Detecting Informed Trading Activities in the Options Markets*

Marc Chesney[†] — University of Zurich and Swiss Finance Institute

Remo Crameri[‡] — University of Zurich and Swiss Finance Institute

Loriano Mancini[§] — EPFL and Swiss Finance Institute

September 7, 2011

*We thank Peter Carr, Fulvio Corsi, Rüdiger Fahlenbrach, Ramo Gençay, Rajna Gibson, Michel Habib, Michael Magill, Richard Meier, Claudia Ravanelli, Ganna Reshetar, and Alex Wagner for helpful comments. Financial support by NCCR-FINRISK (Swiss National Science Foundation) and by the Research Priority Program "Finance and Financial Markets" (University of Zurich) is gratefully acknowledged.

†**Correspondence Information:** Marc Chesney, Department of Banking and Finance, University of Zurich, Plattenstrasse 32, 8032 Zurich, Switzerland. Tel: +41 (0)44 634 45 80. Fax: +41 (0)44 634 49 03. E-mail: marc.chesney@bf.uzh.ch

‡Department of Banking and Finance, University of Zurich. E-mail: remo.crameri@bf.uzh.ch

§Swiss Finance Institute at EPFL, EPFL. E-mail: loriano.mancini@epfl.ch

Detecting Informed Trading Activities in the Options Markets

Abstract

We develop statistical methods to detect informed trading in options markets. We apply these methods to 31 companies from various sectors over 14 years analyzing approximately 9.6 million option prices. We find that option informed trading tends to cluster prior to certain events, takes place more in put than call options, generates easily large gains exceeding millions, is not contemporaneously reflected in the underlying stock price, involves around the money options during calm times and out-of-the-money options during turbulent times. These findings are not driven by false discoveries in informed trades which are controlled using multiple hypothesis testing techniques.

Keywords: Options Trades, Open Interest, Informed trading, False Discovery Rate

JEL Classification: G12, G13, G14, G17, G34, C61, C65

1 Introduction

Most previous studies on option informed trading either focus on trading around specific events, such as mergers and earnings announcements, or investigate whether the cross section of stock returns is driven by option-related variables, such as implied volatilities and signed volumes. The goal of this paper is to understand when option informed trading happens, under what circumstances, and which options are involved. This mechanism has obvious, important implications for market efficiency, capital allocation and investment decisions; e.g. Pan and Poteshman (2006) and Bali and Hovakimian (2009).

Various studies have documented informed trading activities both in stock and option markets. For instance Keown and Pinkerton (1981) report statistical evidence of (illegal) informed stock trading before the first public announcement of proposed mergers. Christophe, Ferri, and Angel (2004) document abnormal short-selling before scheduled corporate earnings announcements. Lee, Mucklow, and Ready (1993) provide related evidence studying bid-ask spreads and market depths. However, as discussed in Grossman (1977), Diamond and Verrechia (1987), and others, option markets offer significant advantages to informed traders as opposed to stock markets. Options offer 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 (Back (1993) and Biais and Hillion (1994)), and possibly more discreetness for trading on private signals. When informed investors trade first in the option market then this market should lead the stock market. Indeed, Cao, Chen, and Griffin (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 strong evidence that signed option trading volumes predict future price changes. [1] Bali and Hovakimian (2009) show that the difference between realized and implied volatilities of individual stocks predicts the cross-sectional variation of expected returns.

[1] Chan, Chung, and Fong (2002) find no evidence of such information but they rely on a noisier measure of signed option volume.

Cremers and Weibaum (2010) find that deviations from put-call parity, in terms of implied volatilities, contain information about future stock returns. Ang, Bali, and Cakici (2010) also find that option volatilities have significant predictive power for the cross section of stock returns, and vice versa. Xing, Zhang, and Zhao (2010) show that firms with the steepest volatility smirks are those experiencing the worst earnings shocks in the following quarter. Similarly, Yan (2011) documents a negative relation between the slope of implied volatility smile and stock return.

We analyze approximately 9.6 million of options prices. The underlying stocks are 31 companies mainly from airline, banking and insurance sectors. The sample period spans 14 years, from January 1996 to September 2009 (the first part of our sample is somehow shorter and ends in April 2006). Our analysis is at the level of the individual option and corresponding company, rather than on the cross section of stock returns. We do not use regression-based methods as in above-referenced studies but we develop our own statistical methods to detect option informed trading.[2]

Our main empirical findings are summarized as follows. First, option informed trading tends to cluster prior to certain events such as merger or acquisition announcements (M&A), 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. This empirical result can be obtained only undertaking a large empirical analysis. Second, prior to a particular event which will impact a particular company, informed trading involves more than one option but rarely the cheapest option, i.e. deep out-of-the-money and with shortest maturity. This finding is consistent with informed investors trading fairly liquid options and attempting not to immediately reveal their private signals. We detect informed trades in cheap options mainly during the Subprime crisis prior to financial disruption announcements. Third, the majority of detected informed trades take place in put rather than call options. As stock prices tend

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

to fall sharply and rise slowly when reacting to negative and positive news, taking long positions in put rather than call options might be more profitable for informed traders. Fourth, estimated option gains of informed traders easily exceed several millions for a single event. Those gains are likely to be realized as they correspond to actual trades. Finally, the underlying stock price does not display any particular behavior on the day of the detected option informed 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. Although we use publicly available data to detect option informed trading, it appears that the information content of such trading is not contemporaneously impounded into the underlying stock price.

As an example, we detect two informed trades involving put options on American Airlines (AMR) and United Airlines (UAL) on the Chicago Board Options Exchange on May 10th and 11th, 2000, namely two weeks before UAL's acquisition of US Airways was announced. These trades generated a total gain of almost \$3 million.[3] As another example, four informed put option trades on EUREX are identified between April and June 2006 with the underlying being EADS, the parent of plane maker Airbus. These trades precede the June 14th, 2006 announcement that deliveries of the superjumbo jet A380 would be delayed by a further six months period, causing a 26% fall in the underlying stock, and a total gain of approximately €8.7 million in these option trades.

We develop two statistical methods to detect option informed trades and obtain the aforementioned empirical results. The first method aims to detect option informed trades as soon as they take place, without using any future information. We look for option trades characterized by unusually large increments in open interest which are close to daily trading volumes. In those

[3] As reported in the New York Times edition of May 25th, 2000, AMR was considered the company most threatened by the merger, explaining therefore the 17% drop in its stock 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 shares which declined \$7.19 to \$53.19 on the announcement day.

cases 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. Applying this simple rule to our dataset, a striking pattern emerges. The more unusual the increment in open interest and volume the higher the future return of the corresponding option. The relation is nearly monotonic. This finding is consistent with informed traders being the originators of the large increments in open interest and volume. A natural question is whether truly informed investors or simply lucky traders were behind those large gains. To answer this question we develop a formal test based on multiple hypothesis testing techniques. Our empirical results show that with high probability informed investors originated those trades. The first method is further refined by considering option hedging. We develop a statistical test to check whether those option trades are hedged with the underlying asset or used for hedging purposes. A few option trades do not pass this test and are probably not attributable to informed investors. Our second method to detect option informed trading encompasses the first method by adding an additional criterion. An option trade is identified as informed when the increment in open interest and volume is unusual, not hedged (as in the first method), and generates large ex-post option gains. As the definition of option informed trading is now more stringent, less option trades are identified as informed according to this method. Interestingly, the two methods provide the same pattern of empirical findings discussed above.

Our approaches to detect option informed trading are distinctly different from previous methods in at least two dimensions, namely accounts for option hedging and controls for false discoveries in informed trades. Previous methods do not check whether option informed trades are actually hedged or used for hedging purposes. We develop a nonparametric test to assess whether such hedging takes place or not. For example, when studying long positions in put options, the idea is to decompose the underlying stock buyer-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 option informed trading would have occurred. Then the test rejects the null hypothesis of absence of hedging when the hedging component is statistically large.

Previous studies do not control for false discoveries in option informed trades. In any statistical method, the probability that an uninformed option trade will appear to be informed simply by chance is not zero. However, this misclassification error can be formally quantified using multiple hypothesis testing techniques. Intuitively, while uninformed option traders should have zero return on average, informed traders should achieve statistically large returns. Under the null hypothesis that all traders are uninformed, the proportion of lucky traders can be calculated using option returns. When the difference between the actual fraction of large returns (due to all traders) and the expected fraction of large returns due to lucky traders is statistically large, the test rejects the null hypothesis that all traders are uninformed. The fraction of truly informed options traders is also estimated.

The most closely related study to ours is Poteshman (2006). Both studies focus on option informed trading and use open interest as a key variable in the detection methods. However, there are also important differences concerning data, method and aims. Poteshman focuses mainly on the airline sector and suspicious trading activities in the days leading up to the terrorist attacks of September 11th. We undertake a more general analysis considering several companies from various sectors over a long time period (14 years) which turn out to be affected by various events. While Poteshman uses quantile regressions, we use our own nonparametric methods to detect option informed trading. Similarly to previous studies, Poteshman does not consider option hedging and does not control for false discoveries in informed trades. We address both issues. The main difference is that we aim to provide a comprehensive study of option informed trading rather than analyzing a specific event.

Some economists even view insider trading as informed trading and argue that laws making insider trading illegal should be revoked. Milton Friedman, laureate of the Nobel Memorial Prize in Economics, said: "You want more insider trading, not less. You want to give the people most likely to have knowledge about deficiencies of the company an incentive to make the public aware of that." Friedman believed that any constraint to informed traders should be removed and that buying or selling pressure is sufficient to impound new information into asset prices. While this phenomenon might occur in stock market, our findings suggest that it does not take place in the options markets.

The paper is organized as follows. Section 2 reviews related literature on informed trading. Section 3 introduces our methodology to detect option informed trades. Section 4 describes the database. Section 5 presents the empirical results. Section 6 quantifies false discoveries in option informed trades. Section 7 discusses various robustness checks. Section 8 concludes.

2 Related Literature

This paper is mainly related to two strands of literature dealing with informed trading activities and linkages of information between option and stock markets. Besides the work cited in the introduction, other studies have investigated the economic mechanism through which new information is impounded into asset prices, which frictions impact this process, how informed traders should exploit their private signals, and related aspects; e.g. Easley, Kiefer, and O'Hara (1997), Glosten and Milgrom (1985), Hasbrouck (1991), Huang and Stoll (1994), Gârleanu, Pedersen, and Poteshman (2009), and Boulatov, Hendershott, and Livdan (2011). Easley and O'Hara (1987, 1992) develop the probability of information-based trading (PIN). This method has been mainly applied to detect informed trades in stock markets as in e.g. Easley, Kiefer, and O'Hara (1997) and Vega (2006).

The second strand of literature investigates the linkage and information flow between options and stock markets; e.g. Conrad (1989), Stoll and Robert (1990), Mayhew, Sarin, and Shastri (1995), Easley, O'Hara, and Srinivas (1998), Chakravarty, Gulen, and Mayhew (2004), Pan and Poteshman (2006), and Lakonishok, Lee, Pearson, and Poteshman (2007). In particular, Easley, O'Hara, and Srinivas (1998) develop a theoretical model in which informed traders choose to trade in both the option and the stock market in a "pooling equilibrium" when the leverage implicit in options is large, the liquidity in the stock market is low, or the overall fraction of informed traders is high. Pan and Poteshman (2006) provide empirical evidence of this equilibrium analyzing put-call ratios. Overall this research indicates that signed option volumes have an impact on future underlying asset price dynamics. Our findings suggest that option informed trades are not reflected into stock prices until the specific event occurs.

This paper is also related to detection of insider trading, viewing the latter as a subclass of informed trading; e.g. Seyhun (1986), Meulbroek (1992) and Biais and Hillion (1994). Our empirical results show that option markets are profitable for informed traders suggesting that informed traders might consider options as superior trading vehicles; e.g. Bhattacharya (1987), Anthony (1988), Stephan and Whaley (1990), Chan, Chung, and Johnson (1993), Manaster and Rendleman (1982), and Lee and Yi (2001). Finally, Chen, Hong, and Stein (2001) forecast asset crashes using shares trading volume. Blume, Easley, and O'Hara (1994) emphasize the role of transaction volume as a tool for technical analysis. We complement this work by showing that certain increments in open interest and volume have predictive power for future movements in the underlying stock. Vijh (1990) studies information-related trading as well.

3 Detecting Option Informed Trades

We propose two methods to detect option informed trades. The first method relies on a broad but empirically successful definition of informed 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 option informed trade 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 informed 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 hedging purposes. These three characteristics, $C_i, i = 1, 2, 3$, lead to the following method to detect informed trading activities in options markets: first on each day the option contract with largest increment in open interest and volume is identified, then the rate of return and dollar gain generated by this transaction are calculated, and finally it is studied whether hedging occurs. Options trades which are delta hedged or used for hedging purposes are not regarded as informed trades. The first method relies only on characteristics C_1 and C_2, and their practical implementation. Both methods require only commonly available datasets. Obviously, informed traders can undertake a large variety of trading activities having various degrees of complexity, splitting their orders, jamming the signals, etc. In this paper we restrict our attention to the economically sensible informed trade characterized by $C_i, i = 1, 2, 3$, above. We now explain how to detect informed trades in put options, the application to call options can easily be deduced. In the empirical section, we apply both methods to a large dataset of put and call options.

3.1 First Criterion: Increment in Open Interest Relative to Volume

For every put 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 put 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 put 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 market maker to issue new put 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 put option selected in (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 informed trades. Let q_t denote the ex-ante joint historical probability of observing unusual large increment in open interest close to the trading volume

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

where $\mathbb{P}$ denotes the empirical probability, N the length of the estimation window, e.g. $N = 500$ trading days, and $\mathbf{1}_{\{A\}}$ the indicator function of event A. 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 the ex-post relative returns and realized gains from transactions with a low ex-ante probability q_t. For each day t the trade with the largest increment in open interest 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 price of the selected put option at day t. When $r_t^{\max}$ is unusually high, an unusual event occurs during the 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 put option.[4] Then we approximate the American put option value by its intrinsic value, significantly simplifying the calculation of option gains. However, given our definition of informed trade, it is likely that on the event day the drop in the stock price is large enough to reach the exercise region—making the previous approximation

[4]On a given day, opening new positions (which increases open interest) and closing existing options (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.

exact. If options are sold rather than exercised, our calculation of realized gains underestimate the actual gains, neglecting time values of options. Hence reported gains should be interpreted in a conservative manner. 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

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

where τ_t is such that $t < \tau_t \leq T$, with T being the maturity of the selected option. If the put options were optimally exercised (i.e. when the underlying asset $S_{\tilde{t}}$ touches in the exercise region), the payoff $(K - S_{\tilde{t}})^+$ corresponds to the price of the option at time $\tilde{t}$. The cumulative gains G_t could be easily calculated for every $\tau_t \leq T$. 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.[5] To avoid this inconsistency, the time τ_t is defined as follows

$$\begin{aligned} \tau_t^* &:= \arg \max_{l \in \{t+1,\dots,T\}} \left[\sum_{\tilde{t}=t+1}^{l} (-\Delta OI_{\tilde{t}}) \cdot \mathbf{1}_{\{\Delta OI_{\tilde{t}} < 0\}} \leq X_t \right] \\ \tau_t &:= \min(\tau_t^*, 30) \end{aligned}$$

giving the informed trader no more than 30 days to collect her gains. In general in the square brackets the sum of negative decrements 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 database provides

[5] 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 $\tau_t \leq t + h$, where τ_t is such that the sum of negative decrements in open interest during $[t + 1, \tau_t]$ equals $X_t = 2000$.

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 (3), we can calculate the time-t ex-post joint historical probability p_t of the event $\{X_t, Z_t, r_t^{\max}\}$

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

The probability $(1-p_t)$ can be interpreted as a proxy for the probability of informed trading in the option market. The higher $(1-p_t)$ 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 informed trading. 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. For example suppose that a trader buys a large number of shares, hedges this exposure buying put options, and the stock price indeed drops a few days later. Using the first two criteria, such a transaction in put option would be classified as informed. Another misclassification would occur in the opposite situation when the investor buys a large amount of put options and hedges her position by buying the suitable amount of the underlying stock.

We attempt to assess indirectly whether unusual trades in put options are actually delta hedged using the underlying asset. The idea is to compare the theoretical total amount of shares bought for non-hedging purposes and the total volume of buyer-initiated transactions in the underlying stock. If the latter is significantly larger than the former, then it is likely that some of the buyer-initiated trades occur for hedging purposes. In the opposite case we conclude that the new option positions are naked. The difficulty is that the volume due to hedging is typically a small component of the total buyer-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 the OptionMetrics database. We therefore check whether all the newly issued options are hedged on a specific day t. Given our definition of informed option trades, such trades certainly account for a large fraction of the newly issued options. For each day t, the total 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.[6] Then the buyer-initiated volume of underlying stock, V_t^{buy}, is divided into volume due to hedging and to non-hedging purposes, $V_t^{\text{buy,hedge}}$ and $V_t^{\text{buy,non-hedge}}$, respectively. Let $\Delta_t^{P,k}$ be the delta of put option k and K_t^P the set of put option (newly issued or already existing) on day t. Similarly for $\Delta_t^{C,k}$ and K_t^C. Let

$$\alpha_t := \sum_{k \in K_t^P} |OI_t^{P,k} - OI_{t-1}^{P,k}| \cdot |\Delta_t^{P,k}| \quad , \quad \gamma_t := \sum_{k \in K_t^C} |OI_t^{C,k} - OI_{t-1}^{C,k}| \cdot \Delta_t^{C,k},$$

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

The α_t and γ_t represent the theoretical number of shares to buy for hedging the new options issued at time t, whereas β_t and δ_t are the theoretical number of shares to buy to rebalance the portfolio of existing options at time 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 buyer-initiated volume of stock at time t for hedging purposes, $V_t^{\text{buy,hedge-theory}}$, is

$$V_t^{\text{buy,hedge-theory}} := \alpha_t + \beta_t + \gamma_t + \delta_t.$$

When the first two criteria of our method do not signal any informed trade, we approximate $V_t^{\text{buy,hedge}}$ by $V_t^{\text{buy,hedge-theory}}$. Then the amount of stock bought for non-hedging purposes is cal-

[6]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.

culated as

$$V_t^{\text{buy,non-hedge}} = V_t^{\text{buy}} - V_t^{\text{buy,hedge-theory}}.$$

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

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

with $Y_t := V_t^{\text{buy,non-hedge}}$, $\mathbf{X}_t := (|r_t|, V_{t-1}^{\text{buy,non-hedge}})$, $K_{\mathbf{H}}(.)$ being a multivariate kernel with bandwidth matrix $\mathbf{H}$, $w_t(\mathbf{x})$ 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 (6).

We can now formally test the hypothesis, H_0, that hedging does not take place at day i. Whenever the observed V_i^{buy} is large enough, say above the 95% quantile of the predicted distribution of $V_i^{\text{buy,non-hedge}}$, it is likely that a fraction of V_i^{buy} is due to hedging purposes. Hence we reject H_0 at day i when

$$V_i^{\text{buy}} > q_{0.95}^{V_i^{\text{buy,non-hedge}}} \tag{7}$$

where $q_{\alpha}^{V_i^{\text{buy,non-hedge}}} = \tilde{F}^{-1}(\alpha|\mathbf{X}_i)$ is the α-quantile of the predicted distribution of $V_i^{\text{buy,non-hedge}}$ estimated using (6). Appendix A shows that the accuracy of the hedging detection method is satisfactory. The null hypothesis H_0 of no hedging (when informed trades occur) concerns long positions in newly issued put options. As these options are not hedged, long positions in the underlying stock are not taken. The corresponding short positions in the same put options are irrelevant for our hedging detection method and might or might not be hedged. It is so because the total volume of the underlying stock is divided into buyer- and seller-initiated and only the former matters when hedging long put options.

3.4 Detecting Option Informed Trades Combining the Three Criteria

Let k_t denote the selected informed trade at day t in put option k. The two methods to detect option informed trades can be described using the following sets of events

- *Ex-ante criteria C_1 and C_3:*

$$\Omega_1 := \{k_t \text{ such that } q_t \leq 5\%\}$$

$$\Omega_2 := \{k_t \text{ such that } H_0 : \text{non-hedging, not rejected at day } t\}$$

- *Ex-post criterion C_2:*

$$\Omega_3 := \{k_t \text{ such that } r_t^{\max} \geq q_{0.90}^{r_t^{\max}}\}$$

$$\Omega_4 := \{k_t \text{ such that } G_t \geq q_{0.98}^{G_t}\}.$$

The first method detects an informed option 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 informed when it belongs to all four sets, i.e. $k_t \in \Omega_1 \cap \Omega_2 \cap \Omega_3 \cap \Omega_4$. At day t the empirical quantiles of $r_t^{\max}$, G_t and $V_t^{\text{buy,non-hedge}}$ are computed using the last two years of data.

4 Data

We organize our dataset in two parts. The first part includes only put options, 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. Options 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 of options. Options data for DAL and KLM were available for somewhat shorter periods. We eliminated obvious data errors such as open interest reported at zero for all existing options by excluding those days from our analysis. 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 database consists of several millions of records for each stock and is necessary to classify trading volumes in buyer- and seller-initiated in order to complete the analysis related to the hedging criterion. Discrepancies among datasets have been carefully taken into account when merging databases.[7] 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. Intraday data for such European companies were not available.

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

[7] 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 BankAmerica Corporation and NationsBank Corporation, whose merger took place in 1998 under the new name of Bank of America Corporation.

Bank (DBK) whose options are traded on EUREX, and Societé Générale (GL), HSBC (HSB) and BNP Paribas (BN) with options listed on Euronext. Options 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 American style.

5 Empirical Results

The two proposed methods to detect option informed trades are applied to the companies listed in the previous section. The first method, which relies only on ex-ante information, aims at detecting informed trades as soon as they take place. On average, less than 0.1% of the total analyzed trades belongs to the set $\Omega_1 \cap \Omega_2$. As an example for AMR our first method detects 141 option informed trades, the total number of analyzed options being more than 137,000. The second method detects only 5 informed trades. For the remaining companies, comparable numbers have been found. Due to space constraints we do not report the details of transactions belonging to $\Omega_1 \cap \Omega_2$ but these are available from the authors upon request. Based on the second method, the number of detected informed trades decreases substantially.

Analyzing the first part of our dataset, 37 transactions on the CBOE have been identified as belonging to the set $\Omega_1 \cap \Omega_2 \cap \Omega_3 \cap \Omega_4$. Nearly all the detected events can be assigned to one of the following three event categories: merger and acquisition (M&A) announcements, 6 transactions; quarterly financial/earnings related statements, 14 transactions; and the terrorist attacks of September 11th, 13 transactions. 4 transactions could not be identified.

Table 1 summarizes the findings. 4 informed trades around M&A announcements are detected in the airline sector. These option trades have underlying stock American Airlines and United Airlines. 3 informed trades took place on May 10th and 11th, 2000, two weeks before UAL's acquisition of US Airways was announced (for details see Footnote 3). Another informed trade took place on January 9th, 2003 with underlying Delta Air Lines, a few weeks before a public announcement on January 21st, 2003 related to the planned alliance among Delta, Northwest and Continental. In both cases, the underlying assets crashed at the public announcements, generating large gains ($3 and $1 million, respectively) through the exercise of these put options.

In the airline sector 8 out of 15 of the selected transactions can be traced back to the terrorist attacks of 9/11. Companies like American Airlines, United Airlines, Boeing and to a lesser extent Delta Air Lines and KLM seem to have been targets for informed trading activities in the period leading up to the attacks. The number of new put options issued during that period is statistically high and the total gains G_t realized by exercising these options amount to more than $16 million. These findings support the evidence in Poteshman (2006) who also documents unusual activities in the option market before the terrorist attacks. Appendix B discusses in details our detected option informed trades before 9/11.

In the banking sector 14 informed trading activities are detected, 6 related to quarterly financial/earnings announcements, 5 to the terrorist attacks of September 11th, and 3 not identified. For example the number of put options with underlying stock Bank of America, Citigroup, J.P. Morgan and Merrill Lynch issued in the days before the terrorist attacks was also at an unusually high level. The realized gains from such trading strategies are around $11 million.

The last set of companies we analyze includes AT&T, Coca Cola, Hewlett Packard and Philip Morris. 2 informed trades occurred before the announcement of the M&A deal between Coca Cola and Procter&Gamble announced on February 21st, 2001 (leading to gains of more than $2 million), and 5 transactions preceding the publication of quarterly financial/earnings statements. News related to earnings shortfalls, unexpected drops in sales and production scale backs are the most common in this last category. For example 3 informed trades in put options with underlying Philip Morris stock are detected. These trades took place a few days before three separate legal cases against the company seeking a total amount of more than $50 million in damages for smokers' deaths and inoperable lung cancer. The realized gains amounted to more than $10 million. Perhaps as expected, no informed option trade is detected with underlying the previous companies in the days leading up to the terrorist attacks of September 11th. For further details on the detected option informed trades we refer the reader to Tables 2 and 3 for the airline sector, Tables 4 and 5 for the banking sector, and Tables 6 and 7 for the last group of companies.

The second part of our dataset focuses on the banking and insurance sectors. To save space the empirical results are collected in the separate appendix Chesney, Crameri, and Mancini (2011). Sections 5.3 and 5.4 present two cases of detected informed trading. A few general comments are in order. Although the sample period spans almost 15 years, from January 1996 to September 2009, the vast majority of detected informed trades occur during the Subprime crisis 2007–2009. Large movements in underlying stocks lead relatively quickly to net profits of more than \$1 million through option trading. Those profits are generally larger than the ones calculated in the first part of our dataset. Due to the rapid collapse of the financial system, the number of corporate and governmental decisions made has sharply increased, giving rise to numerous potential information leakages and informed trading activities.

Below we discuss four cases of detected option informed trades. For the remaining trades one can do a similar analysis. To save space tables and figures are omitted but are available from the authors upon request.

5.1 Acquisition Announcement in the U.S. Airline Sector in May 2000

Our method detects two put option informed 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 June 2000 with underlying AMR is very large: 3,374 on May 10th and 5,720 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 upper left graph in Figure 1 and Figure 2. On May 10th, the underlying stock had a value of \$35.50 and the selected put was traded at \$2.25. For UAL 2,505 put options (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 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" (for details see Footnote 3). 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 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 Figure 2, where the option return largely increased. On the day of the public announcement 4,735 put options of AMR were exercised; see Figure 2. After this large decrement in open interest, 1,494 and 1,376 additional put options were exercised in the following two days respectively (reflected in additional drops in open interests in Figure 2). The unusual increments in open interest observed on May 10th and May 11th are therefore off set 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 Figure 1, from which we can see how fast these gains were realized. In the case of UAL similar conclusions can be reached; see Tables 2 and 3. 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 naked option positions.

5.2 Delayed Delivery Announcement of EADS Superjumbo A380 in May 2006

At the time of the writing of this paper, European Aeronautic Defence and Space (EADS), a large European aerospace corporation and the parent of plane maker Airbus, is under investigation for illegal insider trading activities. On July 2nd, 2006, co-CEO Noël Forgeard and Airbus CEO Gustav Humbert resigned following the controversy caused by the June 14th, 2006 announcement that deliveries of the superjumbo jet A380 would be delayed by a further 6 months. Mr. Forgeard was one of a number of executives who sold his stake in EADS a few months before the public announcement. In June shares of EADS exhibited a 26% fall (the closing price of EADS shares on June 13th was €25.42 and on June 14th €18.73) wiping more than €5 billion from the company's market value. He and 21 other executives are currently under investigation as to whether they knew about the delays in the Airbus A380 project and sold their stock on the basis of this private information, constituting therefore illegal insider trading. In the financial press, the profits resulting from this strategy are estimated to total approximately €20 million.[8]

For the period 2003–2009 our procedure detects 4 put option contracts on EUREX related to informed trades, all of which took place between April 6th and May 22nd, 2006.[9] These options contracts had the following maturities May, June, July, and December 2006. For example, the options maturing in July 2006 exhibited large increments in open interest on May 16th (1,135 contracts), on May 19th (4,061 contracts), and on May 22nd (1,250 contracts). These increments correspond to very high quantiles of their respective two-year empirical distributions. For example, the main increase in open interest (May 19th) corresponds to 99.8% quantile. The 4 options contracts had strikes of €31, €31, €26 and €30 and the underlying traded at €32.4, €27.5, €27.5 and €32.1 respectively on the transaction days. The average returns generated from these trades are large. For example, the selected option contract with maturity June was bought mainly three times April 5h, April 6h, and May 18th at the following prices €0.96, €1.17 and €3.46 when the stock price was respectively at €32.77, €32.37 and €27.50. These contracts were mainly exercised on June 16th at option prices €11.10 and stock price of €19.80. The total gain corresponds to €2.2 million and the average return is 370% within two months. Similar patterns are observed for the other 3 options contracts. Based on all 4 detected options, a total gain of €8.7 million had

[8]The New York Times edition of June 18th, 2008: "Executive Questioned in EADS Insider Trading Case".

[9]On May 12th, 2006, a meeting of the company board took place in Amsterdam in order to discuss possible solutions to the management crisis triggered by the future announcement which was planned for the following month. According to the New York Times edition of June 29th, 2006, 13 people were present, including Noël Forgeard and Gustav Humbert. The delay in A380 deliveries was likely to cost EADS €2 billion over the following four years.

been realized within 60 trading days after the announcement.

Options contracts with underlying EADS are traded at the EURONEXT in Paris as well. Using a database provided by EURONEXT NYSE, our second method detects 3 options contracts related to informed trades which took place between April and May 2006. The total gains of these transactions amount to approximately €18.7 million. Details are available upon request.

5.3 Quarterly Loss of UBS in October 2007

Our detection procedure identified 3 trades in put options which took place in October 2007, maturing in October, December and June 2008. 2 of the 3 acquired options were out-of-the money. These trades preceded the October 30th announcement that UBS, Europe's largest bank by assets, reported its first quarterly loss in almost five years. Declines in the U.S. Subprime mortgage market led to $4.4 billion in losses and writedowns on fixed-income securities. Third quarter net loss was CHF 830 million ($712 million). In the following weeks, UBS stock started an impressive decline, and through the exercise of these puts options net gains of more than CHF 24 million were collected. On February 14th, 2008 UBS saw its shares fall to a four-year low after it produced the worst quarterly loss in the bank's history and revealed new details of its full exposure to the Subprime crisis. Its stock fell more than 8% in Zurich and New York as executives failed to rule out further writedowns—which already totaled $18.1 billion—or give a date for a return to profitability. The fall accelerated after U.S. Federal Reserve Chairman, Ben Bernanke, said investment banks would have further writedowns. UBS confirmed that it lost CHF 12.5 billion in the final quarter of 2007, with full-year losses of CHF 4.4 billion—the first in the decade since it merged with the Swiss Bank Corporation—and had written off $13.7 billion in the final quarter of the preceding year. Our method detected 3 transactions in put options on January 30th, and February 11th and 12th, 2008. All options had short-term maturities and generated high returns after the stock crash on February 14. Estimated gains amounted to nearly CHF 7 million. With respect to call options, we identified 3 trades falling into the period 2007–2009, whose gains amounted to more than CHF 10 million.

5.4 J.P. Morgan's Takeover of Bear Stearns Corporation in March 2008

The financial crisis began spreading more widely in August 2007 with the collapse of two Bear Stearns hedge funds which had heavily invested in Subprime-related securities. On December 20th, 2007 Bear Stearns posted fourth quarter losses of $854 million after mortgage related writedowns of $1.9 billion. It was the first quarterly loss in its 85-year history. In Spring 2008, Bear Stearns was the subject of a multitude of market rumors regarding its liquidity. Early in the week of March 10th, 2008 rumors swirled around Wall Street that European firms had suspended fixed income trading with Bear Stearns. U.S. traders began to stop trading with Bear, hedge funds pulled money from prime brokerage accounts, money market funds reduced their investment in short-term Bear issued debt. The company then suffered a cash crunch. On Thursday, March 13th, Bear shares fell more than 7% to $57. Bear called J.P. Morgan, its clearing bank, to warn that it might not have enough cash to meet its obligations on Friday and needed emergency help. It also called the Securities and Exchange Commission and the Federal Reserve Bank of New York. In an evening conference call among the New York Fed, the Securities and Exchange Commission, the Fed Board of Governors and the U.S. Treasury, the SEC said Bear Stearns might file for bankruptcy the next morning. On Friday, March 14th, the New York Fed, the Fed Board of Governors and the Treasury held a conference call to discuss the options. They decided to issue an overnight non-recourse loan to J.P. Morgan so that the bank could then loan money to Bear Stearns. The loan was intended to get Bear Stearns through to the weekend while the companies and government officials explored Bear Stearns' options and ways to contain potential damage. Bear shares fell 46% to $30.85. Credit rating agencies downgraded Bear Stearns debt and customers continued to pull funds to the point where Bear Stearns officials feared the bank would be insolvent by the time Asian markets opened on Sunday evening. On Sunday evening, March 16, J.P. Morgan announced that it would acquire Bear for about $2 a share and that the Fed would provide J.P. Morgan with a $30 billion loan backed by Bear assets. J.P. Morgan guaranteed billions of dollars in Bear trading obligations. The deal was announced just before Asian markets opened. On Monday, March 17 Bear shares started the day with a drop of nearly 90% to $2.86.

For the period 1999–2009, our procedure detected 16 transactions in put options and 11 in calls. 9 trades in puts and 2 in calls fall into the time period 2007–2009. We now focus on a series of trades in put options which took place in the days leading up to the collapse of Bear Stearns. We detected 6 large trades in put options from March 4th till March 14th, most of them involving deep out-of-the money options. Since the dynamics of such trades are similar, we do not report all details for every detected transaction, but concentrate on a few examples.

On March 10th, Bear Stearns stock traded at $62.30. On that day, 11,757 contracts of put options with strike $30 and maturity end of March were created at CBOE. Due to the deep out-the-money moneyness, these options were traded at the cheap price of $0.625. Such an increment of open interest corresponds to the 99.70% quantile of its historical distribution. The same options exhibited another unusually high increment the following day when its open interest increased by an additional 22,809 contracts. The price of the option even decreased to $0.25 as the stock price increased slightly. On March 17th, when the market reopened after the intense negotiations marathon between Bear Stearns, J.P. Morgan and the Fed, the stock dropped nearly 85% to $2.86, increasing the value of these put option to $27.14. The day of the announcement corresponds to the exercise of 8,150 option contracts. On March 18th, an additional 9,310 put options were exercised, leading to net gains of more than $50 million. On March 12th, the put option with strike $40 and maturity April, exhibited a large increment in open interest: on that day, the stock traded at $61.58, making the option deep out-of-the money and tradable at $1.86. On the day of the announcement, its value increased to $37.14, resulting in a net profit of more than 1,700% in three trading days. The sequential exercise of these options over the following weeks generated net gains of more than $6 million. Another informed trade in put options was detected on March 13th. The put option with strike $25 and maturity March exhibited a large increment in open interest of 26,219 option contracts. Its price was fairly cheap ($0.275) due to its deep out-of-the moneyness. On March 17th, its price jumped to $22.14, and the exercise of almost 5,000 option contracts on that day generated gains of several millions. Five days later, when the option matured, total realized gains amounted to approximately \$50 million. Finally, another informed trade in put options was detected on March 14th. As in the other cases, the involved put option (with short maturity March 2008) was bought for a cheap price when it was deep out-of-the money and exhibited an impressive net return right after the March 17th announcement. After exercise on March 18th and 19th, related gains totaled \$28 million. Additional details can be found in Chesney, Crameri, and Mancini (2011).

6 Controlling False Discoveries in Option Informed Trades

Any statistical method can generate false discoveries in informed trades. Indeed 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 to separate truly informed traders with high gains from uninformed traders which luckily achieved also high gains. Conceptually the task is the same as discriminating between skilled and lucky mutual fund managers based on fund performance. Recently, Barras, Scaillet, and Wermers (2010) use multiple hypothesis testing techniques to achieve that goal. We adopt a similar framework to discriminate between informed and lucky traders in the option market.

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 traders and $\delta_m, m = 1, \ldots, M$, 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. 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, denote $E[S_\gamma^+]$ 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 $E[T_\gamma^+] = E[S_\gamma^+] - \pi_0 \cdot \gamma/2$. Note that under the null hypothesis all traders are uninformed, i.e. $\pi_0 = 1$, and half the size of the test $\gamma/2 = E[S_\gamma^+]$, hence $E[T_\gamma^+] = 0$. 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). We choose λ using the data-driven approach in Barras, Scaillet, and Wermers (2010). The observed fraction of positive and significant t-statistics provides an unbiased estimate of $E[S_\gamma^+]$.

Obviously, we do not observe directly option returns achieved by traders with various degrees of private information. Consistently with our detection method, we use the ex-ante historical probability q_t of observing unusual increments in open interest and volume as a proxy for private information. The working assumption is that the smaller such probability, the higher the degree of private information of the option trader. Indeed, as shown below, q_t turns out to be an accurate proxy for private information as reflected in option returns. For every underlying asset and for every option trade $k = 1, \ldots, K$ in our sample, we compute the corresponding ex-ante historical probability q_t^k as in (2) of observing the 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. The future return r_t^k of option's trade k is computed by considering gains through subsequent exercise, after day t, according to (4). By definition, the probability q_t^k lies on the interval $[0, 1]$. We sort in ascending order all q_t^k and divide such unit interval into $M = 1{,}000$ 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 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.[10] As an example Figure 4 shows estimated δ_m for American Airlines. Estimates for the remaining companies are similar. A striking pattern emerges. The smaller the m, the higher the estimated δ_m. 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. This finding suggests that q_t^k is indeed an accurate proxy for private information as reflected in option returns.

We briefly discuss now the estimates of false discovery rates for American Airlines and Citigroup. For the remaining companies, similar results have been found. Because of space constraints, figures and tables are not reported but available upon request from the authors. For AMR, the total number of analyzed option trades amounts at K = 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 informed traders 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 traders. Our detection procedure found 5 informed trades for AMR, suggesting that our method is more conservative. For the case of Citigroup, option trades K = 246,000 and the estimated fraction of truly informed traders $E[T^+] = 10.6\%$ (with standard error 1.09%, optimal $\lambda = 0.612$, and $\gamma = 0.07$), corresponding to 106 traders. As we have detected only 2 informed option trades, even in this case our detection procedure is conservative.

The probability q_t^k can be used to implement trading strategy as depends only on information available on day t. Low values of q_t tend to predict future drops of the underlying stock providing a signal when to enter long positions in put options and generating the return r_t^k. As can be seen from Figure 4, entering long put positions when $q_t^k < 0.2\%$ easily generates annual returns above 5% on average, reaching 45% for the lowest values of q_t^k. This interpretation of q_t^k as a trading

[10] 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 square estimation somehow more robust we winsorize negative returns at 5%. The impact of winsorizing on the false discovery rate is virtually negligible.

signal further highlights its information content.

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 $V_t^{\text{buy,non-hedge}}$, 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 $\alpha' = 98\%$; 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 but the remaining ones are available from the authors upon request.

When varying the length of the estimation window N between 200 and 1,000, (all other parameters being unchanged) the number of selected transactions does not change significantly. For example in the case of AMR, we selected 5 informed trades when considering the last two trading years ($N = 500$ days); for $N \in [200, 1000]$ the number of detected informed trades ranges between 4 and 6; for UAL, we detected 2 informed 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, 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 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 Conclusions

We develop statistical methods to detect informed trading activities in the options markets. We apply these methods to a large database uncovering various features of option informed trading. We find that option informed trading tends to cluster prior to certain events (such as acquisition or financial disruption announcements), involves often liquid options (which is consistent with an informed trader attempting not to immediately reveal her private signal), takes place more in put than call options (which is consistent with the asymmetric reaction of stock prices to negative and positive news), generates easily large gains exceeding millions (which is likely a conservative estimate), and is not contemporaneously reflected in the underlying stock price (which has obvious implications for trading strategies). These findings are not driven by false discoveries in informed trades which are controlled using multiple hypothesis testing techniques.

Our results have also policy, pricing, and market efficiency implications. If some of the detected informed trades are indeed illegal, for example originated by insiders, it might be optimal for regulators to expend relatively more monitoring efforts on the options markets. Pricing models should account for all relevant information available at time t. However nearly all option prices (and underlying assets) involved in informed 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, our findings suggest that certain increments in open interest and volume might predict large price movements and simple option trading strategies can generate large returns. We left to future research to investigate whether those returns are truly abnormal, questioning market efficiency, or rather reflect compensation for hidden factors.

A Accuracy of the Hedging Detection Method

In this appendix we provide an assessment of the accuracy of our hedging detection method introduced in Section 3.3. Recall that the hypothesis H_0 of no hedging when informed trades occur at day i is rejected whenever $V_i^{\text{buy}} > q_\alpha^{V_i^{\text{buy,non-hedge}}}$, implying that a sizable component of buyer-initiated trades in the stock is due to hedging. We measure the accuracy of the method by computing the probability of rejecting H_0 when the latter does not hold, namely the power of the test. Let $V_i^{\text{buy}} = (1 + h_i)\ V_i^{\text{buy,non-hedge}}$, where $h_i \geq 0$. The h_i represents the ratio between buyer-initiated volume due to hedging and buyer-initiated volume due to non-hedging. By construction H_0 is equivalent to $h_i = 0$ meaning that volume trades due to hedging is zero. The hypothesis H_0 should be rejected when $h_i > 0$, and the higher the rejection rate the more accurate the hedging detection method. Let $q_\alpha := q_\alpha^{V_i^{\text{buy,non-hedge}}}$, the measure of accuracy $\mathbb{A}(h_i)$ reads

$$\mathbb{A}(h_i) := \mathbb{P}\Big[V_i^{\text{buy}} > q_\alpha | h_i\Big] = \mathbb{P}\Big[V_i^{\text{buy,non-hedge}} > q_\alpha/(1 + h_i)|h_i\Big]. \tag{8}$$

The hedging detection method is accurate whenever $\mathbb{A}(h_i)$ increases fast enough in h_i. The probability in (8) can be calculated as $(1 - \tilde{F}(q_\alpha/(1+h_i)|\mathbf{X}_i))$, where $\tilde{F}$ is estimated using (6) and $\alpha = 0.95$ as in our empirical analysis. We computed $\mathbb{A}(h_i)$ for several stocks, sample periods, estimation windows, and different values of h_i and of the conditioning variables $\mathbf{X}_i = (|r_i|, V_{i-1}^{\text{buy,non-hedge}})$. Table 8 gives numerical values of $\mathbb{A}(h_i)$ for Citigroup on the randomly chosen day December 17th, 2001. Corresponding results for other stocks and days are fairly similar and available upon request from the authors. When $h_i = 0$, $\mathbb{A}(h_i)$ is very close to $0.05 = (1 - \alpha)$, which is the non-eliminable size of the test. When h_i increases, $\mathbb{A}(h_i)$ increases as well although certain combinations of the conditioning variables are more favorable than others to reject the hypothesis of no hedging. Overall the power of the test is fairly satisfactory. For example when $h_i = 0.20$, $\mathbb{A}(h_i)$ can be as high as 20%.

B Terrorist Attacks of September 11th

The terrorist attacks have generated many articles, in which political, strategic and economic aspects have been considered. The financial dimension has also been discussed by the press. In particular, the question of whether the terrorist attacks of September 11th had been preceded by abnormal trading volumes, generated widespread news reports just after 9/11. As far as official regulators and control committees have been concerned, they dismiss charges against possible informed traders. The American 9/11 Commission has stated that "exhaustive investigations by the Security and Exchange Commission, FBI and other agencies have uncovered no evidence that anyone with advance knowledge of the attacks profited through securities transactions".[11]

From an academic point of view, this topic did not generate much research interest. The article of Poteshman (2006) is a notable exception. Focused mainly on the airline sector, Poteshman computes the distributions of option market volume statistics both unconditionally and when conditioning on the overall level of option activity, the return and trading volume on the underlying stocks and the return on the overall market. He finds that "when the options market activity in the days leading up to the terrorist attacks is compared to the benchmark distributions, volume ratio statistics are seen to be at typical levels. As an indicator of long put volume, however, the volume ratio statistics appear to be unusually high which is consistent with informed investors having traded in the options market in advance of the attack". In the following the informed option trades detected by our method are discussed in detail.

B.1 Analysis of Options Traded in CBOE

In total 13 transactions satisfy our criteria of informed trade and involve five airlines companies (AMR, UAL, BA and to a lesser extent DAL and KLM) and four banks (BAC, C, JPM and MER). Concerning the airline sector, AMR and UAL are the two companies whose planes were hijacked and crashed by the terrorists. Informed option trade for KLM might be surprising, but supports

[11] The 9/11 Commission Report, Page 172, available on *http://www.9-11commission.gov/report/911Report.pdf.*

the suspicion of "insider trading in KLM shares before September 11th attacks", as reported in a Dutch government investigation (Associated Press Worldstream). The terrorist attacks had indirect implications for BA and DAL, like a potential decrease in the number of passengers. Based on our methodology, AMR, UAL, and BA were more likely object of informed trade than DAL and KLM. With respect to the banking sector, Merrill Lynch, Bank of America, and J.P. Morgan were located in World Trade Center or nearby, and the Travelers Insurance Unit of Citigroup was expected to pay \$500 million in claims.

In the case of American Airlines we will now report the details of the transaction which took place on September 10th. Additional tables are available from the authors upon request. The upper graphs in Figure 1 show the plot of option volume, V_t, versus its increment in open interest, X_t. The informed trades are highlighted with the circles. The left graph covers the period from January 1997 to December 2001, to better visualize the option market condition up to December 2001. The right graph covers the period January 1997–January 2006. The selected transactions are isolated from the bulk of the data, suggesting that they are statistically unusual. For September 2001 Figures 3 and 2 show the dynamic of three variables: open interest, volume and the option return. As claimed in several newspaper articles, the volume and open interest of puts had been unusually high in the days leading up to September 11th. On September 10th 1,535 put contracts were traded and from September 7th to September 10th the open interest increased of 1,312 contracts (at 99.5% quantile of its two-year empirical distribution). The trading volume was more than 60 times the average of the total daily traded volume during the three weeks before September 10th. These puts had a strike price of \$30 and a maturity in October. On September 10th, the stock price was \$29.7 and the put price was \$2.15. On September 17th, when markets reopened after the attacks, the stock price was \$18 and the put price was \$12. Such an investment in put options generated an unusually high return (458% in one week). Put options were obviously exercised on September 17th, the open interest decreased of 597 contracts, generating a gain of almost \$600,000. A few days later, another considerable number of put options (475 contracts) were exercised; see Figure 3. Table 2 reports the gains (G_t) of such a trade. Twenty-six days later the sum of exercised options corresponded to the increment observed on September 10th and lead to a cumulative gain of more than one million (G_t = \$1,179,171). The lower graph in Figure 1 shows the cumulative gain for all transactions selected using our three criteria. The trade in put options of AMR corresponds to the transaction that leads to the highest gains in the shortest time interval in the period we are considering. Figure 3 shows that the trading volume after September 17th was negligible meaning that the main gain was realized through exercise and not selling the options. Similar conclusions can be reached for the other trades selected using our procedure. For example two trading days before the terrorist attacks 4,179 put options (at 98.5% quantile of its two-year empirical distribution) on Boeing were issued. The underlying stock was traded at \$45.18 and the option had a strike of \$50. On September 17th, the stock was traded at \$35.8. Six days afterwards these options were exercised leading to gains of more than \$5 million. Concerning Bank of America, a large increment of 3,380 in open interest (at 96.3% quantile of its two-year empirical distribution) took place on September 7th for an option with a strike of \$60 when the underlying asset had a value of \$58.59 (on September 17th, the underlying stock had a value of \$54.35). The exercise of those options in the following seven days resulted in net gains of almost \$2 million; for Merrill Lynch, on September 10th, 5,615 put options (at 99.1% quantile of its two-year empirical distribution) with strike \$50 were issued, the underlying stock had a value of \$46.85. On September 17th the underlying stock was traded at \$41.48. Less than six days later these options had been exercised leading to gains of around \$4.5 million. For the remaining companies similar results can be reached from the reported tables. Based on Tables 2 and 4, the total gains in the airline sector amount to more than \$16 million, whereas in the banking sector \$11 million in gains have been computed. Interestingly, in nearly all cases the hypothesis of non-hedging cannot be rejected.[12]

[12] In the article "Not much stock in put conspiracy: the attacks on New York City and Washington have led to a new urban legend, namely that inside traders used put options on airline stocks to line terrorist pockets" published on June 3th, 2002 by Kelly Patricia O'Meara in *Insight on the News*, other repeated spikes of volumes of put options on American Airlines and United Airlines during the year before 9/11 are highlighted and used as argument that what occurred in the days leading up to 9/11 was not as unusual as other theories claim. Both our methods do not select those option trades mainly because those spikes in volume do not correspond to large increments in open interest.

B.2 Analysis of Options Traded in EUREX

Several reinsurance companies suffered severe losses from the terrorist attacks of September 11th. Liabilities for Munich Re and Swiss Re—the world's two largest reinsurers—were estimated to be in the amount of billions of dollars a few days after the attacks. At the same time, several newspapers reported that trading in shares of these two companies were at unusual levels in the days leading up to September 11th, divulging some rumors of informed trading activities. A detailed analysis of transactions on the options market has however thus far been ignored. Options with underlying Swiss Re and Munich Re are mainly traded on the EUREX, one of the world's largest derivatives exchanges and the leading clearing house in Europe established in 1998 after the merger of Deutsche Terminbörse (DTB, the German derivatives exchange) and SOFFEX (Swiss Options and Financial Futures). In this section we use the EUREX database provided by Deutsche Bank to analyze transactions in put options with underlying Swiss Re and Munich Re. The database does not contain intraday data and hence the hedging dimension cannot be investigated.

In the case of Munich Re, 4 informed trades are detected between 1999 and 2008 which belong to the set $\Omega_1 \cap \Omega_3 \cap \Omega_4$, one of which took place on August 30th, 2001. As we are mainly interested in informed trades surrounding the terrorist attacks in this subsection, we only discuss the details of this transaction (the others took place on August 29th, 2002; September 2nd, 2002; and October 19th, 2007). The detected put option with underlying Munich Re matured at the end of September, 2001 and had a strike of €320 (the underlying asset was traded at €300.86 on August 30th). That option shows a large increment in open interest of 996 contracts (at 92.2% quantile of its two-year empirical distribution) on August 30th. Its price on that day was €10.22 and the ex-ante probability q_t is slightly lower than 5%. On the day of the terrorist attacks, the underlying stock lost more than 15% (the closing price on September 10th was €261.88 and on September 11th €220.53) and the option price jumped to €89.56, corresponding to a return of 776% in 8 trading days. On September 12th, 1,350 put options with those characteristics were exercised. The gains G_t related to the exercise of the 996 put options issued on August 30th correspond to more than

€3.4 million.

In the case of Swiss Re, 6 informed trades are detected between 1999 and 2008 which belong to the set $\Omega_1 \cap \Omega_3 \cap \Omega_4$, one of which took place a few weeks before the terrorist attacks, on August 20th. This option expired at the end of September, 2001, had a strike of €159.70 and had a large increment in open interest of 3,302 contracts (at 99.8% quantile of its two-year empirical distribution) on August 20th. That option was traded at €0.8 and exhibits an ex-ante probability q_t of 0.4%, meaning that such an event happens on average once a year. The Swiss Re closing share price was €177.56 on August 20th. On September 11th, when the stock price fell from €152.62 to €126.18, the option generated a return of 4,050% in three trading weeks, when its price jumped to €33.2. Through the exercise of these put options in the 9 days following the attacks, the total gains were more than €8 million. Together with Munich Re, a total gain of €11.4 million had been realized in less than two trading weeks by using two options with underlying Munich Re and Swiss Re. To save space the corresponding tables and figures are omitted but are available from the authors upon request.

Option Informed Trades in Airline, Banking and Various sectors Jan 1996 - Apr 2006								
	Airline		**Banking**		**Various**		**Total**	
merger and acquisition announcement	4	(4)	0	(0)	2	(2)	**6**	**(6)**
quarterly financial/earning related announc.	3	(3)	15	(6)	18	(5)	**36**	**(14)**
terrorist attacks of September 11	10	(8)	5	(5)	0	(0)	**15**	**(13)**
not identified	1	(0)	7	(3)	5	(1)	**13**	**(4)**
Total	**18**	**(15)**	**27**	**(14)**	**25**	**(8)**	**70**	**(37)**

Table 1: Number of put option trades identified as informed across sectors and events. An informed option trade is characterized by an unusual high increment in open interest and volume, generates an abnormal return, and is not delta hedged. Entries refer to number of informed trades when not considering the hedging test in Section 3.3, and in parenthesis when considering such a test.

Content of Tables 2, 4 and 6: day on which the transaction took place, Day; 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 informed 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 (2), q_t; p-value of the hypothesis that delta hedging does not take place at time t, p-value; proxy for the probability of informed trading in (5), $1-p_t$.

Content of Tables 3, 5 and 7: day on which the transaction took place, Day of transaction; market condition at day t measured by the average return of the underlying stock during the last two trading weeks, Market condition; minimum return of the underlying stock during the two-week period following the transaction day, Return (comparable with $r_t^{\max}$); day when the underlying stock drops, Crash in stock; short description of the event 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

Day	*Id*	S/K	τ	OI_{t-1}	ΔOI_t	$q_t^{\Delta OI}$	$\Delta OI_t^{\mathrm{tot}}$	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	53976	9	100%	0.006	0.368	0.998

Table 2: Detected option informed trades for the airline sector. For definition of entries see Page 39.

Summary of Airline Sector Jan 1996 - Apr 2006

Day of transaction	Market condition	Return	Crash in stock	Event's description
				American Airlines (AMR) Jan 1996 - Apr 2006
10 May 00	0.4%	−17.6%	24/25 May 00	Announcement 24 May 00: Airline Deal UAL's acquisition of US Airways
11 May 00	0.0%	−17.6%	24/25 May 00	Announcement 24 May 00: Airline Deal UAL's acquisition of US Airways
31 Aug 01	−0.4%	−39.4%	17 Sep 01	9/11 Terrorist attacks in New York
10 Sep 01	−1.4%	−39.4%	17 Sep 01	9/11 Terrorist attacks in New York
24 Aug 05	0.4%	−5.3%	30 Aug 05	August 05: Hurricane Katrina, interrupted production on the gulf coast, jet fuel prices ↑
				United Airlines (UAL) Jan 1996 - Jan 2003
11 May 00	0.3%	−12%	24 May 00	Announcement 24 May 00: Airline Deal UAL's acquisition of US Airways
6 Sep 01	−1.0%	−43.2%	17 Sep 01	9/11 Terrorist attacks in New York
				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 in New York
19 Sep 02	−5.2%	−24.4%	27 Sep 02	Announcement 27 Sep 02: Expected loss for 3rd quarter
9 Jan 03	2.1%	−15.7%	21/22 Jan 03	Announcement 21 Jan 03: Restrictions on planned alliance of Delta, Northwest and Continental
				Boeing (BA) Jan 1996 - Apr 2006
24 Nov 98	−0.2%	−22.0%	02/03 Dec 98	Announcement 02. Dec 98: production scale back and cut in work forces
29 Aug 01	−0.4%	−25.0%	17/18 Sep 01	9/11 Terrorist attacks in New York
5 Sep 01	−0.8%	−25.0%	17/18 Sep 01	9/11 Terrorist attacks in New York
6 Sep 01	−0.9%	−25.0%	17/18 Sep 01	9/11 Terrorist attacks in New York
*7 Sep 01	−1.9%	−25.0%	17/18 Sep 01	9/11 Terrorist attacks in New York
*17 Sep 01	−5.6%	−25.0%	17/18 Sep 01	9/11 Terrorist attacks in New York
				KLM Jan 1996 - Nov 2001
5 Sep 01	−1.9%	−31.6%	17/18 Sep 01	9/11 Terrorist attacks in New York

Table 3: Description of detected option informed trades for the airline sector. For definition of entries see Page 39.

Summary of Banking Sector Jan 1996 - Apr 2006

Day	*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	$1-p_t$
Bank of America (BAC) Jan 1996 - Apr 2006																
13 Jun 00	10196393	0.93	39	272	1996	94.10%	1883	2124	154%	7	1,505,256	28	100%	0.026	0.170	0.998
*13 Nov 00	11596097	1.00	5	1747	6273	99.10%	6240	7270	522%	5	3,081,216	5	100%	0.006	0.047	0.998
7 Sep 01	20400334	0.98	15	8720	3380	96.30%	3607	4303	241%	7	1,774,525	7	100%	0.026	0.091	0.994
Citigroup (C) Jan 1996 - Apr 2006																
30 Aug 01	20201221	1.07	23	9394	4373	94.50%	8880	5427	622%	10	2,045,940	12	100%	0.044	0.096	0.998
*18 Jun 02	20576902	0.96	95	3552	9984	97.90%	−8249	10090	114%	7	7,661,724	30	65%	0.002	0.000	0.998
*17 Jul 02	20732009	0.92	31	4467	4923	91.30%	9420	5148	227%	5	3,579,435	5	100%	0.028	0.000	0.996
28 Apr 04	21436285	0.97	24	38184	17803	99.90%	24618	21429	102%	9	3,172,024	18	100%	0.002	0.197	0.998
J.P. Morgan (JPM) Jan 1996 - Apr 2006																
*5 Oct 00	11674068	0.99	16	4632	2957	94.70%	3587	2843	391%	10	1,411,934	12	100%	0.030	0.004	0.998
*9 Nov 00	11848514	0.98	37	9303	9564	99.30%	10949	10681	164%	10	1,937,044	12	100%	0.004	0.000	0.998
29 May 01	11848586	0.99	18	22044	4290	95.70%	6603	5569	204%	9	1,508,490	10	100%	0.026	0.060	0.996
30 Aug 01	20435891	0.98	51	1370	3145	90.90%	2854	3407	153%	10	1,318,638	30	99%	0.026	0.058	0.998
6 Sep 01	20207536	0.92	16	22459	4778	96.30%	−9130	5359	178%	8	1,415,825	8	100%	0.014	0.075	0.998
18 Jan 02	20556357	1.03	29	6543	6168	97.10%	−85172	8421	225%	7	2,007,110	20	100%	0.024	0.145	0.996
17 Jan 03	21343021	0.95	36	5159	9597	99.10%	−133082	10527	117%	9	2,414,176	24	100%	0.006	0.061	0.998
Merrill Lynch (MER) Jan 1996 - Apr 2006																
*21 Aug 98	10840556	1.05	29	211	3679	99.50%	−6048	4165	428%	10	5,318,200	20	100%	0.002	0.000	0.998
*25 Aug 98	10963647	1.02	25	1410	1962	95.90%	2486	2207	629%	9	2,378,481	14	100%	0.020	0.000	0.998
*28 Aug 98	10840556	0.92	22	5138	2951	98.70%	2735	4703	186%	9	2,143,600	15	100%	0.012	0.000	0.996
*1 Sep 98	11499596	0.96	18	349	2224	96.70%	−1534	2548	136%	7	1,567,550	8	100%	0.014	0.000	0.998
10 Sep 01	20408663	0.94	12	6210	5615	99.10%	9898	7232	243%	5	4,407,171	6	100%	0.008	0.080	0.998
9 Apr 02	20642300	1.04	39	2549	3118	94.50%	5545	3513	129%	3	1,591,786	20	100%	0.010	0.135	0.998
Morgan Stanley (MWD) Jan 1996 - Apr 2006																
17 Aug 98	10174742	1.02	33	1003	1650	99.50%	1779	1660	341%	10	2,050,938	15	100%	0.004	0.197	0.998
*21 Aug 98	10148491	1.03	29	293	2064	99.70%	−3616	2362	554%	10	1,906,663	20	100%	0.004	0.005	0.998
25 Aug 98	10174742	0.98	25	2586	1291	98.70%	1638	2170	674%	9	1,467,850	6	100%	0.014	0.173	0.998
*28 Aug 98	11599638	0.93	22	2010	2010	99.50%	862	2010	265%	9	1,580,556	15	100%	0.002	0.000	0.998
3 Nov 00	10297869	1.04	15	4154	2297	97.90%	3285	3518	437%	8	1,947,447	11	100%	0.020	0.161	0.998
*22 May 01	20310213	1.06	25	1098	1816	90.30%	2284	1929	472%	6	1,871,086	18	100%	0.024	0.041	0.998
*6 Apr 05	31518375	1.03	10	14497	13807	99.90%	18342	18163	576%	8	2,780,148	8	100%	0.002	0.026	0.998

Table 4: Detected option informed trades for the banking sector. For definition of entries see Page 39.

Summary of Banking Sector Jan 1996 - Apr 2006				
Day of transaction	**Market condition**	**Return**	**Crash in stock**	**Event's Description**
Bank of America (BAC) Jan 1996 - Apr 2006				
13 Jun 00	−1.0%	−14.8%	15/16 Jun 00	Announcement 15 Jun 00: Wachovia Corp. Correction of expected earnings for 2nd quarter
*13 Nov 00	−0.4%	−11.7%	14/15 Nov 00	Announcement 14 Nov 00: 3rd quarterly financial statements, potential write-offs for 4th quarter
7 Sep 01	−0.4%	−5.7%	17 Sep 01	9/11 Terrorist attacks in New York
Citigroup (C) Jan 1996 - Apr 2006				
30 Aug 01	−0.5%	−6.7%	17 Sep 01	9/11 Terrorist attacks in New York
*18 Jun 02	0.6%	−5.4%	26 Jun 02	Not identified
*17 Jul 02	−0.3%	−26.7%	22/23 Jul 02	Announcement 22 Jul 02: Senate's investigations into Citigroup (Enron case)
28 Apr 04	−0.3%	−2.8%	10 May 04	Not identified
J.P. Morgan (JPM) Jan 1996 - Apr 2006				
*5 Oct 00	−0.3%	−7.0%	12 Oct 00	Not identified
*9 Nov 00	−0.6%	−4.2%	15 Nov 00	Not identified
29 May 01	0.4%	−3.4%	6 Jun 01	Not identified
30 Aug 01	−0.8%	−7.5%	20 Sep 01	9/11 Terrorist attacks in New York
6 Sep 01	−1.5%	−7.5%	20 Sep 01	9/11 Terrorist attacks in New York
18 Jan 02	−1.4%	−6.6%	29 Jan 02	Announcement 16/22 Jan 02: financial statements for 4th quarter/losses on Enron's loans
17 Jan 03	−0.7%	−5.3%	24 Jan 03	Announcement 22 Jan 03: bigger 4th quarter loss than forecasted
Merrill Lynch (MER) Jan 1996 - Apr 2006				
*21 Aug 98	0.0%	−16.3%	28/30/31 Aug 98	Announcement 17 August 98: Ruble crisis, Russian crisis, Asian crisis
*25 Aug 98	−0.4%	−16.6%	09/10 Sep 98	Announcement 17 August 98: Ruble crisis, Russian crisis, Asian crisis
*28 Aug 98	−2.6%	−16.6%	09/10 Sep 98	Announcement 17 August 98: Ruble crisis, Russian crisis, Asian crisis
*1 Sep 98	−3.7%	−16.6%	09/10 Sep 98	Announcement 17 August 98: Ruble crisis, Russian crisis, Asian crisis
10 Sep 01	−1.2%	−15.5%	17/18 Sep 01	9/11 Terrorist attacks in New York
9 Apr 02	−0.9%	−7.9%	11 Apr 02	Announcement 09 Apr 02: accusations of conflicts of interest, potential fine of > $100mio
Morgan Stanley (MWD) Jan 1996 - Apr 2006				
17 Aug 98	0.7%	−17.2%	28/31 Aug 98	Announcement 17 August 98: Ruble crisis, Russian crisis, Asian crisis
*21 Aug 98	−0.3%	−17.2%	28/31 Aug 98	Announcement 17 August 98: Ruble crisis, Russian crisis, Asian crisis
25 Aug 98	−0.5%	−17.2%	28/31 Aug 98	Announcement 17 August 98: Ruble crisis, Russian crisis, Asian crisis
*28 Aug 98	−3.3%	−17.2%	28/31 Aug 98	Announcement 17 August 98: Ruble crisis, Russian crisis, Asian crisis
3 Nov 00	1.3%	−12.2%	07/08/09 Nov 00	Not identified
*22 May 01	2.3%	−5.7%	30 May 01	Not identified
*6 Apr 05	1.0%	−3.0%	20 Apr 05	Announcement 05 Apr 05: proposal of new CEO, discover credit card unit spin off

Table 5: Description of detected option informed trades for the banking sector. For definition of entries see Page 39.

Summary of various sectors Jan 1996 - Apr 2006

Day	*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	$1-p_t$
AT&T (ATT) Jan 1996 - Apr 2006																
*17 Apr 98	10307639	1.03	29	2178	2442	97.70%	−20484	2963	441%	9	1,605,881	21	100%	0.014	0.022	0.998
*25 Apr 00	10667683	1.04	25	14673	8512	99.50%	9847	12786	593%	10	9,407,938	19	100%	0.002	0.021	0.998
*26 Apr 00	10667683	1.02	24	23185	2637	93.90%	3422	1853	447%	9	2,348,288	15	100%	0.038	0.002	0.998
Coca Cola (KO) Jan 1996 - Apr 2006																
*24 Aug 98	10423228	1.00	26	4338	2134	94.50%	5285	3007	577%	9	2,246,363	6	100%	0.034	0.000	0.998
*26 Aug 98	10423228	0.99	24	7033	1439	88.90%	2910	1792	547%	7	1,381,344	4	100%	0.048	0.015	0.998
*18 Mar 99	11199798	0.98	30	1320	1902	93.10%	993	2082	175%	10	616,950	21	100%	0.006	0.000	0.998
*23 Aug 00	10973464	1.07	59	48	2257	96.10%	4890	2258	208%	7	698,259	17	100%	0.002	0.004	0.998
12 Feb 01	11851575	1.01	96	8130	756	72.80%	1060	759	166%	9	665,280	26	100%	0.012	0.117	0.996
20 Feb 01	20207914	0.97	25	945	1796	93.10%	3153	2349	254%	10	1,340,364	19	100%	0.042	0.248	0.998
28 Jun 02	20556780	1.12	50	12516	4664	98.70%	6891	5130	312%	10	1,935,470	17	100%	0.010	0.100	0.998
*9 Jul 02	20556781	1.03	39	4755	2659	97.30%	8167	3243	669%	9	789,515	29	100%	0.016	0.000	0.998
*10 Jul 02	20703870	0.99	10	5514	3013	97.70%	4528	5533	641%	8	779,200	4	100%	0.022	0.002	0.998
Hewlett Packard (HPQ) Jan 1996 - Apr 2006																
*14 May 98	10552311	1.00	37	2646	2745	96.90%	9720	4943	117%	10	1,470,119	13	100%	0.026	0.000	0.998
15 Sep 99	10087563	1.21	66	1785	1554	93.90%	4079	1917	200%	7	1,501,894	26	100%	0.022	0.344	0.998
*15 Oct 99	10848801	0.97	36	3403	6194	99.30%	−12522	7732	130%	9	1,277,513	4	100%	0.004	0.026	0.998
*28 Sep 00	11163103	0.97	23	2600	1220	85.90%	1449	1353	271%	10	1,166,625	3	100%	0.032	0.000	0.998
*30 Oct 00	11136235	0.96	19	5307	11513	99.90%	66131	5898	118%	10	4,178,669	15	100%	0.002	0.000	0.998
*31 Oct 00	10519981	1.16	18	0	13093	99.90%	43002	295	449%	10	3,917,616	14	100%	0.002	0.000	0.998
*9 Nov 00	10373575	0.95	9	17186	4453	98.50%	6502	7170	176%	3	1,847,794	4	100%	0.012	0.000	0.998
Philip Morris (MO) Jan 1996 - Apr 2006																
28 Jan 99	11211572	1.03	23	1237	3307	92.30%	3647	3314	444%	10	2,329,156	16	100%	0.008	0.187	0.998
30 Mar 99	11439476	0.94	18	5939	20993	99.10%	43843	21330	149%	6	6,038,594	13	100%	0.002	0.160	0.998
21 Aug 00	10577641	1.07	26	3590	5770	97.90%	8428	6262	145%	10	892,463	19	100%	0.010	0.489	0.996
*16 Mar 01	20241596	0.96	36	2902	3416	93.50%	−67790	3539	122%	5	938,726	16	100%	0.014	0.020	0.998
*3 Jun 02	20705047	1.04	47	16001	15344	97.90%	14567	16767	106%	10	3,291,798	16	100%	0.016	0.005	0.998
21 Jun 02	20705047	0.96	29	43143	7298	92.10%	−82813	8816	263%	5	2,079,930	2	100%	0.048	0.211	0.998

Table 6: Detected option informed trades for various sectors. For definition of entries see Page 39.

Summary of various sectors Jan 1996 - Apr 2006

Day of transaction	Market condition	Return	Crash in stock	Event's Description
				AT&T (ATT) Jan 1996 - Apr 2006
*17 Apr 98	0.4%	−2.9%	27 Apr 98	Announcement 20 Apr 98: financial statements for first quarter
*25 Apr 00	0.7%	−19.0%	02/03 May 00	Announcement 02 May 00: financial statements for first quarter
*26 Apr 00	1.5%	−19.0%	02/03 May 00	Announcement 02 May 00: financial statements for first quarter
				Coca Cola (KO) Jan 1996 - Apr 2006
*24 Aug 98	0.6%	−10.5%	31 Aug 98	Announcement 17 Sept 98: international crisis (Russian, Asian) hurts KO's profit
*26 Aug 98	0.0%	−10.5%	31 Aug 98	Announcement 17 Sept 98: international crisis (Russian, Asian) hurts KO's profit
*18 Mar 99	1.4%	−3.0%	31 Mar 99	Announcement 29 Mar 99: unexpected drop in sales due to Pepsi IPO
*23 Aug 00	−0.9%	−3.8%	30 Aug 00	Not identified
12 Feb 01	0.9%	−9.6%	21/22 Feb 01	Announcement 21 Feb 01: Coca-Cola/Procter&Gamble deal
20 Feb 01	−0.5%	−9.6%	21/22 Feb 01	Announcement 21 Feb 01: Coca-Cola/Procter&Gamble deal
28 Jun 02	0.1%	−3.9%	12 Jul 02	Announcement 14 Jun 02: stock options granted to executives are recorded as expense
*9 Jul 02	0.1%	−10.0%	18/19 Jul 02	Announcement 17 Jul 02: financial statements for 2nd quarter
*10 Jul 02	−0.5%	−10.0%	18/19 Jul 02	Announcement 17 Jul 02: financial statements for 2nd quarter
				Hewlett Packard (HPQ) Jan 1996 - Apr 2006
*14 May 98	−0.7%	−13.9%	14 May 98	Announcement 14 May 98: profit warning for 2nd quarter due to Asian crisis
15 Sep 99	−0.1%	−6.2%	29 Sep 99	Announcement 01 Oct 99: fall in 4th revenues growth
*15 Oct 99	−1.0%	−12.6%	27 Oct 99	Announcement 27 Oct 99: earnings shortfall in 4th quarter
*28 Sep 00	0.7%	−12.5%	29/02 Sep/Oct 00	Not identified
*30 Oct 00	−1.8%	−12.8%	10/13 Nov 00	Announcement 13 Nov 00: financial statements for 4th quarter (ended on Oct 31)
*31 Oct 00	−2.0%	−12.8%	10/13 Nov 00	Announcement 13 Nov 00: financial statements for 4th quarter (ended on Oct 31)
*9 Nov 00	−0.5%	−12.8%	10/13 Nov 00	Announcement 13 Nov 00: financial statements for 4th quarter (ended on Oct 31)
				Philip Morris (MO) Jan 1996 - Apr 2006
28 Jan 99	0.1%	−8.7%	10 Feb 99	Announcement 10 Feb 99: punitive damages of 81 million for smoker's death
30 Mar 99	−1.6%	−15.1%	30/31 Mar 99	Announcement 30 Mar 99: punitive damages of 51.5 million for inoperable lung cancer
21 Aug 00	0.7%	−2.6%	30 Aug 00	Not identified
*16 Mar 01	−0.9%	−4.8%	20 Mar 01	Not identified
*3 Jun 02	0.5%	−2.0%	6 Jun 02	Not identified
21 Jun 02	−1.0%	−15.8%	21/24/25 Jun 02	Announcement 21 Jun 02: investors reject stock because of litigation risk

Table 7: Description of detected option informed trades for various sectors. For definition of entries see Page 39.

Accuracy of the hedging detection method for Citigroup on 17 Dec 2001

	h_i										
	0	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50
Percentiles											
20 20	0.051	0.052	0.077	0.089	0.094	0.124	0.151	0.193	0.227	0.277	0.306
20 40	0.046	0.058	0.079	0.106	0.116	0.174	0.196	0.235	0.287	0.290	0.299
20 60	0.051	0.063	0.070	0.100	0.131	0.156	0.157	0.210	0.210	0.265	0.282
20 80	0.069	0.072	0.072	0.075	0.076	0.076	0.076	0.077	0.095	0.125	0.180
40 20	0.055	0.057	0.064	0.087	0.117	0.124	0.168	0.185	0.198	0.207	0.223
40 40	0.053	0.055	0.090	0.096	0.147	0.158	0.167	0.182	0.219	0.239	0.272
40 60	0.056	0.064	0.081	0.120	0.125	0.159	0.183	0.218	0.253	0.284	0.298
40 80	0.041	0.104	0.188	0.190	0.201	0.231	0.254	0.265	0.282	0.291	0.306
60 20	0.051	0.052	0.059	0.078	0.098	0.102	0.161	0.180	0.198	0.200	0.217
60 40	0.049	0.066	0.070	0.098	0.119	0.125	0.136	0.161	0.161	0.249	0.253
60 60	0.051	0.051	0.062	0.065	0.065	0.065	0.097	0.114	0.125	0.126	0.138
60 80	0.050	0.055	0.074	0.075	0.099	0.114	0.151	0.153	0.157	0.192	0.208
80 20	0.049	0.088	0.131	0.147	0.153	0.156	0.166	0.178	0.189	0.195	0.210
80 40	0.049	0.056	0.063	0.075	0.116	0.136	0.158	0.179	0.183	0.192	0.195
80 60	0.049	0.071	0.085	0.085	0.092	0.100	0.110	0.136	0.150	0.183	0.183
80 80	0.033	0.070	0.070	0.080	0.084	0.099	0.099	0.099	0.151	0.154	0.231

Table 8: Entries are the probabilities of rejecting the hypothesis H_0 of no hedging when informed trades occur for the Citigroup stock on day i = December 17th, 2001, i.e. $\mathbb{A}(h_i)$ in (8), for various levels of h_i and $\mathbf{X}_i$. h_i is the ratio between volume due to hedging and volume due to non-hedging. $\mathbf{X}_i = (|r_i|, V_{i-1}^{\text{buy,non-hedge}})$ are the conditioning variables, i.e. stock return on day i and buyer-initiated volume due to non-hedging on day $i-1$, respectively. *Percentiles* are the levels of percentiles for the distributions of $|r_i|$ and $V_{i-1}^{\text{buy,non-hedge}}$, respectively, used as values of the conditioning variables in (6).

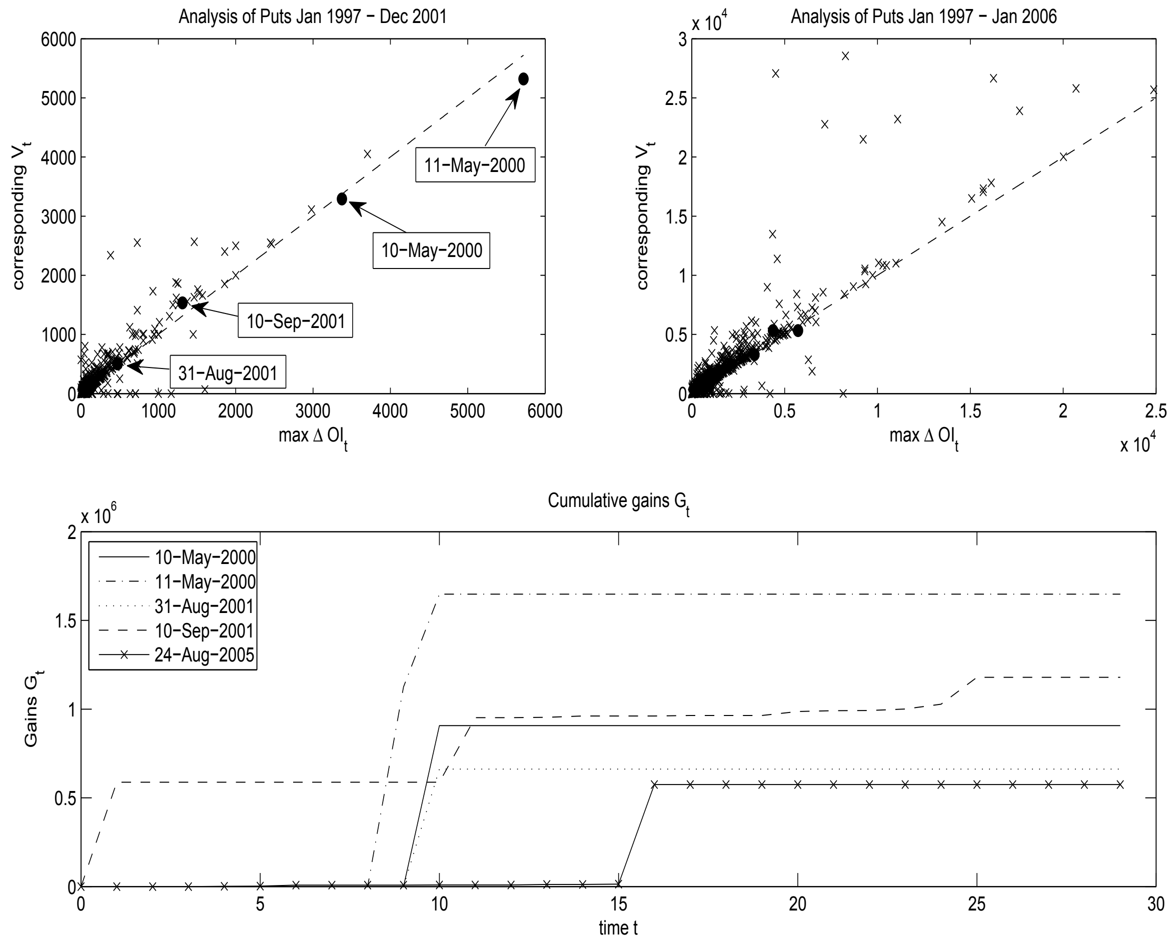

Figure 1: Upper graphs show on the x-axis maximal daily increment in open interest across all put options with underlying American Airlines (AMR), and on the y-axis the corresponding trading volume. Upper-left graph covers the period January 1997 – December 2001, upper-right graphs the period January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

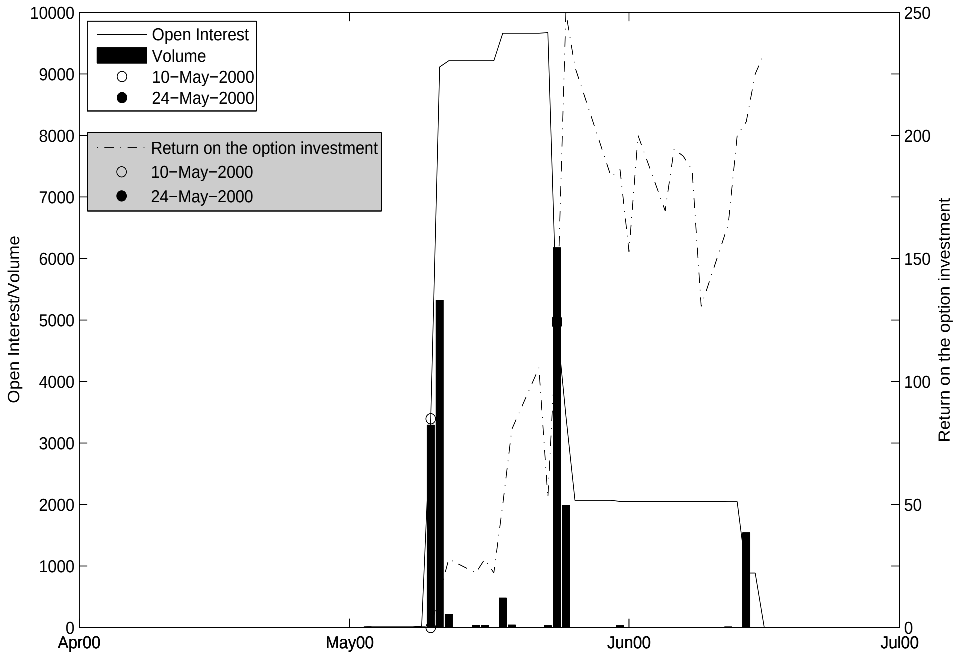

Figure 2: Selected put option for informed trading with underlying stock American Airlines (AMR) before the United Airlines (UAL) announcement of $4.3 billion acquisition of US Airways in May 2000. The solid line shows the daily dynamic of open interest, the bars show the corresponding trading volume (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.

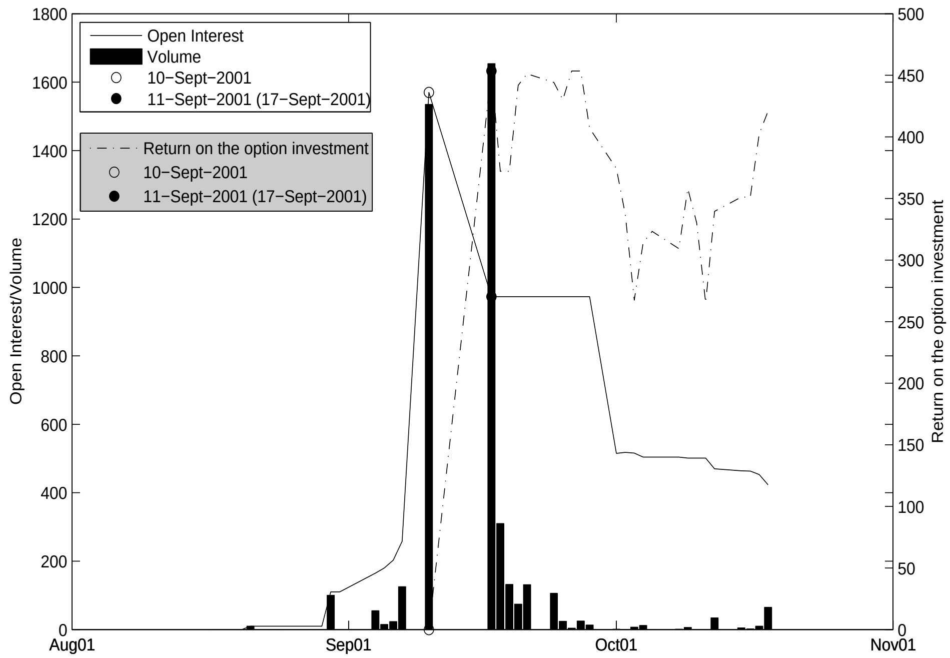

Figure 3: Selected put option for informed trading with underlying stock American Airlines (AMR) in the days leading up to the terrorist attacks of September 11th, 2001. The solid line shows the daily dynamic of open interest, the bars show the corresponding trading volume (left y-axis) and the dash-dot line the option return (right y-axis). The empty circle is the day of the transaction, the filled circle (partially covered by the highest bar) is the day when the market reopened after the terrorist attacks. This put option had a strike of \$30 and matured at the end of October 2001.

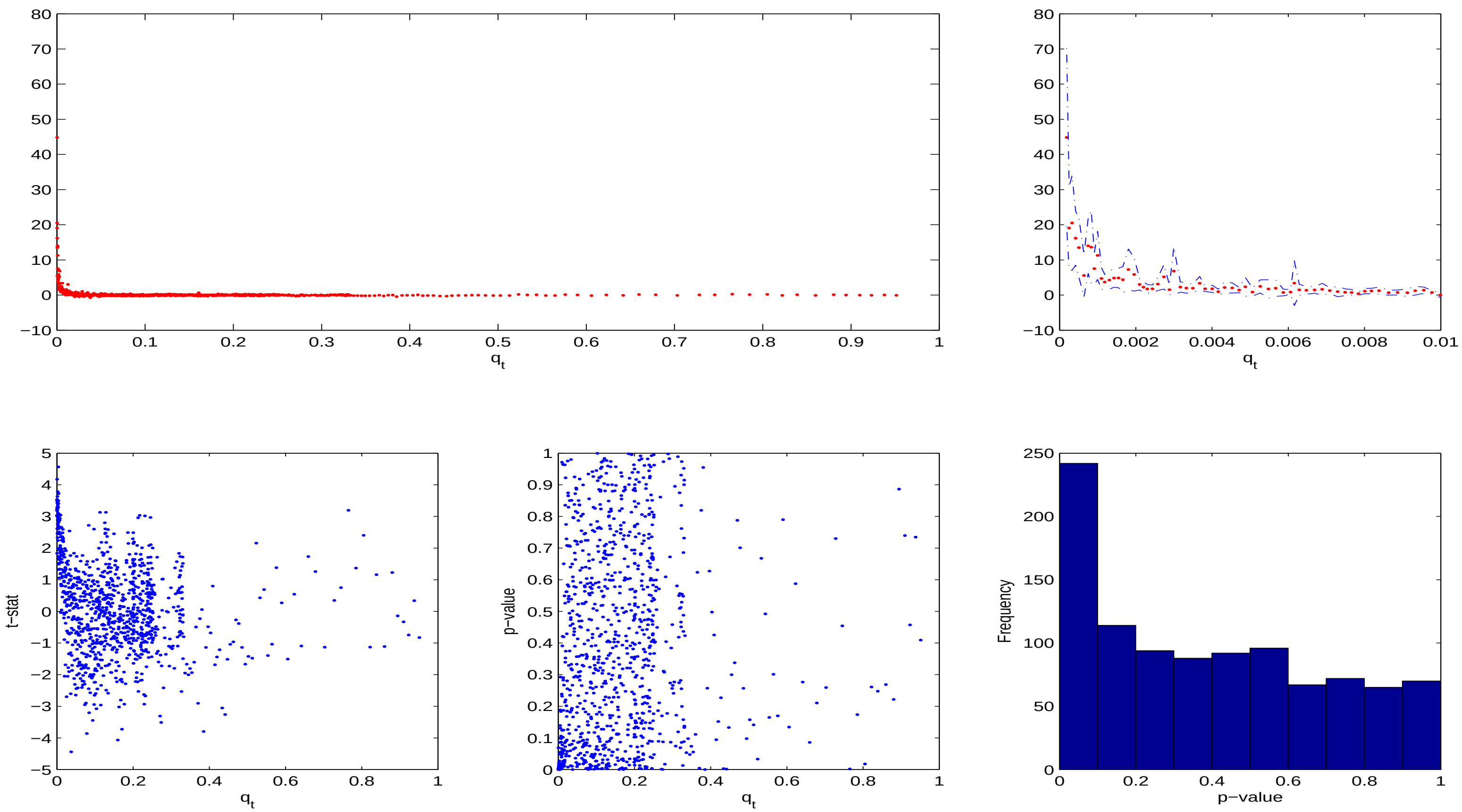

Figure 4: False Discovery Rate for American Airlines. The upper-left graph shows on the x-axis the ex-ante probability q_t, the right-end point in each subinterval I_m, and on the y-axis the corresponding average option returns δ_m associated to the mth option trader. The upper-right graph shows the same quantities when $0 \leq q_t \leq 0.01$. 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 $H_0 : \delta_m = 0, m = 1, \ldots, M$, corresponding p-values, and histogram of p-values, respectively.

References

Ang, A., T. Bali, and N. Cakici, 2010, "The Joint Cross Section of Stocks and Options," Working paper, Baruch College.

Anthony, J., 1988, "The Interrelation of Stock and Options Market Trading-Volume Data," *Journal of Finance*, 43, 949–964.

Back, K., 1993, "Asymmetric Information and Options," *Review of Financial Studies*, 6, 435–472.

Bali, T., and A. Hovakimian, 2009, "Volatility Spreads and Expected Stock Returns," *Management Science*, 55, 1797–1812.

Barras, L., O. Scaillet, and R. Wermers, 2010, "False Discoveries in Mutual Fund Performance: Measuring Luck in Estimated Alphas," *Journal of Finance*, 65, 179–216.

Bhattacharya, M., 1987, "Price Changes of Related Securities: The Case of Call Options and Stocks," *Journal of Financial and Quantitative Analysis*, 22, 1–15.

Biais, B., and P. Hillion, 1994, "Insider and Liquidity Trading in Stock and Options Markets," *Review of Financial Studies*, 7, 743–780.

Blume, L., D. Easley, and M. O'Hara, 1994, "Market Statistics and Technical Analysis: The Role of Volume," *Journal of Finance*, 49, 153–181.

Boulatov, A., T. Hendershott, and D. Livdan, 2011, "Informed Trading and Portfolio Returns," *Review of Economic Studies*, forthcoming.

Cao, C., Z. Chen, and J. Griffin, 2005, "Informational Content of Option Volume Prior to Takeovers," *Journal of Business*, 78, 1073–1109.

Chakravarty, S., H. Gulen, and S. Mayhew, 2004, "Informed Trading in Stock and Option Markets," *Journal of Finance*, 59, 1235–1257.

Chan, K., P. Chung, and W. Fong, 2002, "The Informational Role of Stock and Option Volume," *Review of Financial Studies*, 15, 1049–1075.

Chan, K., P. Chung, and H. Johnson, 1993, "Why Option Prices Lag Stock Prices: A Trading-Based Explanation," *Journal of Finance*, 48, 1957–1967.

Chen, J., H. Hong, and J. Stein, 2001, "Forecasting Crashes: Trading Volume, Past Returns, and Conditional Skewness in Stock Prices," *Journal of Financial Economics*, 61, 345–381.

Chesney, M., R. Crameri, and L. Mancini, 2011, "Detecting Informed Trading Activities in the Options Markets: Appendix on Subprime Financial Crisis," Technical report, University of Zurich.

Christophe, S., M. Ferri, and J. Angel, 2004, "Short-Selling Prior to Earnings Announcements," *Journal of Finance*, 59, 1845–1875.

Conrad, J., 1989, "The Price Effects of Option Introduction," *Journal of Finance*, 44, 487–498.

Cremers, M., and D. Weibaum, 2010, "Deviations from Put-Call Parity and Stock Return Predictability," *Journal of Financial and Quantitative Analysis*, 45, 335–367.

Diamond, D., and R. Verrechia, 1987, "Constraints on Short-Selling and Asset Price Adjustment to Private Information," *Journal of Financial Economics*, 18, 277–311.

Easley, D., N. Kiefer, and M. O'Hara, 1997, "One Day in the Life of a Very Common Stock," *Review of Financial Studies*, 10, 805–835.

Easley, D., and M. O'Hara, 1987, "Price, Trade Size, and Information in Securities Markets," *Journal of Financial Economics*, 19, 69–90.

Easley, D., and M. O'Hara, 1992, "Time and the Process of Security Price Adjustment," *Journal of Finance*, 47, 577–605.

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.

Fan, J., and Q. Yao, 2003, *Nonlinear Time Series: Nonparametric and Parametric Methods*. Springer-Verlag, New York.

Gârleanu, N., L. Pedersen, and A. Poteshman, 2009, "Demand-Based Option Pricing," *Review of Financial Studies*, 22, 4259–4299.

Glosten, L., and P. Milgrom, 1985, "Bid Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Agents," *Journal of Financial Economics*, 14, 71–100.

Grossman, S., 1977, "The Existence of Futures Markets, Noisy Rational Expectations and Information Externalities," *Review of Economic Studies*, 44, 431–449.

Hall, P., R. Wolff, and Q. Yao, 1999, "Methods for Estimating a Conditional Distribution Function," *Journal of the American Statistical Association*, 94, 154–163.

Hasbrouck, J., 1991, "Measuring the Information Content of Stock Trades," *Journal of Finance*, 46, 179–207.

Huang, R., and H. Stoll, 1994, "Market Microstructure and Stock Return Predictions," *Review of Financial Studies*, 7, 179–213.

Keown, A., and J. Pinkerton, 1981, "Merger announcements and Insider Trading Activity: An Empirical Investigation," *Journal of Finance*, 36, 855–869.

Lakonishok, J., I. Lee, N. Pearson, and A. Poteshman, 2007, "Option Market Activity," *Review of Financial Studies*, 20, 813–857.

Lee, C., and M. Ready, 1991, "Inferring Trade Direction from Intraday Data," *Journal of Finance*, 46, 733–746.

Lee, J., and C. Yi, 2001, "Trade Size and Information-Motivated Trading in the Options and Stock Markets," *Journal of Financial and Quantitative Analysis*, 36, 485–501.

Lee, M., B. Mucklow, and M. Ready, 1993, "Spreads, Depths, and the Impact of Earnings Information: An Intraday Analysis," *Review of Financial Studies*, 6, 345–374.

Manaster, S., and R. Rendleman, 1982, "Option Prices as Predictors of Equilibrium Stock Prices," *Journal of Finance*, 37, 1043–1057.

Mayhew, S., A. Sarin, and K. Shastri, 1995, "The Allocation of Informed Trading Across Related Markets: An Analysis of the Impact of Changes in Equity-Option Margin Requirements," *Journal of Finance*, 5, 1635–1653.

Meulbroek, L., 1992, "An Empirical Analysis of Illegal Insider Trading," *Journal of Finance*, 47, 1661–1699.

Pan, J., and A. Poteshman, 2006, "The Information in Option Volume for Future Stock Prices," *Review of Financial Studies*, 19, 871–908.

Poteshman, A., 2006, "Unusual Option Market Activity and the Terrorist Attacks of September 11, 2001," *Journal of Business*, 79, 1703–1726.

Seyhun, H. N., 1986, "Insiders' Profits, Costs of Trading, and Market Efficiency," *Journal of Financial Economics*, 16, 189–212.

Stephan, J., and R. Whaley, 1990, "Intraday Price Change and Trading Volume Relations in the Stock and Stock Option Markets," *Journal of Finance*, 45, 191–220.

Stoll, H., and E. Robert, 1990, "The Dynamics of Stock Index and Stock Index Futures Returns," *Journal of Financial and Quantitative Analysis*, 25, 441–468.

Storey, J., 2002, "A Direct Approach to False Discovery Rates," *Journal of the Royal Statistical Society*, 64, 479–498.

Vega, C., 2006, "Stock Price Reaction to Public and Private Information," *Journal of Financial Economics*, 82, 103–133.

Vijh, A., 1990, "Liquidity of the CBOE Equity Options," *Journal of Finance*, 45, 1157–1179.

Xing, Y., X. Zhang, and R. Zhao, 2010, "What Does Individual Option Volatility Smirk Tell Us About Future Equity Returns?," *Journal of Financial and Quantitative Analysis*, 45, 641–662.

Yan, S., 2011, "Jump Risk, Stock Returns, and Slope of Implied Volatility Smile," *Journal of Financial Economics*, 99, 216–233.