Directional Options Trading Volume around Analysts' Announcements*

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Abstract

We study the information content of options trading volume for future stock returns predictability around analysts' recommendation announcements. We exploit the directionality of the options trading volume measure from the ISE database to examine which category of options trading volume is more informative in predicting stock returns around such events. We find that a measure of option order flow related to open buy is informative on the day just before the analysts' news and on the day of the news. The significance and sign of our results validate the prevailing tipping hypothesis in the literature, shedding new light on directional options trading volume measures. Our results are corroborated by a rich set of robustness check and change in the specification of our measures.

Keywords: Option Trading, Option Signed Volume, Analyst Recommendation, Stock Return Predictability;

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1 Introduction

Options volume is a strong predictor of stock returns. Its predictive ability is generally stronger around days with news arrivals compared to other days. A key reason why option volume predicts stock returns is related to news arrivals and, more specifically, investors who possess valuable private information may use the options markets to execute trades based on that information. In this paper, we exploit directional (long and short) option strategies around unscheduled events belonging to the analysts' domain. In particular, we study the predictability information of a directional options trading volume on days around analysts' recommendation announcements to predict stock returns.

We adopt a more comprehensive data set from the International Securities Exchange (ISE) on daily directional option volumes (buy and sell positions). This includes options trading volume for each symbol traded at the ISE with respect to both calls and puts. This database allows us to extend previous literature which has looked at the role of options trading volume before news arrivals by monitoring the direction of the option strategies around those events. Our variable of interest is the directional open buy call-put volume (OB) ratio as the ratio between the numbers of call and put contracts purchased by non-market makers to open new positions, similarly to Pan and Poteshman (2006) and Weinbaum et al. (2022). Therefore, we are able to better discern the role of investors' preferences captured by directional (long and short) option strategies before analysts' announcements. While an aggregate measure of option volume on calls or puts will provide a blurred representation of the investors' role in the stock markets (e.g. hedgers, speculators), a signed options trading activity will shed new light on the role of investors' preferences and informed trading before and around analysts' news.

Previous literature has documented that the relationship between the information content of options trading volume and the future stock returns depends on the nature of the news arrivals (see Weinbaum et al., 2022). If the incoming information comes from either a scheduled or unscheduled event, this would consequently affect the volatility and so the option prices in a different way.[1] However, some studies investigate unscheduled events to control for potential contamination due to the arrival of new information. An example sample bias associated with scheduled events is that options trading volume would significantly change before a news event due to investors either hedging or speculating on the pending information (e.g. Hayunga and Lung, 2014). Motivated by this discussion, in our paper we focus on unscheduled events, namely analysts' recommendation announcements.

In particular, in this study we exploit the directionality of the option volume information in several ways. First, we are interested in investigating whether a change in directional options demand pressure has a significant association with future analysts' announcements. Previous literature has studied such relationship, however only looking at aggregate measures of options trading volume (e.g. Roll et al., 2010) or looking at both unscheduled and scheduled events (e.g. Weinbaum et al., 2022). In our study, we extend previous evidence since we are able to discern options' traders beliefs and positions by investigating which components of signed option volume predict stock returns.

Second, we aim to shed more lights on one of the main hypothesis highlighted in the literature on the interplay between analysts and option traders, namely the tipping hypothesis. Several hypotheses on the relationship between analysts' announcements and options traders have been discussed in the literature (see Lin and Lu, 2015). The three main hypotheses as documented in the literature are as follows: i) tipping, ii) reverse tipping, and iii) common information.[2] However, the prevailing view in the financial analyst literature belongs to the first mechanism, that is the analyst tipping hypothesis (e.g. Irvine et al., 2007; Christophe et al., 2010; Lin and Lu, 2015). In this paper, aided by signed option volume data, we

[1]According to Weinbaum et al. (2022), the difference between scheduled and unscheduled announcements is reflected on the implied volatility features. In fact, implied volatilities are known to increase prior to scheduled events (e.g. earnings announcements) and drop off sharply immediately after them (e.g. Patell and Wolfson, 1979, 1981). Other news events such as unscheduled events are not accompanied by a drop in implied volatility upon release.

[2]According to Lin and Lu (2015), first analysts could inform options traders about their upcoming recommendation or target price change, earnings forecast revision (analyst tipping). Second, options traders could leak their trading information to analysts, leading to changes in recommendation or revisions by analysts (reverse tipping). Finally, analysts and options traders may gather information independently, but options traders could exploit this more quickly (common information).

contribute to the identification of the interplay between analyst and option trader by testing the analyst tipping hypothesis in a more refined and directional manner.

In fact, according to studies linking market sentiment with asset pricing (e.g. Buraschi and Jiltsov, 2006; Han, 2008), speculators would enter in new call option positions before an unscheduled events when their expectations on the future stock market price are bullish, while hedgers will enter new put option positions in the opposite bearish scenario. We know that an optimistic investor chooses to buy calls or sell puts, whilst a pessimistic investor chooses to buy puts or sell calls. When working with option trading volume data which aggregates investors positions on both calls and puts, the channel at work might be offset or blurred. The directionality of the option trades on each type of contract allows us to uncover a clearer relationship between option trades and analysts' announcements and to further verify the analyst tipping theory. Lastly, we will also provide evidence on the relationship between signed option trading volume and analysts' target price announcements.

The main findings of our paper are as follows. With respect to analysts' recommendations, we observe that the call-put option trading volume ratio peaks (drops) in the days before the analysts' news day related to an upgrade (downgrade), reaching its maximum value on the news day. Option volume is found to be more informative on both news days and the days before. Moreover, high OB predicts high absolute cumulative abnormal returns (CARs) in the pre-announcement week. Specifically, OB on the day before the announcement and on the event day is found to be positively and more strongly associated with the future stock returns. Hence, we uncover evidence that options traders are executing orders in the right direction for the upcoming analysts' revisions, with greater predictability being associated with upgrades. We find similar patterns for target prices, that is the OB ratio on the day before and on the day of target price announcement is informative for future stock returns. These findings are consistent with informed trading in the options market prior to analysts' announcements as well as with the tipping hypothesis. Our findings are robust to sub-sampling and after controlling for several variables associated with the stocks and options markets.

Our study relates to the literature examining information content in the options market, especially on options trading volume, around both scheduled (e.g. earnings announcements) and unscheduled corporate events. The majority of the studies investigating the information of options around events concentrates on scheduled events (e.g. Jin et al., 2012; Ge et al., 2016; Weinbaum et al., 2022). The literature on options information content around unscheduled corporate events is more scarce (see, e.g. Jayaraman et al., 2001; Cao et al., 2005; Jin et al., 2012; Hayunga and Lung, 2014; Chan et al., 2015; Lin and Lu, 2015).[3] More specifically, we touch upon studies on the relationship between option volume and underlying stock returns (e.g. Stephan and Whaley, 1990; Amin and Lee, 1997; Easley et al., 1998; Chan et al., 2002; Cao et al., 2005; Pan and Poteshman, 2006; Ge et al., 2016; Weinbaum et al., 2022), among others. We are also closely related to the general literature on the lead-lag relation between the option and stock markets and on the idea that stock returns are predictable by exploiting information extracted from the option market (see Pan and Poteshman, 2006; Cremers and Weinbaum, 2010; Xing et al., 2010; An et al., 2014; Weinbaum et al., 2022), among others.[4] This strand of research has been explored by studies in relation to price discovery Chakravarty et al. (2004), corporate events, such as earnings announcements (Xing et al., 2010; Roll et al., 2010; Jin et al., 2012; Johnson and So, 2012), mergers and acquisitions (Cao et al., 2005; Chan et al., 2015), and option transactions Hu (2014). Overall, these studies suggest that options returns and options-based measures contain useful information that shows up in stock returns with a lag Cremers and Weinbaum (2010); Xing et al. (2010).[5] Finally, we relate on the literature on the financial analysts and

[3]For example, Jin et al. (2012) show that volatility spreads and skews have higher predictive ability before earnings announcements than before key product announcements. Chan et al. (2015) find that volatility spreads and implied volatility skews predict acquirer announcement returns. Lin and Lu (2015) show that the predictive ability of the option-based measures for future returns is greater ahead of events. Moreover, Ge et al. (2016) consider stock return predictability around corporate news days using option volume.

[4]The idea that options contain a superior set of information compared to the stock market has a long tradition (see Black, 1975; Manaster and Rendleman Jr, 1982; Diltz and Kim, 1996).

[5]However, studies arguing that options do not contribute to the equity price discovery process (e.g. Chan et al., 2002; Muravyev et al., 2013).

stock markets (see, for example Womack, 1996; Barber et al., 2001; Jegadeesh et al., 2004).

The remainder of the paper is organized as follows. Section 2 presents the theoretical background behind our study and hypotheses. In Section 3 we describe the options and stock market data employed and the construction of our variable of interest. Section 4 illustrates the behaviour of the option trading volume and abnormal returns around analysts' recommendations. Section 5 reports the main empirical exercises of the paper with respect to analysts' recommendations, while Section 6 provides additional tests in order to validate the tipping hypothesis as well as examining the role of target price announcements. Section 7 concludes the paper. Additional results and material are relegated to the paper Appendix.

2 Study hypotheses

The options market has often been considered as an ideal venue in which informed traders may take advantage of the high leverage to capitalize on their private information Black (1975). Options can also be used to trade on negative information in the presence of short-sale constraints on the underlying stocks. A seminal study by Easley et al. (1998) argues that options are preferred by informed traders when the implicit leverage is high and the options market is liquid.[6] It is also well-known that options are used for hedging positions. Given these characteristics associated with the options market, that are the high leverage and the downside protection, we would expect at least some new information about the stock price to be reflected in option prices first.

In fact, the options market has been found to be the venue where informed investors trade on private information about the underlying asset.[7] This finding is supported by Easley

[6] A large body of theoretical literature has suggested that informed investors may indeed migrate towards the options market for leverage purposes (see, e.g., Biais and Hillion, 1994; Boyer and Vorkink, 2014; Ge et al., 2016). Pan and Poteshman (2006) build on this earlier theoretical work by Easley et al. (1998), which suggests that informed traders could use either options or stock and outlines conditions when options would be preferred, e.g., when implicit leverage in options is high and options are relatively liquid.

[7] For example, Cao (1999) argues that agents with information about future contingencies should be able to trade more effectively on their information in the presence of options, thus improving informational efficiency. Moreover, Cao and Wei (2010) find evidence that information asymmetry is greater for options

et al. (1998), Chakravarty et al. (2004), Pan and Poteshman (2006) who find that options order flows contain information about the future direction of the underlying stock price. Ni et al. (2008) show that options markets attract traders informed about future volatility and also show that options order flows forecast stock volatility. In sum, the literature suggests that options markets stimulate greater informational efficiency by allowing for more informed trading.

However, one of the great puzzles in finance is about the level of trading volume in financial markets, which seems far in excess of what could reasonably be anticipated based on the arrival of new private information. Some of this seemingly excessive trading could be among agents who are not informed at all, but simply believe they are. The literature has also provided evidence that at least some traders are truly informed. Easley et al. (2002) find evidence that informed traders are active in equity markets and that information risk is priced in the cross-section of stock returns. Further, Pan and Poteshman (2006) find that put/call ratios in transactions involving new positions are good predictors of future stock returns. This is consistent with informed traders exploiting the enhanced leverage of the options market to maximize profitability, thus indicating that options are not viewed as redundant securities by agents.[8] In addition, options could attract volume as vehicles that can be used to hedge positions in the underlying stock (or in other options).

Overall, the literature about option volume predicting stock returns is vast (e.g. Stephan and Whaley, 1990; Amin and Lee, 1997; Easley et al., 1998; Chan et al., 2002; Cao et al., 2005; Pan and Poteshman, 2006; Ge et al., 2016; Weinbaum et al., 2022). Thus, it is reasonable to interpret most option volume, especially opening volume, as containing directional information about future stock prices.[9] Thus, this theoretical background and previous

than for the underlying stock, implying that agents with information find the options market a more efficient venue for trading.

[8] Although the theoretical literature about informed trading such as Kyle (1985) and Glosten and Milgrom (1985) emphasizes the distinction between informed and uninformed agents, trading itself is driven by agents with convictions, whether or not they possess valid information.

[9] According to Ge et al. (2016), investors can also trade for hedging purposes, in which case we would find no return predictability. If investors use complicated strategies, part of the trading volume may have a relation with future equity return which is opposite to that predicted by the informed trading story. However,

studies motivate our first hypothesis that informed investors trade in the options market exploiting their private information, therefore their signed trading volume predicts future equity returns. In other words, long option volume (open buy ratio) is informative about future stock returns before analysts' recommendations news and on news days. Similarly, this applies to analysts' target price updates.

In addition, a separate stream of literature on analysts studies stock market trading patterns around analyst news days. For instance, Irvine et al. (2007) report the abnormal trading volume of institutional investors before the upcoming initial buy recommendations of analysts, while Christophe et al. (2010) find abnormal short-selling activity before analyst downgrades. Both articles argue that analysts might tip certain groups of investors about the upcoming analyst news. A prevailing hypothesis on the relationship between stock and/or options information and stock returns around analysts' announcement, which is also uncovered by these studies, is the tipping hypothesis.

The tipping hypothesis assumes that informed traders acquire information from analysts before public announcements of the recommendation changes, forecast revisions, or initiations. They capitalize on tips by trading in the options market prior to the events such that the excess demand pressure in the options market can predict analyst-related news. We believe that analysts have economic incentives to tip their preferred clients concerning the contents of upcoming updates. Irvine et al. (2007) provide evidence that some institutional investors receive tips from sell-side analysts with regard to forthcoming analysts' reports, and Christophe et al. (2010) suggests that some traders are tipped by analysts about upcoming downgrades and reveal the tips through short sales. Lin and Lu (2015) explore several hypotheses finding that the analyst tipping to options traders mechanism is the most consistent explanation for their predictive patterns. These studies are also more generally related to the recent work by Weinbaum et al. (2022) in which the focus is on the option trading volume pattern around both scheduled and unscheduled events. Especially ahead of

Lakonishok et al. (2007) show that only a small fraction of trades in individual equity options are parts of complicated strategies such as straddles, strangles, and spreads.

unscheduled news releases or on the news day itself, such traders should prefer long option positions.

Thus, by exploiting our directional option volume database, we aim to merge the above stands of literature. This leads to our next study hypotheses, that is: a tipping hypothesis is what would most likely relate option trading volume and future stocks returns around both recommendations and target price revisions. Lastly, we also speculate that the tipping view should be more evident when the direction of the trading and the post-news returns are concordant.

The closest studies to ours in this attempt were Roll et al. (2010) and Weinbaum et al. (2022). With the aim to disentangle the role of hedging vis- a-vis informed trading in options markets, Roll et al. (2010) analyze the cross-section of the ratio of options volume to stock volume (O/S) in order to study whether this ratio varies across stocks consistently with hedging demand and informed trading. Weinbaum et al. (2022) examine different categories of option trading volume to ascertain their information content about future stock prices around corporate news announcements. They uncover a predictability pattern for open buy option trading on news days and ahead of unscheduled events. On the other hand, sales of options predict returns only ahead of scheduled news releases.

However, we first examine the directional predicability of OB with respect to analysts' recommendation announcements. Second we shed new light on the tipping hypothesis by exploiting directional option trading signals, that is looking at options traded in the correct direction of analysts' recommendations and target price updates. Third, we aim to validate the presence of the tipping mechanism with respect to both recommendations, different analysts and sample cross-sectional characteristics, and target price revisions for a more recent and comprehensive sample period.

3 Data

We classify our sample data into three main groups, namely options volume, analysts' recommendations and target price announcements, and other stocks and options variables. We employ multiple databases. Options volume data come from the International Securities Exchange (ISE). We obtain recommendations, target prices and other analysts related data from the Institutional Brokers' Estimate System (IBES). Stocks returns and other options variables are computed from data collected from the Center for Research in Security Prices (CRSP) and OptionMetrics. Market data are collected from the Center for Research in Security Prices (CRSP); institutional ownership information from Thomson Reuters (13F) Institutional Holdings; and accounting data from COMPUSTAT North America. The availability of the options volume data contained in ISE dictates our sample period ranging from May 2005 to June 2021. We discuss our data sources in the next subsections into more detail.

3.1 Options volume data

The source of the options volume data adopted in our paper is the International Securities Exchange (ISE) Open/Close Trade Profile, which provides daily buy and sell trading volume for each option series traded at the ISE, disaggregated by whether the trades open new option positions or close existing positions.We restrict the sample to include only individual equity options, dropping the options on exchange-traded funds (ETFs) and indexes. The sample period of this database ranges from May 2005 to June 2021.

For each option, daily trading volume is broken down into four categories: i) traders buying options to open new positions (open buy), ii) traders selling options to open new positions (open sell), iii) traders buying options to close existing positions (close buy), and iv) traders selling options to close existing positions (close sell). The trading volume is further classified by trader type (firm or customer).[10] Given that the main focus of our

[10]The ISE data include volumes due to trades of both firm proprietary traders and public customers. Firm volume are further broken down to Proprietary and Broker/Dealer volume, we exclude Broker/Dealer

paper is on return predictability from option volume around analysts' announcements, we restrict the analysis to options on individual stocks. We merge the ISE data with CRSP, and we restrict the sample to securities that are U.S. common stocks (CRSP share code 10 or 11).[11]

Similarly to previous studies (see Pan and Poteshman, 2006; Weinbaum et al., 2022), we compute the directional open buy call-put volume (OB) ratio as:

$$OB_{i,t} = \frac{CB_{i,t}}{CB_{i,t} + PB_{i,t}}$$

where CB_{tt} and $PB_{i,t}$ are the numbers of call and put contracts purchased by non-market makers to open new positions on date t and for stock i.[12] Most of our analyses adopt the OB ratio. We require that the ratio is available on news day and the previous trading day as in Weinbaum et al. (2022). Additional robustness checks also present results based on alternative definitions of the OB ratio and OS ratio.

3.2 Analysts' recommendations, target prices, and related data

For analysts recommendation and target price announcements, we extract the data from the IBES analyst recommendation and target price detail files, respectively. In particular, we consider recommendation revisions.[13] A recommendation is considered a change if the broker has upgraded or downgraded the stock within the last two years (e.g. Barber et al., 2007; Loh and Stulz, 2011). For target prices, we use all available target prices on IBES with a twelve-month horizon within our sample.

volume following Weinbaum et al. (2022).

[11] The ISE data are similar to the signed option volume data used in Pan and Poteshman (2006), but with two main differences: a) their dataset covers CBOE listed options and not transactions executed at the ISE, and b) their data cover the years 1990 through 2001, were not released to the public until 2006. In contrast, the ISE data are publicly available to market participants.

[12] To note that we reverse the OB ratio compared to the definition in Pan and Poteshman (2006); Weinbaum et al. (2022) to fix the direction of the ratio to be positively related to call options and positive news.

[13] Prior literature has shown that revisions and not levels contain material information and impact stock prices Jegadeesh et al. (2004).

3.3 Stock variables and controls

We obtain all the analyst related information from IBES. We collect market data from the Center for Research in Security Prices (CRSP), accounting data from COMPUSTAT North America, and institutional ownership information from Thomson Reuters (13F) Institutional Holdings.

We construct option controls, namely the at-the-money (ATM) implied volatility (IV), the IV spread (SPREAD), and the IV skew (SKEW) from OptionMetrics. ATM is the OptionMetrics ATM 30-day implied volatility.[14] SPREAD is calculated as the difference between an ATM call and ATM put (see Bali and Hovakimian, 2009; Cremers and Weinbaum, 2010). The IV skew is defined as the difference between the IVs of an OTM put option and an ATM call option on the same stock as in Xing et al. (2010). Both these implied measures reflect information about option trading. The IV spread measures the deviations from put-call parity.In the case of positive (negative) information, call-buying pressure (put-buying pressure) may push call (put) IVs up. The IV skew reflects informed traders buying OTM put options to express their negative information. Thus, it measures the left shape of the IV and is found to contain negative predictive information for future stock returns (see Lin and Lu, 2015). Hence, following existing literature, we add these two informed options trading measures as controls in our empirical analysis. For a more detailed definition of the data and computed variables, see Appendix A.

3.4 Data matching and screening

Prior literature has shown that analysts' revisions often piggyback on corporate news (e.g. Altınkılıç and Hansen, 2009). To isolate the impact of analysts' activity, we apply the following filters that are typically used in the literature: i) we remove brokers that have issued 20 recommendations or less in a particular year (4.4% of the sample) to eliminate

[14]The ATM IV is the average of ATM call and put implied volatilities. OptionMetrics computes implied volatility using a binomial tree, taking into account discrete dividend payments and the possibility of early exercise and using historical LIBOR/Eurodollar rates for interest rate input.

the recommendations and target prices from small and potentially not visible; ii) we remove stocks if their price is less than $5 during the period [-10,10] trading days; iii) we keep only common stock i.e., CRSP share codes 10 or 11; iv) we exclude recommendations or target prices if there is an earnings announcement within [-5,+5] trading days around their release i.e., day 0 is the recommendation or target price announcement date; v) we remove observations if there is recommendation for the same firm by different analyst in the period [-5,+5] trading days.

In addition to the above data screening, to isolate the impact target prices, we further exclude cases where the analyst has issued also a recommendation during the period [-1,+1]. Finally, we match the analyst data with the option trading data from the International Securities Exchange (ISE). This database covers only ISE listed options, therefore decreasing our sample size.

4 Abnormal returns, option volume and analysts' announcements

We first investigate the daily abnormal returns of stock i (AR_i) over the $[-5, +5]$ event window surrounding the analyst recommendation announcements. Following Hayunga and Lung (2014), we define AR_i as the stock daily return in excess of the risk-free rate minus the daily return predicted by the three-factor model of Fama and French (1993) augmented by the momentum (MOM) factor (see Carhart, 1997). Specifically, for each stock-trading day t, we estimate the following regression specification:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{i,MRP}\mathrm{MRP}_t + \beta_{i,SMB}\mathrm{SMB}_t + \beta_{i,HML}\mathrm{HML}_t + \beta_{i,MOM}\mathrm{MOM}_t + \varepsilon_{i,t} \quad (1)$$

where $r_{i,t} - r_{f,t}$ is the stock daily excess return and MRP_t (market risk premium), SMB_t (small minus big) and HML_t (high minus low) are the familiar market, size and value factors in Fama and French (1993) three-factor model and the one year momentum MOM. We then estimate a 255-day estimation window that covers day -260 to day -5 (i.g. five days prior to the analyst recommendation announcement). We calculate abnormal returns $\mathrm{AR}_{i,t}$ as

$$\mathrm{AR}_{i,t} = (r_{i,t} - r_{f,t}) - \left[\widehat{\beta}_{i,MRP}\mathrm{MRP}_t + \widehat{\beta}_{i,SMB}\mathrm{SMB}_t + \widehat{\beta}_{i,HML}\mathrm{HML}_t + \widehat{\beta}_{i,MOM}\mathrm{MOM}_t\right] \quad (2)$$

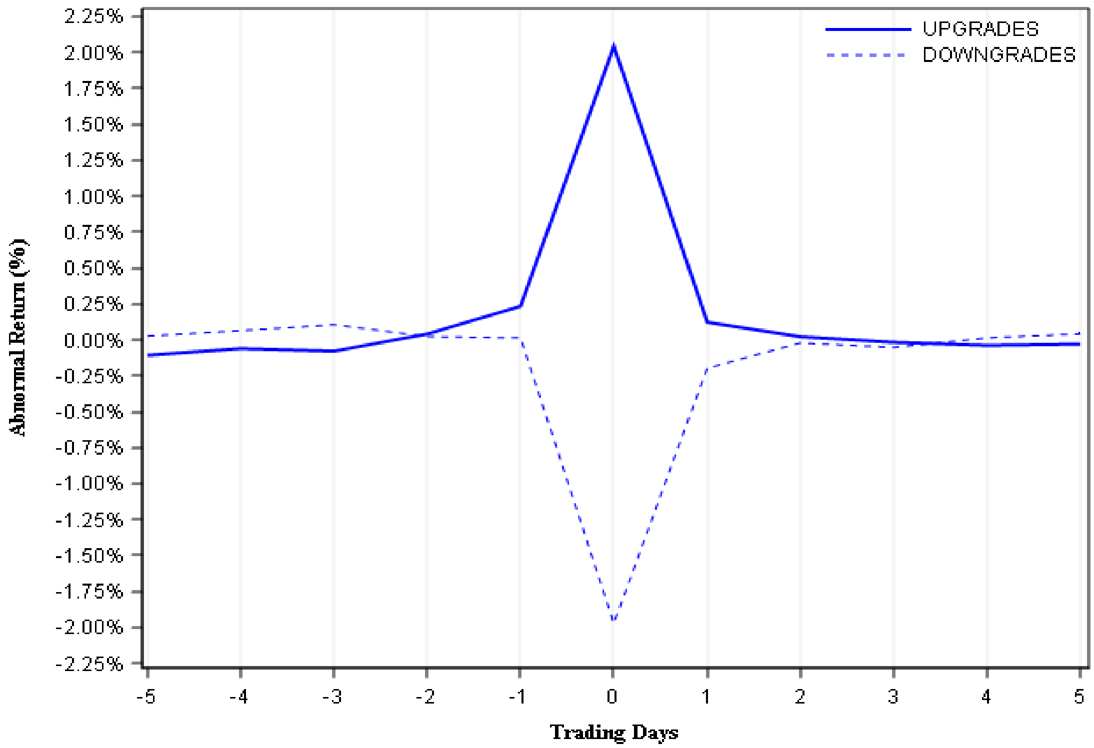
where $\widehat{\beta}_{i,M}$, $\widehat{\beta}_{i,S}$ and $\widehat{\beta}_{i,H}$ are the estimated coefficients of 1.

In Figure 1, we show the daily abnormal returns (AR) in the stock markets around analysts' recommendations divided into upgrades and downgrades. Both stocks AR associated with downgrades and upgrades show a large absolute AR on event day 0. Interestingly the abnormal price change is found to be symmetric between upgrades and downgrades, with an AR close to 2% and -2% on event day 0, respectively. The abnormal price change increases (decreases) for upgrades (downgrades) around day -1. The level of the AR resolves in one day after the announcement, consistent for both upgrades and downgrades.

Next, to provide a first insight about the way the ratio (and its components) moves around analysts' announcements, we plot the open buy call-put volume ratio in Figure 2. We show the ratio dynamics over the period $[-5, 5]$, where day 0 is the analysts' recommendation day, separately for positive and negative announcements, that is upgrades and downgrades.

We observe that the call-put option trading volume ratio increases already 3 days before the analysts' news day related to an upgrade, reaching its maximum value on the news day. This captures the higher trading pressure associated with call option purchased around positive news. On the other hand, the ratio drops the days before an analyst's downgrade reflecting the greater number of trades in put options. Overall, call-put open buy volume ratios increase (decrease) before positive (negative) analysts' news events. The trading volume peak (drop) resolves in the days after the upgrade (downgrade) news. This graphical analysis provides a first evidence in support of our hypothesis that open buy volume ratio should aid the prediction of next-day returns around news events. Option traders are more

Figure 1: **Abnormal returns around analysts' recommendations**

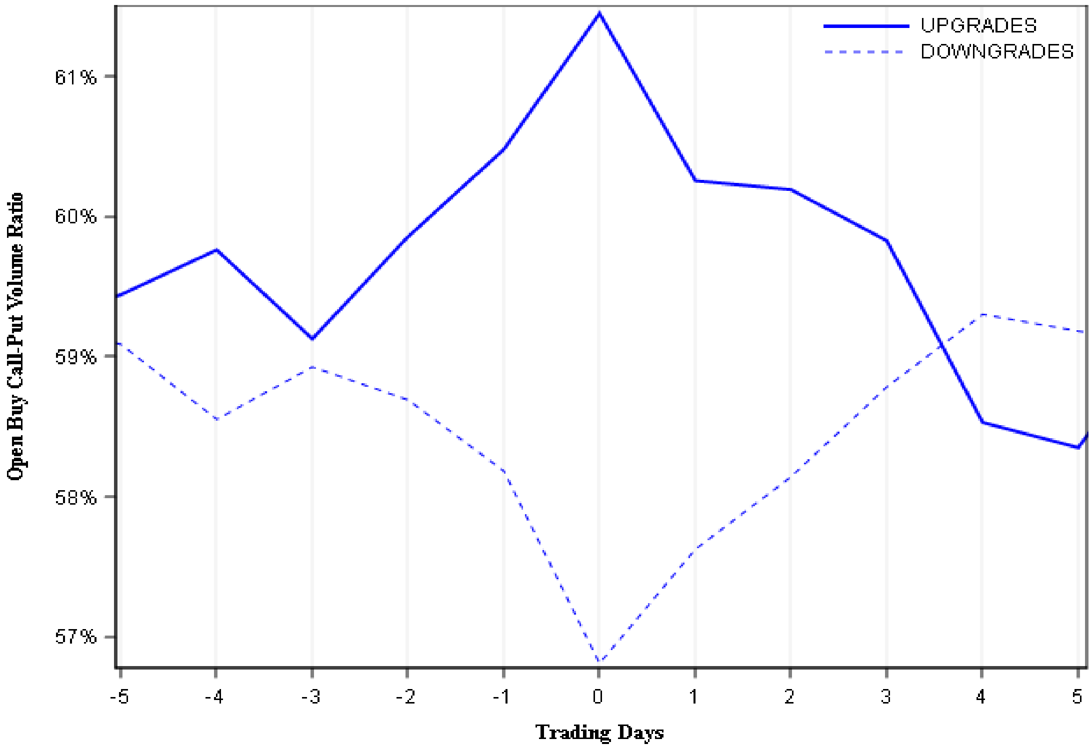


Notes: This figure shows daily abnormal stock market returns (AR) for firms that experience a change (day 0) in the consensus analysts' recommendation (upgrades or downgrades) over the $[-5, +5]$ event window (where day 0 is the analysts' recommendation day). The figure presents the values in the vertical line and the trading days in the horizontal line. Our sample is from May 2005 to June 2021.

active and option volume should be more informative on both news days and the days before.

In addition, to provide more insights into the dynamics of the call-put ratio, in Figure 3 we plot the median values of trading volume for only open buy calls and open buy puts, separately for upgrades and downgrades. Regarding open buy call, we observe that before the announcement day, the trading volume begins to increase from day -4, however peaking sharply at day -1 and reaching its maximum value on the news day (for both upgrades and downgrades). More specifically, the open buy call volume reacts much stronger to upgrades reaching a value that is 10% higher compared to downgrades, in percentage of its value on day -5. Regarding open buy put, we notice an opposite reaction to positive and negative news. In fact, the open buy put volume associated to downgrades peaks about 15% more than the

Figure 2: **Open buy call-put volume ratio around recommendations**

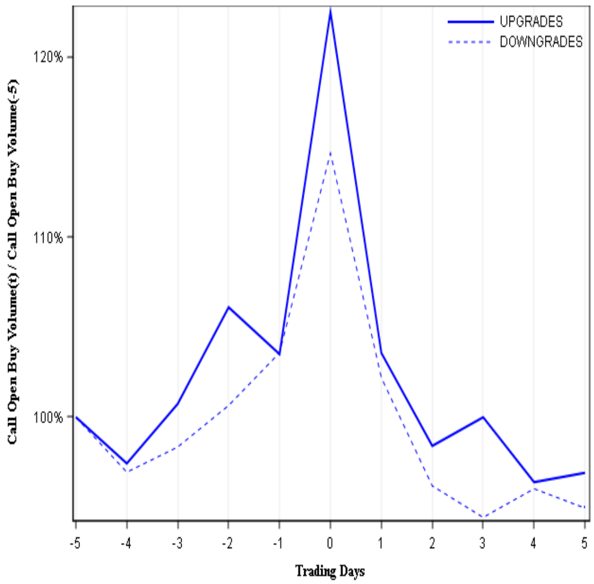


Notes: This figure presents median values of the call open buy volume as a percentage of total open buy volume. Values are presented over the period $[-5, 5]$ (where day 0 is the analysts' recommendation day). Recommendation days are divided into upgrades and downgrades days. Results are presented with a solid line for upgrades and dotted line for downgrades. The volume values are presented on the vertical axis and the trading days on the horizontal axis. Our sample is from May 2005 to June 2021.

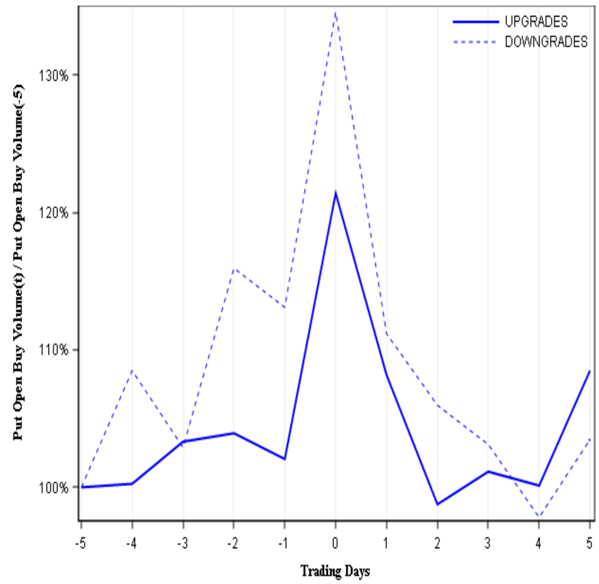
one associated to upgrades. Again, the volume spikes sharply at day -1 and it reaches its maximum on the news day. The trading volume quickly resolves after the news day for both open buy calls and puts. This decomposition of the trading volume with respect to calls and puts separately shows how the majority of the trading activity is placed on day -1 and on the news day which could be a potential signal of the analysts' tipping hypothesis. In the next sections, we empirically test these hypotheses and aim to shed more lights on the role of informed directional option trading for returns' predictability around recommendations.

Figure 3: **Open buy call and put volume around recommendations**

Panel A: Open buy call



Panel B: Open buy put



Notes: This figure presents median values of call open buy volume and put open buy volume. Call open buy and put open buy results are presented in Panel A and B, respectively. Values are presented as a percentage of the same measure on day -5 over the period $[-5, 5]$ (where day 0 is the analysts' recommendation day). Recommendation days are divided into upgrades and downgrades days. Results are presented with a solid line for upgrades and dotted line for downgrades. The volume values are presented on the vertical axis and the trading days on the horizontal axis. Our sample is from May 2005 to June 2021.

5 Options volume, returns predictability, and analysts' recommendations

In this section, we exploit the open buy (OB) ratio from the ISE data to study whether an order flow related to purchases of options is informative to predict returns around analysts' recommendations. To this aim, we estimate the following pooled cross-sectional panel regression:

$$\begin{aligned}\text{CAR}_{i,[0,1]} = \beta_{OB} OB_{i,t-h} + \beta_i OptionCONTROLS_{i,t-h} + \gamma_i FirmCONTROLS_{i,t} \\ + \delta_i AnalystCONTROLS_{i,t} + YearFE + FirmFE + \epsilon_{i,t},\end{aligned}$$

where for stock i, $\mathrm{CAR}_{[0,1]}$ is the two-day cumulative abnormal return based on the Fama-French four-factor (FF4) model, namely the Fama and French (1993) three-factor model augmented with the momentum factor (see Carhart, 1997), with day 0 being the recommendation announcement day t. To estimate expected returns and derive the factor loadings we estimate the F4 model using the last year's daily returns, specifically the estimation period, in trading days, is $-255. -5]$ relative to the recommendation release day.

OB_i is the open buy call-put volume ratio for stock i over the announcement day and the days before the announcement. The controls adopted include options variables, namely the ATM implied volatility (IV), implied volatility skew ($SKEW$) by Xing et al. (2010), and the call-put implied volatility spread ($SPREAD$) by Cremers and Weinbaum (2010). We also include firms variables that prior literature has found to be associated with stock price reactions around the release of analyst reports, namely the stock return weekly reversal over the week before the analysts' announcement (REV), the firm's momentum during the last six months (MOM), the firm's (log) market capitalization ($MKTCAP$), and the log of book-to-market ratio (BM). Finally, prior literature has also shown that analyst and broker characteristics may affect the informativeness of their reports (e.g. Mikhail et al., 1997; Clement, 1999; Jacob et al., 1999). Therefore, we control for the firm's information environment, namely for the number of years the analyst is following a particular firm, that is the log of analyst firm experience (AF), the log of the size of the brokerage house ($BSIZE$), which is the number of analysts employed by the brokerage during the last twelve months, the firm's percentage of institutional ownership (IO), and also the log of analyst experience ($EXPER$).

Furthermore, prior research has shown that analysts may also release concurrently some of their estimates with recommendations. For example, Kecskés et al. (2017) show that recommendation revisions that are supported by earnings forecasts are more informative. Prior research has also shown that target prices contain distinct information not subsumed by recommendations or earnings forecasts (e.g. Brav and Lehavy, 2003; Asquith et al., 2005).

Thus, we also input a dummy taking into account the concurrent release of earnings forecast, and target price estimates by the same broker within the three-day period around the announcement date, defined as EF and TP, respectively. More detail on the control are reported in the paper Appendix A. Finally, we run the model including year and firm fixed effects to control for common shocks to the macroeconomic environment and time-invariant unobserved differences among firms, respectively. All continuous variables are winsorized at the 1st and 99th percentiles, and the model is estimated using double-clustered standard errors along firm and time dimensions.[15]

First, we are interested in the role of OB to predict future stock returns around all analysts' recommendations as well as when considering only upgrades and downgrades separately. To this aim, we test whether the predictive ability of OB is greater in the week before the announcement ($h \in [5, 1]$) days ahead, compared to the further week before the announcement ($h \in [10, 6]$) week ahead. To do so, we average the coefficients and standard errors of OB over the two weeks preceding the event day. The results of this exercise are reported in Table 1. In Panel A, we show the results for the univariate regression equation 5 for all recommendations, upgrades and downgrades. We observe that the (average) coefficient of OB is found significant only in the week before the announcement day, ($h \in [5, 1]$) days ahead, for all recommendations. When we look at upgrades and downgrades separately, we observe that the predictive ability of OB the week before the announcement is entirely driven by upgrades. An increase in the OB ratio in the week before the announcement would lead to an increase in the stock returns on the day after the event. Interestingly, we do not observe any significant predictive power for OB in the week ranging from 10 to 6 days before the event day. These findings are robust to the addition of the control variables in Panel B of Table 1. We confirm the greater significance of OB in predicting stock returns around upgrades (at the 1% significance level) compared to downgrades (at the 10% significance level).

[15] Regressions using panel data often suffer from correlated residuals across firms or across time. This would lead to biased standard errors and t-statistics. Petersen (2009) proposes an efficient way to address this concern by double clustering the standard errors along both time and firm dimensions. This double clustering simultaneously adjusts for the cross-sectional and serial correlations in residuals.

Hence, from this first empirical exercise, we can conclude that the information content of OB to predict future stock returns around analysts' announcements is entirely placed in the five days before the event day, and it is stronger with respect to upgrades.

Therefore, we uncover a strong and significant role for the average directional option trading over the week before the analysts' announcements. In what follows, we aim to test in which of the preceding days the information content of the OB ratio is stronger. We are interested in the coefficients β_{OB} with respect to the days before and on the announcement day. We run the same regression model 5 where now OB_i is the open buy call-put volume ratio for stock i over the announcement day and the 5 days before the announcement. We present the results for the announcement day being all analysts' recommendations (upgrades and downgrades), only upgrades, and only downgrades in Tables 2, 3 and 4, respectively.

Table 2 shows the cross-sectional regressions for all recommendation announcement days both in an univariate setup (Panel A) and with control variables (Panel B). From the univariate regressions, we observe that our variable of interest, OB, is significantly predicting the next period stock returns mostly the day before the announcement day and on the event day. The OB coefficient sign is positive implying that an increase in call options purchases around the recommendations day would lead to an increase in the stock returns post-event. In other words, when the OB ratio increases, the next period stock return would also increase. By looking at the ratio dynamics, we can observe that higher the ratio, higher the number of call options which are purchased to open a new position compared to put options. This suggests that when the ratio increases, we would expect more optimistic traders' expectations translating in a positive stock return after an analyst's recommendation announcement. The coefficients' sign we detect is consistent with previous literature adopting the open buy ratio (e.g. Weinbaum et al., 2022).[16]

When we include the set of control variables in Panel B, we confirm a similar finding.

[16] To be noted that the ratio in Weinbaum et al. (2022) is computed as number of put options purchased over both call and put options buys, therefore in their case leading to a negative relationship with the future stock returns.

Table 1: **Stock returns predictability around previous weeks**

	ALL RECOMMENDATIONS		UPGRADES		DOWNGRADES	
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
h	[10,6]	[5,1]	[10,6]	[5,1]	[10,6]	[5,1]
OB [t0,t1]	0.1378	0.4566***	0.1786	0.3766***	0.1465	0.2274
	(0.1421)	(0.1239)	(0.1538)	(0.1308)	(0.1574)	(0.1385)
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Obs	23,406	23,844	12,099	12,329	11,307	11,515
Adj-R2	0.0570	0.0568	0.1660	0.1649	0.1889	0.1929
Panel B	(1)	(2)	(3)	(4)	(5)	(6)
h	[10,6]	[5,1]	[10,6]	[5,1]	[10,6]	[5,1]
OB [t0,t1]	0.0132	0.5190***	0.1371	0.3477**	-0.0568	0.2186*
	(0.1387)	(0.1268)	(0.1502)	(0.1330)	(0.1562)	(0.1292)
ATM [t0,t1]	0.7505**	1.2929***	2.9422***	3.4007***	-1.4662***	-1.4293***
	(0.3192)	(0.4289)	(0.5194)	(0.5153)	(0.4257)	(0.4989)
SKEW [t0,t1]	-1.8285**	-2.3668*	-1.9614	-2.2283*	-0.1129	0.8769
	(0.8341)	(1.1927)	(1.2359)	(1.2718)	(1.1226)	(1.5604)
SPREAD [t0,t1]	2.4372	5.4897***	2.1773	3.0550	-0.4197	3.7364
	(1.4847)	(1.9266)	(2.9833)	(2.4381)	(2.2032)	(2.8488)
REV	-0.0464***	-0.0424***	-0.0236***	-0.0168**	-0.0260***	-0.0282***
	(0.0098)	(0.0088)	(0.0086)	(0.0075)	(0.0086)	(0.0083)
MOM	-0.3584	-0.2360	0.0936	0.1560	0.3287	0.3227
	(0.2345)	(0.2391)	(0.3019)	(0.2814)	(0.2422)	(0.2490)
MKT CAP (log)	-0.5552***	-0.5288***	-0.7406***	-0.7431***	-0.1887	-0.1992*
	(0.1028)	(0.0964)	(0.1121)	(0.1067)	(0.1266)	(0.1169)
AF (log)	-0.0219	-0.0154	-0.2187	-0.2438	0.6859***	0.6822***
	(0.1651)	(0.1713)	(0.2046)	(0.2038)	(0.2445)	(0.2419)
IO (%)	-0.4346	-0.4423	-0.4864	-0.3676	0.2460	0.1257
	(0.3372)	(0.3331)	(0.4642)	(0.4612)	(0.4563)	(0.4241)
BM (log)	-0.0113	-0.0334	0.1925	0.1719	0.0745	0.0571
	(0.0836)	(0.0792)	(0.1284)	(0.1243)	(0.1071)	(0.1097)
BSIZE (log)	-0.0357	-0.0356	0.2635***	0.2706***	-0.2610***	-0.2670***
	(0.0328)	(0.0315)	(0.0449)	(0.0469)	(0.0356)	(0.0347)
EXPER (log)	0.0683**	0.0559**	0.2303***	0.2197***	-0.1768***	-0.1924***
	(0.0277)	(0.0268)	(0.0304)	(0.0293)	(0.0399)	(0.0387)
EF	-0.1868*	-0.1906*	-0.0164	0.0087	-0.2591***	-0.2784***
	(0.0936)	(0.0971)	(0.0836)	(0.0881)	(0.0865)	(0.0863)
TP	0.7635***	0.7761***	0.4575***	0.4306***	-0.2842***	-0.2781***
	(0.0921)	(0.0914)	(0.1017)	(0.0940)	(0.0995)	(0.1010)
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Obs	20,112	20,491	10,418	10,614	9,694	9,877
Adj-R2	0.0785	0.0819	0.2051	0.2090	0.2111	0.2131

Notes: This table presents pooled cross-sectional regressions where the dependent variable is the four-factor adjusted stock return on the analysts' announcement day being either any recommendation (upgrades and downgrades) or upgrades and downgrades considered separately. OB is the ISE open buy ratio, IV is the ATM implied volatility, $SKEW$ is the implied volatility skew Xing et al. (2010), $SPREAD$ is the call-put implied volatility spread Cremers and Weinbaum (2010), REV is the stock return weekly reversal, MOM the firm momentum, $MKTCAP$ is the firm market cap (log), AF is the number of analyst following stock i (log), IO is the institutional ownership (in percentage), BM is the firm book-to-market (log), $SIZE$ is the broker size (log), and AFE is the analyst firm experience (log). EF and TP are dummy variables for taking into account, respectively, confounding earning forecast announcements and target price announcements over the same days. Robust standard errors clustered by time and firm are reported in parentheses. Panel A reports the regression results for the univariate models, whereas Panel B for the model including the control variables. The coefficients and standard errors of OB are averaged across the two weeks before the announcement day, namely ($[-10,-6]$) and ($[-5,-1]$). ***, **, * indicate significance level at the 1%, 5%, and 10%, respectively. The last rows report the number of observation and the adjusted-R^2. Our sample is from May 2005 to June 2021.

Table 2: **Stock returns predictability around all recommendations announcements**

Panel A	$h=5$	$h=4$	$h=3$	$h=2$	$h=1$	$h=0$
	(1)	(2)	(3)	(4)	(5)	(6)
OB (t)	0.2239**	0.1535	0.1123	0.1735**	0.3689***	0.8843***
	(0.0916)	(0.0991)	(0.0930)	(0.0790)	(0.0754)	(0.0938)
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Obs	18,290	18,451	18,470	18,583	19,573	20,505
Adj-R2	0.0361	0.0298	0.0354	0.0308	0.0308	0.0426

Panel B	$h=5$	$h=4$	$h=3$	$h=2$	$h=1$	$h=0$
	(1)	(2)	(3)	(4)	(5)	(6)
OB (t)	0.2091**	0.1031	0.1289	0.1667*	0.3764***	0.7910***
	(0.0997)	(0.1008)	(0.0993)	(0.0836)	(0.0882)	(0.0992)
ATM (t)	0.4450	1.0351**	0.8973**	1.7270***	1.1659**	-1.1327**
	(0.3545)	(0.4028)	(0.4152)	(0.4901)	(0.4756)	(0.5271)
SKEW (t)	-0.3442	-1.7504	-0.9836	-3.5677***	-2.7231**	1.1052
	(1.0397)	(1.0915)	(1.3328)	(1.2457)	(1.1698)	(1.0573)
SPREAD (t)	1.5301	2.8576	3.3766*	1.7634	2.1967	-1.6997
	(1.1051)	(1.9408)	(1.8869)	(1.7413)	(1.5864)	(1.4388)
REV	-0.0469***	-0.0458***	-0.0384***	-0.0410***	-0.0429***	-0.0481***
	(0.0101)	(0.0093)	(0.0080)	(0.0102)	(0.0079)	(0.0091)
MOM	-0.4435*	-0.4768*	-0.5029*	-0.3385	-0.1946	-0.4201
	(0.2594)	(0.2524)	(0.2744)	(0.2440)	(0.2447)	(0.2567)
MKT CAP (log)	-0.5168***	-0.4415***	-0.4891***	-0.4847***	-0.5323***	-0.7131***
	(0.1107)	(0.1030)	(0.1081)	(0.1084)	(0.1084)	(0.1147)
BM (log)	0.0179	-0.0579	-0.0025	-0.0491	-0.0295	-0.0062
	(0.0845)	(0.0926)	(0.0924)	(0.0913)	(0.0822)	(0.0908)
AF (log)	-0.0648	-0.0455	0.0263	0.0424	-0.0293	0.0092
	(0.2040)	(0.1959)	(0.2166)	(0.1803)	(0.1990)	(0.2081)
BSIZE (log)	-0.0427	-0.0389	-0.0166	-0.0020	-0.0348	-0.0380
	(0.0334)	(0.0339)	(0.0332)	(0.0351)	(0.0325)	(0.0381)
IO (%)	-0.7097*	-0.4851	-0.7684**	-0.1693	-0.6939*	-0.6660*
	(0.3995)	(0.3768)	(0.3777)	(0.3685)	(0.3983)	(0.3703)
EXPER (log)	0.0722**	0.0459	0.0500	0.0535*	0.0567**	0.0706**
	(0.0279)	(0.0307)	(0.0308)	(0.0318)	(0.0272)	(0.0298)
EF	-0.1645*	-0.1372	-0.2190***	-0.1725*	-0.1691*	-0.1780*
	(0.0949)	(0.0971)	(0.0823)	(0.0974)	(0.0998)	(0.0979)
TP	0.7472***	0.7472***	0.7614***	0.7519***	0.7356***	0.8121***
	(0.0889)	(0.0936)	(0.0901)	(0.0965)	(0.0868)	(0.0886)
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Obs	16,016	16,170	16,192	16,257	17,174	17,972
Adj-R2	0.0897	0.0887	0.0865	0.0889	0.0877	0.1003

Notes: This table presents pooled cross-sectional regressions where the dependent variable is the four-factor adjusted stock return on the analysts' announcement day being either a recommendation to upgrade or downgrade. OB is the ISE open buy ratio, IV is the ATM implied volatility, $SKEW$ is the implied volatility skew Xing et al. (2010), $SPREAD$ is the call-put implied volatility spread Cremers and Weinbaum (2010), REV is the stock return weekly reversal, MOM the firm momentum, $MKTCAP$ is the firm market cap (log), AF is the number of analyst following stock i (log), IO is the institutional ownership (in percentage), BM is the firm book-to-market (log), $SIZE$ is the broker size (log), and AFE is the analyst firm experience (log). EF and TP are dummy variables for taking into account, respectively, confounding earning forecast announcements and target price announcements over the same days. Robust standard errors clustered by time and firm are reported in parentheses. ***, **, * indicate significance level at the 1%, 5%, and 10%, respectively. The last rows report the number of observation and the adjusted-R^2. Our sample is from May 2005 to June 2021.

The OB stronger significance (at the 1% level) is mostly placed on the day before the analysts' recommendations as well as on the same day of the news release. The OB coefficient magnitude at time 0 (0.791) is found to be approximately double the one at time -1 (0.376). This finding signals that investors begin to trade on the day before the announcement with a great share of these order flows taking place on the same day of the news. We also detect a 5% significant impact of OB at time -5 and a 10% significant impact at time -2 suggesting evidence of earlier trades before the announcement day, however with a smaller coefficient size. For instance, the predictive power of open buy call-put ratios almost double (quadruple) on the day before news days and (on news days) compared to the earlier trades in day -5.

Again, also in presence of controls, the sign of the coefficient associated to OB is still found to be positive. Thus, on average, an increase in 1% in the OB ratio the day before the recommendations day would lead to an increase in almost 0.4% in the stock returns post-event. This result also suggests that controlling for the other options-based variables commonly associated with option trading information (e.g. $SPREAD$, $SKEW$) does not impact the predictive ability of the directional option open buy trading volume. The OB ratio contains a useful information set associated with traders' beliefs and expectations related to the post-announcement stock returns which are not enclosed in other trading or risk proxies extracted from the options market. It is also interesting to note that, while ATM implied volatility (implied volatility skewness) revert (become insignificant) on the announcement day, the OB ratio is still strongly and positively affecting the next day stock returns.

Moreover, while other options-based controls may proxy for risk patterns and aggregate trading pressure around analysts' announcements (e.g. Pan and Poteshman, 2006; Cremers and Weinbaum, 2010; Xing et al., 2010; Lin and Lu, 2015), the directionality of the OB ratio allows us to better understand the directional views of investors. The significant predictive role of the ratio suggests that the number of call options purchased to open a new position compared to put options is highly informative to predict future stock returns after the analysts' revisions. This information is found to be incremental to other important measures adopted as controls because of its directionality related to investors' preferences and beliefs.

The pattern of the trading activity which we have uncovered from Table 2 for the significance and information role of the OB ratio is also in line with the tipping hypothesis. We detect an overall trading activity in the week preceding the announcement day which might have been driven by both informative and non-informative trading. However, the significant increase of option trading on the exact day before the analyst' recommendation suggests a more precise informative trading which is possibly related with a tipping activity. We speculate that analysts tip investors before the recommendations or revisions (being these upwards or downwards), and investors' exploit this information the week before the event day, and mostly on the day before. The positive sign associated with the OB ratio implies that investors purchase more call options around analysts' recommendation which will indeed predict an increase in stock returns.

Next, we investigate whether this predictive ability and tipping hypothesis is confirmed when we split all recommendations in only upgrades and only downgrades. From Table 3, we observe that in the univariate case (Panel A), the role of OB in predicting future stock returns after an analyst upgrades is found significant on the week before the event. It significantly and positively predicts future stock returns post-upgrade, already at day -5 (at the 5% significance level) and especially on day -1 and event day (at the 1% significance level). However, from Panel B, it is noteworthy that when we control for additional variables, the significance of OB is uncovered only the day before the analyst' upgrade which is consistent with the tipping hypothesis. The positive relationship between OB and stock returns implies that an increase in OB due to a greater purchase of call options leads to an increase in the stock returns after an analyst's upgrade. When investors are informed about an upcoming upgrades they exploit this information by purchasing call options exactly the day before the revision.

From Table 4, we can observe that in the univariate case the OB ratio is uncovered

Table 3: **Stock returns predictability around recommendations: upgrades**

Panel A	$h=5$	$h=4$	$h=3$	$h=2$	$h=1$	$h=0$
	(1)	(2)	(3)	(4)	(5)	(6)
OB (t)	0.2171**	0.2166*	0.0906	0.0218	0.3233***	0.3384***
	(0.1054)	(0.1120)	(0.1012)	(0.0887)	(0.0858)	(0.1125)
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Obs	9,685	9,773	9,779	9,845	10,373	10,874
Adj-R2	0.1829	0.1514	0.1647	0.1700	0.1734	0.2015

Panel B	$h=5$	$h=4$	$h=3$	$h=2$	$h=1$	$h=0$
	(1)	(2)	(3)	(4)	(5)	(6)
OB (t)	0.1743	0.1088	0.0589	-0.0079	0.2613***	0.1726
	(0.1207)	(0.1157)	(0.1210)	(0.1064)	(0.0952)	(0.1221)
ATM (t)	2.9013***	2.6889***	2.5379***	3.5304***	3.5528***	2.3531***
	(0.4168)	(0.4391)	(0.4867)	(0.5224)	(0.5261)	(0.5004)
SKEW (t)	-0.2547	0.2611	-0.1710	-3.0688**	-2.1058*	0.1139
	(1.4234)	(1.0782)	(1.3171)	(1.4271)	(1.2006)	(1.0775)
SPREAD (t)	-0.6284	1.3806	4.2963*	-1.6234	3.0631	-1.4615
	(1.1988)	(2.1339)	(2.3779)	(1.6147)	(2.1900)	(1.8615)
REV	-0.0174*	-0.0249***	-0.0180*	-0.0138	-0.0078	-0.0156**
	(0.0088)	(0.0093)	(0.0094)	(0.0087)	(0.0081)	(0.0076)
MOM	0.1384	-0.2775	-0.2237	-0.0091	0.1227	-0.0343
	(0.3147)	(0.3225)	(0.3278)	(0.3405)	(0.3139)	(0.3079)
MKT CAP (log)	-0.5797***	-0.6253***	-0.6696***	-0.6772***	-0.6945***	-0.8478***
	(0.1207)	(0.1164)	(0.1255)	(0.1300)	(0.1240)	(0.1261)
AF (log)	-0.4451*	-0.4002	-0.3740	-0.3132	-0.3516	-0.2270
	(0.2564)	(0.2508)	(0.2471)	(0.2553)	(0.2257)	(0.2274)
IO (%)	-0.5669	-0.4597	-0.6628	-0.1672	-0.2226	-0.6770
	(0.5102)	(0.5557)	(0.5138)	(0.5071)	(0.5609)	(0.4924)
BM (log)	0.2222*	0.1853	0.1671	0.1510	0.1330	0.2085
	(0.1286)	(0.1341)	(0.1332)	(0.1343)	(0.1374)	(0.1285)
BSIZE (log)	0.2586***	0.2780***	0.2771***	0.2679***	0.2771***	0.2771***
	(0.0476)	(0.0488)	(0.0457)	(0.0465)	(0.0428)	(0.0510)
EXPER (log)	0.2227***	0.2247***	0.1956***	0.1997***	0.2189***	0.2244***
	(0.0316)	(0.0315)	(0.0320)	(0.0337)	(0.0337)	(0.0314)
EF	-0.0364	-0.0212	-0.0772	0.0006	-0.0039	-0.0132
	(0.0919)	(0.0961)	(0.0866)	(0.0963)	(0.0947)	(0.0821)
TP	0.4276***	0.4659***	0.4451***	0.4629***	0.4407***	0.4426***
	(0.1084)	(0.1142)	(0.0974)	(0.1088)	(0.1057)	(0.1039)
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Obs	8,296	8,373	8,389	8,436	8,905	9,326
Adj-R2	0.2242	0.1952	0.1996	0.2137	0.2233	0.2471

Notes: This table presents pooled cross-sectional regressions where the dependent variable is the four-factor adjusted stock return on the analysts' announcement day being a recommendation to upgrade. OB is the ISE open buy ratio, IV is the ATM implied volatility, $SKEW$ is the implied volatility skew Xing et al. (2010), $SPREAD$ is the call-put implied volatility spread Cremers and Weinbaum (2010), REV is the stock return weekly reversal, MOM the firm momentum, $MKTCAP$ is the firm market cap (log), AF is the number of analyst following stock i (log), IO is the institutional ownership (in percentage), BM is the firm book-to-market (log), $SIZE$ is the broker size (log), and AFE is the analyst firm experience (log). EF and TP are dummy variables for taking into account, respectively, confounding earning forecast announcements and target price announcements over the same days. Robust standard errors clustered by time and firm are reported in parentheses. ***, **, * indicate significance level at the 1%, 5%, and 10%, respectively. The last rows report the number of observation and the adjusted-R^2. Our sample is from May 2005 to June 2021.

significant only on the day of a downgrade and fundamentally not in any of the days before. When we include the additional variables in Panel B, we confirm the significance of OB only on the event day. First of all, the sign of the OB coefficient on the event day and in the days before (despite being not significant) is found to be mainly positive. Therefore, there is a positive relationship between the option trading activity and the CAR [0,1] after a downgrade. The relationship is in line with the economic rationale since in this case a decrease in OB driven by a greater purchase of put options would suggest a decrease in the CAR after an analyst's downgrade. In addition, we notice that the tipping hypothesis seems not to be confirmed with respect to downgrades. This implies that investors exploit more and trade more on the good news and *positive* tips rather than on the bad news related to a stock.

We also perform a battery of robustness checks in order to confirm the OB predictive power as well as the tipping hypothesis. First, we remove the financial firms from our sample since could be suffering from sample bias and analysts' information contagion. Overall the results are found to be qualitatively and quantitatively the same. Second, we perform the same analysis by adopting only the ISE signed volume data by customers. Also in this case, the results are not affected. Third, we filter our options pool by only limiting our sample to volume from options with maturity less than 30 or less than 90 days. The results, once again, appear to be robust. Finally, we also change our fixed effects specification including broker-year fixed effect, industry-year fixed effect, or quarterly fixed effect. The main results of the paper remain unchanged.[17]

[17]The whole set of robustness checks and empirical results is available from the authors upon request.

Table 4: **Stock returns predictability around recommendations: downgrades**

Panel A	$h = 5$	$h = 4$	$h = 3$	$h = 2$	$h = 1$	$h = 0$
	(1)	(2)	(3)	(4)	(5)	(6)
OB (t)	0.1899*	-0.0617	0.1792	0.1750	0.0768	0.4585***
	(0.1121)	(0.1170)	(0.1394)	(0.1055)	(0.0985)	(0.1147)
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Obs	9,052	9,123	9,136	9,184	9,704	10,117
Adj-R2	0.1949	0.1983	0.2047	0.1994	0.2036	0.2137

Panel B	$h = 5$	$h = 4$	$h = 3$	$h = 2$	$h = 1$	$h = 0$
	(1)	(2)	(3)	(4)	(5)	(6)
OB (t)	0.1019	-0.1126	0.2415*	0.1393	0.0401	0.4117***
	(0.1144)	(0.1354)	(0.1299)	(0.1027)	(0.0993)	(0.1180)
ATM (t)	-1.8879***	-1.2478**	-1.6551***	-1.0040*	-1.6827***	-3.0431***
	(0.4442)	(0.4852)	(0.5019)	(0.5724)	(0.5442)	(0.7066)
SKEW (t)	0.8253	-0.7107	1.0851	-1.6403	-0.8683	1.2779
	(1.2104)	(1.2913)	(1.7163)	(1.8200)	(1.4682)	(1.4887)
SPREAD (t)	0.6476	1.0588	2.0428	1.6911	0.1734	-0.4202
	(1.4769)	(2.3722)	(2.0684)	(3.0231)	(2.3167)	(2.1522)
REV	-0.0274***	-0.0289***	-0.0240**	-0.0321***	-0.0322***	-0.0314***
	(0.0102)	(0.0092)	(0.0096)	(0.0099)	(0.0091)	(0.0090)
MOM	0.1142	0.3708	0.1889	0.1421	0.2246	0.1828
	(0.2680)	(0.2790)	(0.2978)	(0.2881)	(0.2609)	(0.2465)
MKT CAP (log)	-0.2309*	-0.1838	-0.1583	-0.2913**	-0.2411*	-0.3139**
	(0.1300)	(0.1227)	(0.1279)	(0.1214)	(0.1260)	(0.1282)
AF (log)	0.6935**	0.8630***	0.7621**	0.8314***	0.7155***	0.6952**
	(0.2819)	(0.2806)	(0.2938)	(0.2650)	(0.2646)	(0.2863)
IO (%)	0.4003	-0.0438	-0.0414	-0.0464	-0.1316	0.2368
	(0.4679)	(0.5147)	(0.5240)	(0.4904)	(0.4524)	(0.5020)
BM (log)	0.0067	0.0085	0.1342	0.0724	0.0899	0.0386
	(0.1204)	(0.1226)	(0.1167)	(0.1298)	(0.1218)	(0.1155)
BSIZE (log)	-0.2905***	-0.2569***	-0.2164***	-0.2226***	-0.2692***	-0.2598***
	(0.0387)	(0.0418)	(0.0402)	(0.0417)	(0.0416)	(0.0419)
EXPER (log)	-0.1786***	-0.2016***	-0.1709***	-0.1759***	-0.1723***	-0.1743***
	(0.0424)	(0.0452)	(0.0469)	(0.0441)	(0.0415)	(0.0445)
EF	-0.2583***	-0.1765*	-0.2573***	-0.2394***	-0.2682***	-0.3108***
	(0.0863)	(0.0908)	(0.0886)	(0.0901)	(0.0926)	(0.0948)
TP	-0.2200*	-0.2951**	-0.1689	-0.2904***	-0.2801**	-0.2537**
	(0.1130)	(0.1150)	(0.1137)	(0.1077)	(0.1101)	(0.1033)
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Obs	7,720	7,797	7,803	7,821	8,269	8,646
Adj-R2	0.2176	0.2154	0.2187	0.2240	0.2232	0.2441

Notes: This table presents pooled cross-sectional regressions where the dependent variable is the four-factor adjusted stock return on the analysts' announcement day being a recommendation to downgrade. OB is the ISE open buy ratio, IV is the ATM implied volatility, $SKEW$ is the implied volatility skew Xing et al. (2010), $SPREAD$ is the call-put implied volatility spread Cremers and Weinbaum (2010), REV is the stock return weekly reversal, MOM the firm momentum, $MKTCAP$ is the firm market cap (log), AF is the number of analyst following stock i (log), IO is the institutional ownership (in percentage), BM is the firm book-to-market (log), $SIZE$ is the broker size (log), and AFE is the analyst firm experience (log). EF and TP are dummy variables for taking into account, respectively, confounding earning forecast announcements and target price announcements over the same days. Robust standard errors clustered by time and firm are reported in parentheses. ***, **, * indicate significance level at the 1%, 5%, and 10%, respectively. The last rows report the number of observation and the adjusted-R^2. Our sample is from May 2005 to June 2021.

6 Further testing the tipping hypothesis

6.1 Recommendation revisions

In order to validate the tipping hypothesis, in this subsection we test the predictive role of the directional option volume for recommendation revision taken as dependent variable. We employ an ordered probit model to examine whether OB plays any informational role on upcoming recommendation revisions. We define an analyst's recommendation revision for stock i at time t as follows:

$$REC\_REV_{i,t} = \begin{cases} +2 & \text{if recommendation change } = +2, +3, \text{ or } +4 \\ +1 & \text{if recommendation change } = +1 \\ -1 & \text{if recommendation change } = -1 \\ -2 & \text{if recommendation change } = -2, -3, \text{ or } -4 \end{cases}$$

$$REC\_CHANGE_{i,t} = \beta_{OB} OB_{i,t-h} + \beta_i CONTROLS_{i,t-h} + YearFE + FirmFE + \epsilon_{i,t}, \quad (3)$$

where $REC\_CHANGE_{i,t}$ is the dependent continuous random variable being the recommendation revisions, $OB_{i,t-h}$ is the key variable of interest, and $CONTROLS_{i,t-h}$ is a vector of control variables as defined earlier. We run the model including year and firm fixed effects.

Table 5 presents the results of the linear probability model for both recommendation revisions. In the first columns (1) and (2), we show the results for the OB weekly averages in the 10 to 6, and 5 to 1-days before the event day, respectively. We confirm a significant and positive estimate on OB only in the week exactly before the event day for recommendation revisions.

In columns from (3) to (8), in both panels, we present the results specifically for the five days before the event day. We observe that OB is positively and significantly related to recommendation changes with higher coefficient and significance level found on the day before ($h = 1$) and event day ($h = 0$). The results suggest that an increase in the pre-event OB increases the probability that an analyst tend to upgrade the stock i in the event day. OB is also significant (at the 5% level) four and two days before the revision, however the coefficient magnitude associated is about half of the one found on the day before. This implies that, for instance, there is a 7.5% probability that an increase in OB two days before the event would lead to an analyst's upgrade in the stock i, whereas a probability of 13.2% that the same happens due to an increase in OB the day before the event. The results are still robust after we control for several additional variables related to options and stock market information. Therefore, the results provide evidence for the analyst tipping hypothesis, consistent with previous studies (e.g. Irvine et al., 2007; Lin and Lu, 2015).

Table 5: **Recommendation revisions predictability**

Recommendation Revisions

	(1) $h \in [10, 6]$	(2) $h \in [5, 1]$	(3) $h = 5$	(4) $h = 4$	(5) $h = 3$	(6) $h = 2$	(7) $h = 1$	(8) $h = 0$
OB [t0,t1]	0.0198	0.1610***	0.0149	0.0807**	0.0365	0.0744**	0.1316***	0.2270***
	(0.0456)	(0.0442)	(0.0351)	(0.0356)	(0.0292)	(0.0305)	(0.0333)	(0.0339)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Obs	20,112	20,491	16,016	16,170	16,192	16,257	17,174	17,972
Adj-R2	0.0352	0.0376	0.0340	0.0331	0.0367	0.0348	0.0352	0.0362

Notes: This table presents pooled cross-sectional regressions where the dependent variable is the recommendation revision. OB is the ISE open buy ratio, and the controls are as in the previous analysis. Robust standard errors clustered by time and firm are reported in parentheses. ***, **, * indicate significance level at the 1%, 5%, and 10%, respectively. The last rows report the number of observation and the adjusted-R^2. Our sample is from May 2005 to June 2021.

6.2 The role of top brokers

In this subsection, we investigate the information content of the *OB* ratio when linked to recommendations issued by top brokers.[18] If options traders are found to be tipped, then we would expect them to trade on this private information when this is more credible as issued by top brokers, and therefore this would move the market to a bigger extent. First, we notice that abnormal returns around recommendations issued by top brokers, both upgrades or downgrades, are higher than recommendations issued by non-top broker (see Figure B1 in Appendix). Second, we run pooled panel regression models as in equation 5, where the sample is now divided into recommendations from top brokers and non-top brokers. The variable of interest is the *OB* ratio, the controls included are as before, and we run the models with year and firm fixed effects. The results are presented in Table 6, for top brokers (Panel A) and non-top brokers (Panel B).

When we look at the regression models presented in column (1), we find that the weekly average *OB* ratio is still found positively and significant in predicting the post-event returns, being a recommendation issued by both top and non-top brokers. Interestingly, we observe that the average coefficient for the *OB* ratio over the week before the recommendation from a top broker is almost double the one associated with a recommendation day from a non-top broker. This implies that the information content of the directional option volume before a recommendation coming from a main broker has a greater predictive role for future post-event returns.

When we focus the attention on each of the days before the event, we confirm that the *OB* significance is mainly found one day before or the event day for recommendations from both top brokers and non. However, we notice that every time the *OB* coefficient is found significant, the magnitude of the coefficient of *OB* associated with top brokers' recommendations is greater than the one associated with non-top brokers. Overall, the

[18] The list of top brokers includes Goldman Sachs, Bank of America, JPMorgan Chase, Morgan Stanley, Barclays, Deutsche Bank, Wells Fargo, Citigroup, UBS, Bear Stearns, and Lehman Brothers (the last two ceased to exist after 2008).

findings suggest that the information content enclosed in the directional option volume is stronger when the recommendations are issued by top brokers. In addition, we can also conclude that the tipping hypothesis appears to be more evident for top brokers compared to non-top brokers.

Table 6: **Stock returns predictability around top brokers vs non-top brokers recommendations**

Panel A: Top Brokers

	(1) $h \in [5,1]$	(2) $h=5$	(3) $h=4$	(4) $h=3$	(5) $h=2$	(6) $h=1$	(7) $h=0$
OB [t0,t1]	0.7719***	0.4743**	0.0216	0.2303	0.2934*	0.4613***	1.1001***
	(0.2121)	(0.1970)	(0.1860)	(0.1755)	(0.1534)	(0.1592)	(0.1722)
Controls	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Obs	6,513	5,091	5,087	5,161	5,163	5,463	5,764
Adj-R2	0.1032	0.1148	0.1143	0.1136	0.1162	0.1132	0.1289

Panel B: Non-Top Brokers

	(1) $h \in [5,1]$	(2) $h=5$	(3) $h=4$	(4) $h=3$	(5) $h=2$	(6) $h=1$	(7) $h=0$
OB [t0,t1]	0.4370***	0.1444	0.0768	0.1785	0.1381	0.3232***	0.6096***
	(0.1351)	(0.1139)	(0.1219)	(0.1190)	(0.0971)	(0.1131)	(0.1055)
Controls	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Obs	13,978	10,925	11,083	11,031	11,094	11,711	12,208
Adj-R2	0.1015	0.1044	0.1019	0.1126	0.1141	0.1077	0.1273

Notes: This table presents pooled cross-sectional regressions where the dependent variable is the four-factor adjusted stock return on the analysts' announcement day being either a recommendation to upgrade or downgrade. In Panel A we present the results for recommendations from top brokers, whereas in Panel B from non-top brokers. OB is the ISE open buy ratio, and the control variables included are as defined before. Columns (1) in both Panels report the regression results for the model in which the coefficients and standard errors of OB are averaged across the week before the event day ($[-5,-1]$). Robust standard errors clustered by time and firm are reported in parentheses. ***, **, * indicate significance level at the 1%, 5%, and 10%, respectively. The last rows report the number of observation and the adjusted-R^2. Our sample is from May 2005 to June 2021.

6.3 Value vs. growth stocks

Another test to further validate our tipping hypothesis is to compare the predictability results when the sample is divided into high book-to-market stocks (value stocks) and low book-to-market stocks (growth stocks). The former are generally larger stocks, more well-established, and stable companies which are considered to be underpriced based on their fundamentals. Hence, we would expect that option traders would be more likely to exploit any private information with respect to a value stock, therefore this leading to a greater tipping channel for value stocks.

Table 7 presents the empirical results with respect to this exercise. When we look at the regression models presented in column (1), we find that the weekly average OB ratio is still found positively and significant in predicting the post-event returns for both value and growth stocks. However, the average coefficient associated with value stocks appear to be larger, suggesting that the predictability of the OB ratio is stronger within the value stocks sample. During the days before the recommendation event, we observe that OB is found to be significant on the dat of the event ($h = 0$) for both value and growth stocks. However, it is striking to see that, on the day before the event, the stronger significance is associated with the OB of value stocks, this showing both a larger positive coefficient (0.49 vs 0.20) and also a larger statistical significance (1% vs 10%) compared to the coefficient of growth stocks. These additional results still confirm that the OB predictability uncovered on the day before the recommendation event appears to be associated with a tipping channel.

Table 7: **Stock returns predictability for value stocks vs growth stocks recommendations**

Panel A: Value stocks

	(1) $h \in [5, 1]$	(2) $h = 5$	(3) $h = 4$	(4) $h = 3$	(5) $h = 2$	(6) $h = 1$	(7) $h = 0$
OB [t0,t1]	0.6517***	0.3723**	0.1228	0.2944	0.1515	0.4931***	0.9123***
	(0.1880)	(0.1767)	(0.1226)	(0.1884)	(0.1514)	(0.1250)	(0.1523)
Controls	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Obs	8,374	6,480	6,547	6,536	6,637	7,067	7,462
Adj-R2	0.1015	0.1050	0.1014	0.0980	0.1003	0.1114	0.1244

Panel B: Growth stocks

	(1) $h \in [5, 1]$	(2) $h = 5$	(3) $h = 4$	(4) $h = 3$	(5) $h = 2$	(6) $h = 1$	(7) $h = 0$
OB [t0,t1]	0.4417***	0.0687	0.1118	0.0869	0.0975	0.2035*	0.7596***
	(0.1570)	(0.1406)	(0.1352)	(0.1255)	(0.1062)	(0.1116)	(0.1204)
Controls	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Obs	11,610	9,536	9,623	9,656	9,620	10,107	10,510
Adj-R2	0.1155	0.1217	0.1164	0.1174	0.1211	0.1179	0.1299

Notes: This table presents pooled cross-sectional regressions where the dependent variable is the four-factor adjusted stock return on the analysts' announcement day being either a recommendation to upgrade or downgrade. In Panel A we present the results for recommendations for value stocks (above median book-to-market), whereas in Panel B for growth stocks (below median book-to-market). OB is the ISE open buy ratio, and the control variables included are as defined before. Columns (1) in both Panels report the regression results for the model in which the coefficients and standard errors of OB are averaged across the week before the event day ($[-5, -1]$). Robust standard errors clustered by time and firm are reported in parentheses. ***, **, * indicate significance level at the 1%, 5%, and 10%, respectively. The last rows report the number of observation and the adjusted-R^2. Our sample is from May 2005 to June 2021.

6.4 Options volume and target prices

Finally in this subsection, we focus on the role of the predictive power of OB for abnormal returns around target prices announcements over our sample period. More specifically, we are interested in a more directional understanding of the predictability coming from the options markets in predicting returns around target prices updates.

A target price is a concise and explicit estimate of the analyst's expectation of the future value of a stock, typically over a 12-month horizon. A target price, therefore, reflect the analyst's opinion regarding the firm's expected value. Target prices are quoted regularly in the financial news media, and they have become more prevalent in recent years (e.g. Brav and Lehavy, 2003; Gleason et al., 2013; Ho et al., 2021). Evidence shows that they contain distinct information over and above earnings forecasts and recommendations (see Brav and Lehavy, 2003; Asquith et al., 2005; Bradshaw et al., 2013). Despite that, they have been largely ignored by the academic literature, with more limited attention compared to earnings forecasts and recommendations Bradshaw (2011).

Perhaps, the underlying reason is that target prices have been found to be persistently optimistic, erroneous and analysts are not able to systematically provide accurate target prices (see Asquith et al., 2005; Bonini et al., 2010; Bilinski et al., 2013; Bradshaw et al., 2013; Bilinski et al., 2019; Bradshaw et al., 2019; Dechow and You, 2020). In addition, analysts do not seem to devote as much effort as they do with other outputs.[19] Finally, anecdotal evidence suggests that practitioners and investors are quite skeptical and often ignore target prices.[20] Given the mixed views on target prices, the option market offers a unique opportunity to re-examine the information content of target prices.

[19] For example, the survey by Brown et al. (2015) that seeks to penetrate the analysts' "black box"—i.e., to provide insights into analysts' inputs and compensation incentives— is focused exclusively on earnings forecast and recommendations and ignores target prices.

[20] See, for example, an article by Barron's, June 28, 2019, "Do Wall Street Stock Price Targets Really Matter? What Investors Need to Know" https://www.barrons.com/articles/wall-street-analyst-stock-price-targets-51561597085; and an article in the Real Money, Jan 23, 2021, "Price Targets: How They Mislead and How They Can be Used" https://realmoney.thestreet.com/investing/price-targets-how-they-mislead-and-how-they-can-be-used-15546017.

Given the mixed views on target prices, the option market offers a unique opportunity to re-examine the information content of target prices. This is because option markets' participants are typically more sophisticated, compared to their stock market counterparts and thus, more competent processors of information. Therefore, documenting that the option market reacts to the announcement of target prices, would add significant empirical evidence that target prices indeed contain valuable material information. In addition, if the option market reaction also anticipates the announcement of target prices will reinforce the view that target prices are not largely ignored by investors.

From Table 8, we observe that the OB ratio is found to be significant to predict future returns after a target price update in the univariate regression framework in Panel A, and this predictability is still found to be placed mostly on the day before and on the day of the announcement. When we control for other variables, in Panel B, we still find that the predictability of OB holds robust, positive and significant at the 1% level both on the day before and on the day of the announcement. This additional test corroborates our previous results and shows additional evidence of potential tipping also before target price updates.

Table 8: **Stock returns predictability around all target price announcements**

	ALL TARGET PRICES						
Panel A							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	[-5,-1]	t = -5	t = -4	t = -3	t = -2	t = -1	t = 0
OB (t)	0.0929	0.0149	-0.0210	0.0356	0.0371	0.1269***	0.5444***
	(0.0637)	(0.0428)	(0.0402)	(0.0456)	(0.0473)	(0.0363)	(0.0476)
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES
Observations	112,707	88,707	88,684	89,258	89,981	95,073	95,946
Adjusted R-squared	0.0617	0.0666	0.0694	0.0662	0.0700	0.0711	0.0750

Panel B							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	[-5,-1]	t = -5	t = -4	t = -3	t = -2	t = -1	t = 0
OB (t)	0.0898	0.0287	0.0022	0.0198	0.0212	0.1357***	0.4996***
	(0.0720)	(0.0492)	(0.0455)	(0.0526)	(0.0472)	(0.0397)	(0.0514)
ATM (t)	0.4758*	0.5798*	0.5527*	0.5351	0.4825	0.5428*	-1.1387***
	(0.2833)	(0.3311)	(0.3017)	(0.3291)	(0.3092)	(0.2795)	(0.2612)
SKEW (t)	0.5773	0.2011	0.4128	0.3117	0.5601	0.2724	2.8241***
	(0.4433)	(0.4589)	(0.4379)	(0.4115)	(0.4605)	(0.4018)	(0.6494)
SPREAD (t)	1.4071**	-0.1252	-0.1563	0.4715	1.2447**	1.9077***	-0.6005
	(0.6718)	(0.5200)	(0.6028)	(0.6741)	(0.6078)	(0.6917)	(0.9358)
REV	-0.0145**	-0.0227***	-0.0195***	-0.0167**	-0.0156**	-0.0144**	-0.0178***
	(0.0061)	(0.0071)	(0.0061)	(0.0070)	(0.0063)	(0.0061)	(0.0057)
MOM	0.3680**	0.3499**	0.3908**	0.3619**	0.3615**	0.3278**	0.3747**
	(0.1603)	(0.1493)	(0.1647)	(0.1736)	(0.1636)	(0.1511)	(0.1623)
MKT CAP (log)	-0.3453***	-0.2890***	-0.3435***	-0.3293***	-0.3343***	-0.3289***	-0.4711***
	(0.0593)	(0.0651)	(0.0664)	(0.0648)	(0.0613)	(0.0643)	(0.0647)
AF (log)	-0.1184	-0.2241*	-0.1359	-0.1754	-0.0911	-0.1152	-0.1378
	(0.1022)	(0.1174)	(0.1270)	(0.1232)	(0.1179)	(0.1109)	(0.1270)
IO (%)	-0.4212*	-0.4658	-0.4320	-0.4030	-0.5417*	-0.4459*	-0.4727
	(0.2479)	(0.3010)	(0.2699)	(0.2823)	(0.2859)	(0.2389)	(0.2978)
BM (log)	-0.0543	-0.0204	-0.0541	-0.0239	-0.0295	-0.0224	-0.0484
	(0.0475)	(0.0502)	(0.0518)	(0.0517)	(0.0525)	(0.0513)	(0.0489)
BSIZE (log)	-0.0018	0.0089	0.0038	0.0146	0.0058	0.0070	0.0086
	(0.0108)	(0.0108)	(0.0125)	(0.0120)	(0.0113)	(0.0121)	(0.0121)
EXPER (log)	0.0204*	0.0309***	0.0209*	0.0286**	0.0176	0.0142	0.0218*
	(0.0114)	(0.0114)	(0.0117)	(0.0122)	(0.0122)	(0.0124)	(0.0126)
EF	-0.0809**	-0.0569	-0.0588*	-0.0530*	-0.0832**	-0.0850**	-0.0852**
	(0.0325)	(0.0345)	(0.0309)	(0.0305)	(0.0347)	(0.0337)	(0.0356)
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES
Observations	97,716	76,718	76,733	77,246	77,859	82,271	82,992
Adjusted R-squared	0.0693	0.0753	0.0784	0.0743	0.0788	0.0791	0.0860

Notes: This table presents pooled cross-sectional regressions where the dependent variable is the four-factor adjusted stock return on the day of the analysts' target price update. OB is the ISE open buy ratio, IV is the ATM implied volatility, $SKEW$ is the implied volatility skew Xing et al. (2010), $SPREAD$ is the call-put implied volatility spread Cremers and Weinbaum (2010), REV is the stock return weekly reversal, MOM the firm momentum, $MKTCAP$ is the firm market cap (log), AF is the number of analyst following stock i (log), IO is the institutional ownership (in percentage), BM is the firm book-to-market (log), $SIZE$ is the broker size (log), and AFE is the analyst firm experience (log). EF and TP are dummy variables for taking into account, respectively, confounding earning forecast announcements and target price announcements over the same days. Robust standard errors clustered by time and firm are reported in parentheses. ***, **, * indicate significance level at the 1%, 5%, and 10%, respectively. The last rows report the number of observation and the adjusted-R^2. Our sample is from May 2005 to June 2021.

7 Conclusion

In this paper we examine the information content of option trading volume by exploiting the directionality of trades in relation to calls and puts. We study whether this directional measure carries any predictive ability for future stock returns around analysts' recommendation announcements.

By adopting the ISE database on directional option trading volume measures, we find that a measure of option order flow related to open buy (OB) is more informative in predicting stock returns around such events. In particular, option volume is found to be more informative on both news days and the days before. We observe that the call-put option trading volume ratio peaks (drops) in the days before the analysts' news day related to an upgrade (downgrade), reaching its maximum value on the news day. Moreover, high OB predicts high absolute cumulative abnormal returns (CARs) in the pre-announcement week. Specifically, OB on the day before the announcement and on the event day is found to be positively and more strongly associated with the future stock returns.

Interestingly, we uncover evidence that options traders are executing orders in the right direction for the upcoming analysts' revisions, with greater predictability being associated with upgrades. These findings are consistent with informed trading in the options market prior to analysts' announcements. Our results are corroborated by a rich set of robustness checks, control variables associated with the stocks and options markets, and changes in the specification of our measures. Overall, our results validate the prevailing tipping hypothesis in the literature shedding new light from a directional option trading volume perspective to confirm and enhance previous important findings and hypotheses in the financial analysts literature.

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Appendix

Appendix A Variables definitions

- OB: the open buy put-call volume ratio defined as:

$$OB_{i,t} = \frac{PB_{i,t}}{PB_{i,t} + CB_{i,t}}$$

  where PB_{tt} and $CB_{i,t}$ are the numbers of put and call contracts purchased by non-market makers to open new positions on date t and for stock i (see Weinbaum et al., 2022).

- OS: the open sell put-call volume ratio defined as:

$$OS_{i,t} = \frac{PS_{i,t}}{PS_{i,t} + CS_{i,t}}$$

  where PB_{tt} and $CB_{i,t}$ are the numbers of put and call contracts sold by non-market makers to open new positions on date t and for stock i (see Weinbaum et al., 2022).

- IV: is the average of the ATM call and put implies volatilities. OptionMetrics computes implied volatilities using a binomial tree, taking into account discrete dividend payments and the possibility of early exercise and using historical LIBOR/Eurodollar rates for interest rate inputs.

- $SPREAD$: Volatility Spread (SPREAD): following Bali and Hovakimian (2009) and Cremers and Weinbaum (2010), the implied volatility spread is computed as the difference between the at-the-money call implied volatility (with delta of 0.50) and at-the-money put implied volatility (with delta of -0.50), using options with maturity of 30 days.

- $SKEW$: following Xing et al. (2010), we define the implied volatility skew as the difference between the out-of-the-money put implied volatility (with delta of -0.20) and at-the-money call implied volatility (with delta of 0.50), both using maturities of 30 days.

- MOM_F: the firm momentum computed as the six month buy-and-hold abnormal return (FF4) prior to the event i.e., computed over the period [-125, -5] (day 0 the event day).

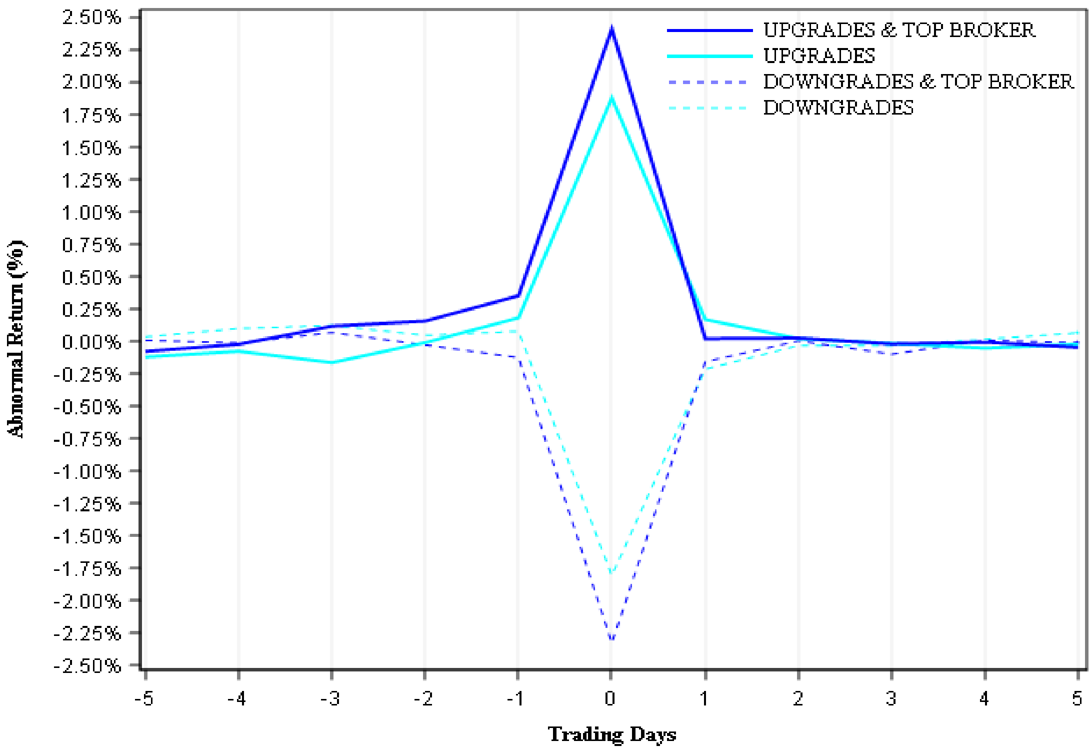
- $SIZE$: the natural logarithm of the firm market value of equity at the end of the last fiscal quarter prior to the release of the announcement.

- AF: the number of analyst following taken as the log of one plus the number of analysts that issued at least one earnings forecast for the firm prior to the release of the announcement.

- IO: the institutional ownership taken as percentage of shares held by institutional shareholders measured at the end of the last calendar quarter before the release of the announcement.
- BM: the book-to-market taken as the log of the book value of equity divided by its market value at the end of the last quarter before the release of the announcement.
- BS: the broker size taken as the log of one plus the number of analysts employed by the brokerage firm in the last 12-month period.
- AFE: the analyst firm experience taken as the log of one plus the number of quarters the analyst has been issuing earnings forecasts for the specific firm.

Appendix B Additional results

Figure B1: **Abnormal returns around top brokers' recommendations**



Notes: This figure shows daily abnormal stock market returns (AR) for firms that experience a change (day 0) in the consensus analysts' recommendation (upgrades or downgrades) from a top broker over the $[-5, +5]$ event window (where day 0 is the analysts' recommendation day). The figure presents the values in the vertical line and the trading days in the horizontal line. Our sample is from May 2005 to June 2021.