at time t, p-value; and ex-post probability of abnormal trading in Eq. (5), $1-p_t$. * means that the hypothesis of non-hedging can be rejected at a 5% level.

Summary of airline sector Jan 1996–Apr 2006																
Date	*Id*	S / K	τ	OI_{t-1}	ΔOI_t	$q_t^{\Delta OI}$	ΔOI_t^{tot}	Vol_t	$r_t^{\max}$	τ_2	G_t	τ_3	*%ex.*	q_t	p-Value	$1-p_t$
American Airlines (AMR) Jan 1996–Apr 2006																
10 May 00	10821216	1.01	38	20	3374	99.7%	3378	3290	106%	9	906,763	11	100%	0.002	0.286	0.998
11 May 00	10821216	1.02	37	3394	5720	99.9%	5442	5320	98%	10	1,647,844	11	100%	0.002	0.349	0.998
31 Aug 01	20399554	0.91	22	96	473	95.7%	571	500	455%	7	662,200	11	100%	0.016	0.645	0.984
10 Sep 01	20428354	0.99	40	258	1312	98.5%	1701	1535	453%	2	1,179,171	26	100%	0.012	0.096	0.998
24 Aug 05	27240699	0.97	24	1338	4378	93.5%	8395	5319	163%	8	575,105	17	100%	0.048	0.123	0.952
United Airlines (UAL) Jan 1996–Jan 2003																
11 May 00	11332850	0.95	37	35	2505	98.7%	2534	2505	132%	10	1,156,313	26	100%	0.002	0.373	0.998
6 Sep 01	20444473	1.06	44	21	1494	96.3%	1189	2000	1322%	7	1,980,387	28	100%	0.030	0.165	0.998
Delta Air Lines (DAL) Jan 1996–May 2005																
*1 Oct 98	10904865	1.01	16	140	974	97.7%	483	924	261%	6	537,594	12	100%	0.016	0.000	0.996
29 Aug 01	20402792	0.98	24	1061	202	89.7%	224	215	1033%	9	328,200	13	100%	0.044	0.528	0.998
19 Sep 02	20718332	0.99	30	275	1728	98.7%	550	1867	132%	7	331,676	22	100%	0.004	0.190	0.998
9 Jan 03	21350972	1.10	44	274	3933	99.7%	4347	4512	112%	9	1,054,217	30	100%	0.002	0.065	0.998
Boeing (BA) Jan 1996–Apr 2006																
24 Nov 98	10948064	0.99	53	3758	1047	93.5%	1285	1535	467%	7	883,413	24	100%	0.040	0.481	0.996
29 Aug 01	20400312	0.92	24	1019	2828	96.7%	3523	3805	382%	10	1,972,534	8	100%	0.028	0.252	0.998
5 Sep 01	20429078	1.01	45	472	1499	92.1%	2538	1861	890%	8	1,805,929	22	100%	0.048	0.085	0.998
6 Sep 01	11839316	0.75	135	13228	7105	99.3%	13817	7108	118%	7	2,704,701	3	100%	0.006	0.150	0.998
*7 Sep 01	20400311	0.90	15	7995	4179	98.5%	4887	5675	306%	6	5,775,710	7	100%	0.016	0.000	0.998
*17 Sep 01	20400309	0.90	5	116	5026	98.9%	2704	5412	124%	4	2,663,780	5	100%	0.010	0.000	0.998
KLM Jan 1996–Nov 2001																
5 Sep 01	20296159	0.91	17	3	100	99.3%	34	100	467%	9	53,976	9	100%	0.006	0.368	0.998

two trading weeks). The same impact can be found for UAL: the stock price after the public announcement dropped to \$52.50 (−14.63% when compared to the value on May 11th) raising the put's value to \$12.63 (corresponding to a return of 140% in two trading weeks). In the case of AMR, the decline in the underlying stock can be seen in Fig. 2, where the option return largely increased.

On the day of the public announcement 4735 put options of AMR were exercised; see Fig. 2. After this large decrement in open interest, 1494 and 1376 additional put options were exercised in the following two days respectively (reflected in additional drops in open interests in Fig. 2). The unusual increments in open interest observed on May 10th and May 11th are therefore offset by the exercise of options when the underlying crashed. The corresponding gains G_t from this strategy are more than \$1.6 million within two trading weeks. These are graphically shown in the lower graph in Fig. 1, from which we can see how fast these gains were realized. In the case of UAL similar conclusions can be reached; see Tables 1 and 2. Based on these trades, a total gain of almost \$3 million was realized within a few trading weeks using options with underlying AMR and UAL. The non-hedging hypothesis cannot be rejected suggesting that such trades are unhedged option positions. Comparable abnormal trades have been found for American Airlines, United Airlines and Boeing (and to a lesser extent for Delta Air Lines and KLM) before the terrorist attacks of 9/11, and are discussed in the separate appendix.

6. Controlling false discoveries in abnormal trades

Any statistical method can generate false discoveries in abnormal trades, i.e., the probability that an option trade can satisfy various criteria simply by chance is not zero. Controlling for false discovery is then an important task, which allows abnormal trades with high gains to be truly separated from liquidity trades that luckily achieved also high gains. To separate the two groups of trades we use a multiple hypothesis testing technique. Barras et al. (2010) adopted a similar approach to discriminate between skilled and lucky mutual fund managers based on fund performance.

For the sake of presentation, we phrase the discussion in terms of informed versus uninformed traders. We say that abnormal trades with high gains are generated by informed traders (and lucky uninformed traders). In practice, traders with private information and/or who are hedging their human capital are probably originating put option abnormal trades, which is the *joint hypothesis* discussed in the introduction. In the presentation of the multiple hypothesis test we omit such a distinction.

Suppose we observe option returns generated by M traders characterized by different degrees of information, ranging from highly accurate private information to no information (or possibly even misleading information). Let π_0 denote the fraction of uninformed

Table 2
Abnormal trades in the airline sector: Description of events. The table shows the day on which the transaction took place, Date; average return of the stock during the last two trading weeks, Return; minimum return of the stock during the two-week period following the transaction day, Min; day when the stock drops, Drop; and why the stock drops, Event's description. * means that the hypothesis of non-hedging can be rejected at a 5% level.

Summary of airline sector Jan 1996–Apr 2006				
Date	Return	Min	Drop	Event's description
American Airlines (AMR) Jan 1996–Apr 2006				
10 May 00	0.4%	−17.6%	24/25 May 00	UAL's acquisition of US Airways
11 May 00	0.0%	−17.6%	24/25 May 00	UAL's acquisition of US Airways
31 Aug 01	−0.4%	−39.4%	17 Sep 01	9/11 terrorist attacks
10 Sep 01	−1.4%	−39.4%	17 Sep 01	9/11 terrorist attacks
24 Aug 05	0.4%	−5.3%	30 Aug 05	Hurricane Katrina
United Airlines (UAL) Jan 1996–Jan 2003				
11 May 00	0.3%	−12%	24 May 00	UAL's acquisition of US Airways
6 Sep 01	−1.0%	−43.2%	17 Sep 01	9/11 terrorist attacks
Delta Air Lines (DAL) Jan 1996–May 2005				
*1 Oct 98	−1.7%	−11.4%	07/08 Oct 98	Not identified
29 Aug 01	0.0%	−44.6%	17 Sep 01	9/11 terrorist attacks
19 Sep 02	−5.2%	−24.4%	27 Sep 02	Expected quarter loss
9 Jan 03	2.1%	−15.7%	21/22 Jan 03	Restrictions on alliance
Boeing (BA) Jan 1996–Apr 2006				
24 Nov 98	−0.2%	−22.0%	02/03 Dec 98	Production scale back
29 Aug 01	−0.4%	−25.0%	17/18 Sep 01	9/11 terrorist attacks
5 Sep 01	−0.8%	−25.0%	17/18 Sep 01	9/11 terrorist attacks
6 Sep 01	−0.9%	−25.0%	17/18 Sep 01	9/11 terrorist attacks
*7 Sep 01	−1.9%	−25.0%	17/18 Sep 01	9/11 terrorist attacks
*17 Sep 01	−5.6%	−25.0%	17/18 Sep 01	9/11 terrorist attacks
KLM Jan 1996–Nov 2001				
5 Sep 01	−1.9%	−31.6%	17/18 Sep 01	9/11 terrorist attacks

traders and δ_m, $m = 1, \ldots, M$, the expected return generated by trader m. Under the null hypothesis all option traders are uninformed. Formally, this multiple hypothesis reads $H_{0,m} : \delta_m = 0, m = 1, \ldots, M$. Each hypothesis is tested at significance level γ, e.g., $\gamma = 10\,\%$, using a two-side t-statistic, i.e., $H_{0,m}$ is rejected when the corresponding t-statistic is either below the 5th or above the 95th percentiles of its distribution under $H_{0,m}$. When the null hypothesis is true, all p-values based on t-statistics are uniformly distributed between 0 and 1. When the null hypothesis is not true, large option returns and corresponding low p-values are generated by both informed and lucky traders. Under such alternative hypothesis, $E[S_\gamma^+]$ is the expected fraction of p-values below $\gamma/2$ corresponding to positive and significant t-statistics. The key step is to adjust $E[S_\gamma^+]$ for the presence of lucky traders. The expected fraction of truly informed traders is $E[T_\gamma^+] = E[S_\gamma^+] - \pi_0\, \gamma/2$.[8] The last step is the estimation of π_0. Intuitively, large p-values correspond to estimated δ_m not statistically away from zero and hence generated by uninformed traders. The fraction of p-values above a certain threshold λ is extrapolated over the interval [0,1]. Multiplying this fraction of p-values by $1/(1 - \lambda)$ provides an estimate of π_0. This estimation approach has been developed by Storey (2002); see, e.g., Romano et al. (2008) for a review. We choose λ using the data-driven approach in Barras et al. (2010). The observed fraction of positive and significant t-statistics provides an unbiased estimate of $E[S_\gamma^+]$.

Obviously, we do not observe option returns achieved by traders with various degrees of private information. Consistently with our detection method, we use the historical probability q_t of observing unusual increments in open interest and volume, as well as high gains, as a proxy for private information. The working assumption is that the smaller such probability is, the higher the degree of private information of the option trader.

For every underlying asset, for every day t, and for every option trade $k = 1, \ldots, K_t$ in our sample, we compute the historical probability q_t^k as in Eq. (2) of observing an increment ΔOI_t^k in open interest and distance $Z_t^k := (V_t^k - \Delta OI_t^k)$ between trading volume and increment in open interest, and corresponding maximal return as in Eq. (5). By definition, the probability q_t^k lies in the interval [0,1]. We sort in ascending order all q_t^k and divide such unit interval into $M = 1000$ subintervals $I_1, \ldots, I_M$ such that in every subinterval the same number of q_t^k is available. Then we group all option trades q_t^k and corresponding returns r_t^k according to which subinterval I_m they belong. This procedure allows us to construct M hypothetical option traders, each one of them characterized by a different degree of private information and option returns. In subintervals I_m, $m = 1, \ldots, M$, the lower the value of m, the more informed the trader is, and therefore, the more likely it is that she will generate large positive return r_t^k. Within each subinterval I_m, we regress unadjusted annualized option returns r_t^k on a subinterval-specific constant δ_m, estimating the expected return of trader m.[9]

[8] Note that under the null hypothesis all traders are uninformed, i.e., $\pi_0 = 1$, and by definition half the size of the test $\gamma/2 = E[S_\gamma^+]$. Therefore the expected fraction of truly informed traders is $E[T_\gamma^+] = 0$.

[9] In the regression, we do not adjust option returns for market return or any other variable because the focus is on the ability of the option trader to generate large returns, including those returns based on predicting future market or other variable movements. In order to make least squares estimation more robust we exclude negative returns below the 5% empirical quantile. The impact of winsorizing on the false discovery rate is virtually negligible.

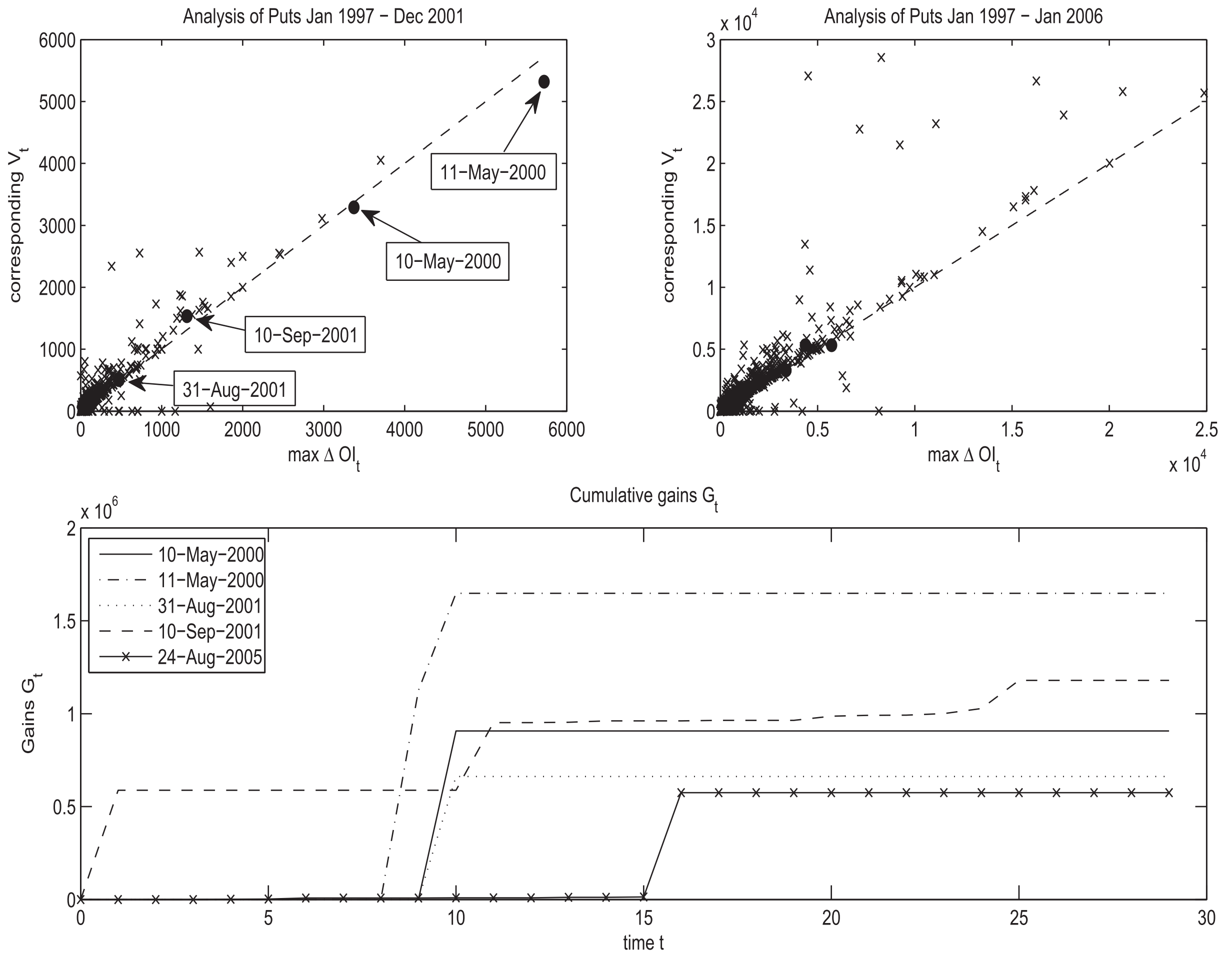

Fig. 1. Detecting abnormal trades: American Airlines' example. Upper graphs show on the x-axis maximal daily increment in open interest across all put options with underlying American Airlines (AMR), and on the y-axis the corresponding trading volume. Upper-left graph covers the period January 1997–December 2001, and upper-right graphs the period January 1997–January 2006. Lower graph shows cumulative gains G_t in USD as in Eq. (4) for detected option abnormal trade on AMR. Gains correspond to those realized by daily exercising/selling the options.

As an example Fig. 3 shows estimated δ_m for American Airlines. The lower the value of m, the higher the estimated δ_m, and the relation is nearly monotonic. Moreover, for small m, the estimated δ_m are positive and significant, whereas for increasing m, δ_m becomes statistically indistinguishable from zero.

We briefly discuss now the estimates of false discovery rates for American Airlines and Citigroup. For AMR, the total number of analyzed option trades amounts at 137,000, implying that each regression coefficient δ_m has been computed by relaying on 137 option returns r_t^k. The expected fraction of truly abnormal trades has been estimated to be $E[T^+] = 9.8\,\%$ (with standard error 1.15%, optimal $\lambda = 0.65$, and $\gamma = 0.11$), corresponding to 98 trades. As the ex-ante procedure detects 141 abnormal trades for AMR, the test result suggests that some of these trades may be actually liquidity uninformed trades. In contrast, the ex-post procedure is more conservative and detects only 5 abnormal trades, which implies that these trades are most likely abnormal trades. For the case of Citigroup, option trades amount at 246,000 and the estimated fraction of truly abnormal trades $E[T^+] = 10.6\,\%$ (with standard error 1.09%, optimal $\lambda = 0.612$, and $\gamma = 0.07$), corresponding to 106 trades. The ex-post method detects only 2 abnormal trades. Thus also in this case the detection procedure is conservative and detected trades are most likely abnormal. For the remaining companies we found similar results. Because of space constraints, figures and tables are not reported but available upon request from the authors.

Finally, to assess the ability of the FDR test at controlling for false discoveries, we run the following experiment.[10] We identify the major natural disasters, such as floods, hurricanes, volcanic eruptions, oil spills, and earthquakes from 2000 to 2011. As the exact timing of the event is in principle unpredictable, this should rule out any abnormal trade that generates large returns upon the occurrence of the natural disaster. Then, we consider all the option trades over the two weeks prior to the relevant event in the companies that were affected ex-post by the event. Given the setup, no option trade should be classified as abnormal.

[10] We thank an anonymous referee for suggesting this experiment.

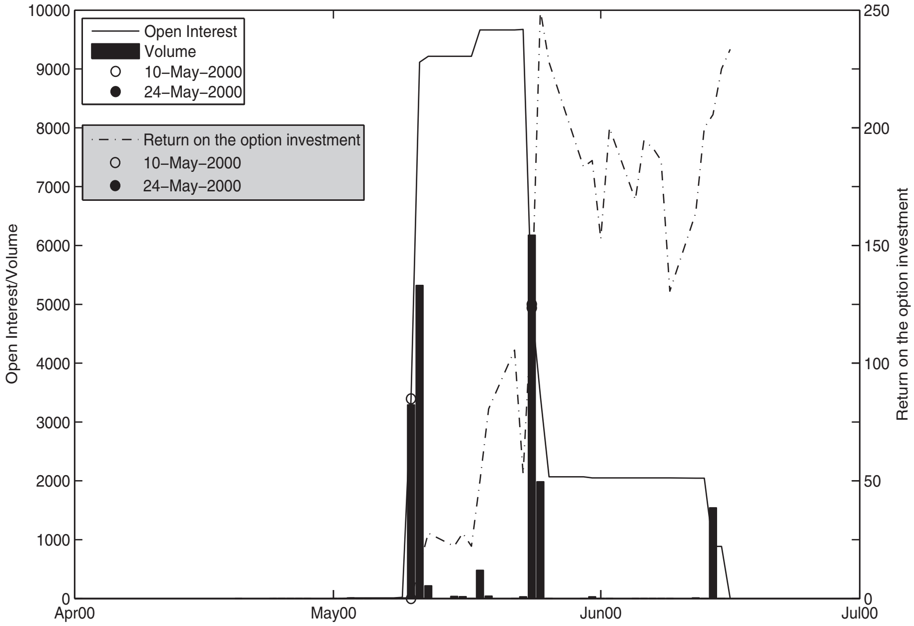

Fig. 2. Selected abnormal trade: American Airlines' example. Selected put option for abnormal trading with underlying stock American Airlines (AMR) before the United Airlines (UAL) announcement of $4.3 billion acquisition of US Airways in May 2000. The solid line shows the daily dynamic of open interest, the bars show the corresponding trading volume (left y-axis) and the dash–dot line the option return (right y-axis). The empty circle is the day of the transaction, the filled circle is the day of the announcement (partially covered by the highest bar). This put option had a strike of $35 and matured at the end of June 2000.

Table 3 provides the list of natural disasters and affected companies, as well as the rationale for including these companies. For example we consider British Petroleum before the oil spill in the U.S. Gulf Coast in 2010. The list of companies is constrained by option data availability, i.e., open interest and volume for individual options. Computing q_t as in Eq. (2) and considering $q_t < 5\,\%$, a very small number of suspicious option trades is detected over the two weeks prior to a natural disaster. When applying the FDR test all such trades are attributed to luck, confirming the validity of our procedure. Detailed test results are available from the authors upon request.

7. Robustness checks

The input parameters in our detection procedure are: the length N of the estimation window, chosen to be $N = 500$ trading days, used for the computation of the ex-ante probability q_t, the conditional distribution of $V_t^{\text{sell,non - hedge}}$, and the quantiles $q_{\alpha}^{r_t^{\max}}$ and $q_{\alpha'}^{G_t}$; the time period after the transaction day used for the computation of $r_t^{\max}$, chosen to be 10 trading days; the time horizon τ_t used for the calculation of the gains G_t, chosen to be 30 trading days; the quantile levels α and α' in $q_{\alpha}^{r_t^{\max}}$ and $q_{\alpha'}^{G_t}$ used for the computation of the sets Ω_3 and Ω_4, chosen to be $\alpha = 90\,\%$ and $\alpha' = 98\,\%$; and the probability level used to select trades belonging to the set Ω_1, chosen to be 5%. In what follows we set the input parameters to different values and we repeat all previous analysis for all companies. To save space we report only some of the results and for a few companies giving a sense of the robustness of our results. Additional results are available from the authors upon request.

When varying the length of the estimation window N between 200 and 1000 (all other parameters being unchanged), the number of selected transactions does not change significantly. For example in the case of AMR, we selected 5 abnormal trades when considering the last two trading years ($N = 500$ days); for $N \in [200, 1000]$ the number of detected abnormal trades ranges between 4 and 6; for UAL, we detected 2 abnormal trades when considering the last two trading years ($N = 500$ days); this number remains unchanged with respect to the original choice for $N > 450$ and decreases by one when $N \in [200, 450]$. In the case of BAC and AT&T, the deviation from the original number of selected trades is less than 2. With respect to the choice of the time period used for the computation of $r_t^{\max}$ and τ_t, our results are also robust. We let the length of the first period vary in the range [1,30] days and the second one in [1,40] days. In the case of AMR, the number of transactions ranges from 2 to 8, being therefore centered around the original number and with a small deviation from it. For UAL, the corresponding range is from 1 to 4, for BAC from 2 to 8 and for AT&T from 1 to 6. The number of detected trades is obviously a decreasing function of α and α' (all other parameters being unchanged). In the case of AMR, when $\{\alpha, \alpha'\} \in [0.85, 0.95] \times [0.96, 1]$, the number of transactions selected does not exceed 15. For UAL, the number of selected trades varies between 1 and 10, for BAC between 5 and 25, and for AT&T between 1 and 18. Finally, with respect to the probability level used to determine the set Ω_1, our findings are very robust as well. When increasing the level from 1% to 10%, the number of trades selected for AMR varies between 1 and 6; for UAL it ranges between 2 to 4, and for BAC and AT&T from 1 to 7. We simultaneously changed several parameters and found that the number of detected transactions does not change significantly and in almost all cases in

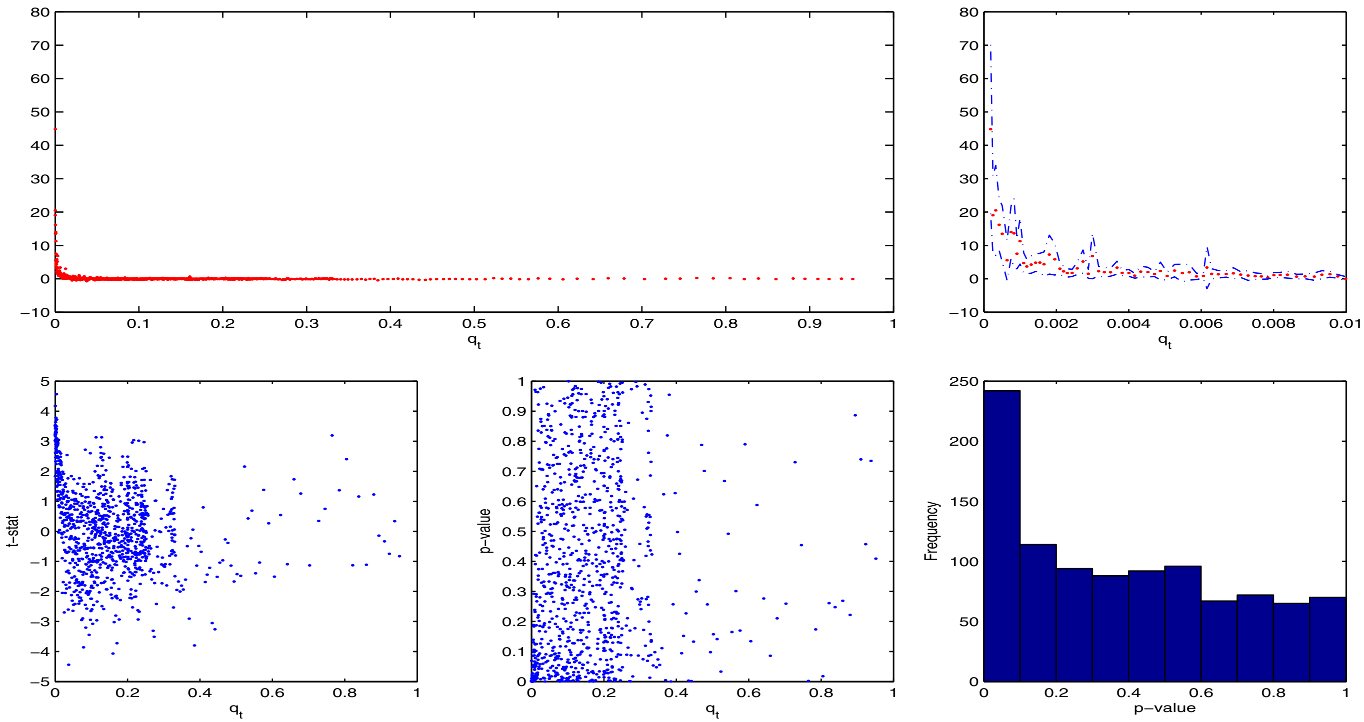

Fig. 3. False discovery rate: American Airlines' example. The upper-left graph shows on the x-axis the probability q_t (the right-end point in each subinterval I_m), and on the y-axis the corresponding average option returns δ_m associated to the mth option trader. The upper-right graph shows the same quantities when $0 \le q_t \le 0.01$. Dashed–dotted lines represent 95% confidence intervals for δ_m. The lower graphs, from left to right, show t-statistics of option returns associated to the M option traders for the null hypothesis $H_0 : \delta_m = 0, m = 1, \ldots, M$, p-values, and frequency histogram of p-values, respectively.

Table 3
List of natural disasters and involved companies. The table lists some of the natural disasters that occurred between 2000 and 2011, the date of the event, and some of the companies that were affected ex-post by the event. The rationale for including the companies is the following. Central Europe floods: Advanced Micro Devices was operating a main chip fabrication plant in Dresden which was eventually only marginally affected by the floods. Hurricane Katrina: ExxonMobil was operating a major refinery near the U.S. Gulf Coast. Eruptions of Eyjafjallajökull: the International Air Transport Association imposed an air travel ban and transportation companies like FedEX were negatively affected. Deepwater Horizon oil spill: British Petroleum was responsible for the oil spill and operated the oil prospect. Japan earthquake: the earthquake has led to a fall in the oil price, which has added pressure on British Petroleum's share price.

Natural disasters and false discoveries of informed trades		
Event	Date	Company
Central Europe floods	11 Aug 02	Advanced Micro Devices
Hurricane Katrina	29 Aug 05	ExxonMobil
Eruptions of Eyjafjallajökull (Iceland)	14 Apr 10	FedEX
Deepwater Horizon oil spill	20 Apr 10	British Petroleum
Japan earthquake	11 Mar 11	British Petroleum

steps of one. We recall that approximately 9.6 million of options are analyzed. Based on these results, we conclude that our findings are robust.

8. Conclusion

We develop two statistical methods to detect option abnormal trades, i.e., unusual trades in option contracts that generate large gains, are not used for option hedging purposes, and are made a few days before the occurrence of a specific event. The first method uses only ex-ante information and aims at detecting abnormal trades as soon as they take place. The second method relies on a more stringent definition of abnormal trades and also uses ex-post option returns. We control for false discoveries in abnormal trades using a multiple hypothesis testing technique.

We apply the two methods to 9.6 million of daily option prices. Our empirical findings can be summarized as follows. Detected option abnormal trades tend to cluster prior to major corporate events, such as acquisitions or financial disruption announcements, involve often liquid options, generate easily large gains exceeding millions, and are not contemporaneously reflected in the underlying stock price.

Our findings have policy, pricing, and market efficiency implications. If some of the detected abnormal trades are indeed illegal, it can be optimal for regulators to expend relatively more monitoring efforts on option markets. Pricing models should account for all relevant current information. However, nearly all option prices (and underlying assets) involved in abnormal trades do not show any specific reaction to large increments in open interest and volume. The strong movements in detected options are simply due to subsequent large movements in stock prices originated by specific firm news. Finally, certain increments in open interest and volume appear to predict large price movements and simple option trading strategies can generate large returns. Further research is necessary to assess whether those returns question market efficiency or rather reflect compensation for risk factors.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.jempfin.2015.03.008.

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