Analyst Tipping: New Evidence from Directional Options Trading Volume and FINRA Rule 2241*

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Abstract

We study the predictive information content of directional options trading volume for stock returns following analyst recommendations. We observe that options volume related to open buy positions is particularly informative immediately before the announcement day, in line with the prevailing tipping hypothesis. Moreover, following the implementation of FINRA Rule 2241 in December 2015, aimed at curtailing tipping practices, our difference-in-differences approach reveals the curbing of analyst tipping in subsequent years. Our findings remain robust across sub-samples, additional tests, and after accounting for several control variables.

Keywords: Option Trading; Option Signed Volume; Analyst Recommendation; Analyst Tipping; FINRA Rule 2241.

JEL classification: G1, G12, G14, G24, G28.

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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. This predictability is primarily attributed to investors exploiting valuable private information in options markets, particularly during unscheduled events including analyst recommendation revisions.[1] In these cases, the predictability has been usually linked to the *tipping* hypothesis, suggesting information leakage to investors about upcoming revisions.[2] In this paper, our objective is twofold. First, we provide new insights into this predictability channel by adopting a novel dataset of directional (long and short) option trades. Second, we aim to assess the impact of the FINRA (Financial Industry Regulatory Authority) Rule 2241 implemented in 2015 with a specific provision to address tipping practices.[3]

Investors can earn profits in many ways. They can profit from unexpected deviations from public forecasts attributed partially to their forecasting abilities. Additionally, they can profit from possessing private or privileged information. While trading on such information is often illegal, market participants may still have incentives to trade based on that information. Generally, the options market is recognized as the preferred trading venue for informed investors who possess such privileged information about the underlying asset due to its advantages including leverage, hedging, and the absence of shorting constraints (see, e.g. Black, 1975; Easley et al., 1998; Pan and Poteshman, 2006; Johnson and So, 2012; Bondarenko and Muravyev, 2022).

These options characteristics render options-based measures, such as options volume, to be

[1]An incomplete list of related studies includes, see, e.g. Jin et al. (2012), Johnson and So (2012), Hayunga and Lung (2014), Chan et al. (2015), Ge et al. (2016), and Weinbaum et al. (2022).

[2]See, for instance, Irvine et al. (2007), Christophe et al. (2010), Lung and Xu (2014), Lin and Lu (2015), Markov et al. (2017), Kadan et al. (2018).

[3]FINRA governs research analysts' activities in the United States especially establishing standards for the interactions between research analysts and other personnel within a brokerage firm or investment bank, and ensuring the objectivity and independence of research analysts and to prevent conflicts of interest.

strong predictors of stock returns, especially on days with news arrivals. In general, trading on private information is most profitable ahead of stock price jumps where asymmetric information is prevalent (see Kim and Verrecchia, 1994). However, recent 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. The purchases of options are informative on news days and ahead of unscheduled events but not before scheduled events, such as earnings announcements (see Weinbaum et al., 2022).[4] Unscheduled events are, in fact, more likely to be associated with private information.

Analyst recommendation revisions are relatively frequent unscheduled announcements, that can trigger market reactions, thereby offering opportunities for investors to achieve abnormal returns either from their superior set of skills or, more notably, the leakage of privileged information. Indeed, prior literature provides extensive evidence that aggregate options trading volume leads the stock market movements ahead of analysts' recommendations (e.g. Hayunga and Lung, 2014; Lung and Xu, 2014; Lin and Lu, 2015). The prevailing explanation for this predictive channel aligns with the tipping hypothesis (e.g. Irvine et al., 2007; Christophe et al., 2010; Lin and Lu, 2015; Kadan et al., 2018). Nonetheless, empirically identifying informed trading activity is a challenging task. This becomes even more cumbersome in the options market due to the complexities related to additional layers or information associated with underlying stocks, strike prices, maturities, options strategies, and the adoption of options for speculation (e.g. Augustin and Subrahmanyam, 2020).

While it has been shown that aggregate measures of option volumes have a significant association with future analysts recommendations (e.g. Hayunga and Lung, 2014; Lin and Lu, 2015),

[4]According to Weinbaum et al. (2022), the difference between scheduled and unscheduled announcements is reflected in the implied volatility features. Implied volatilities are known to increase before 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.

when working with option volume data which aggregates investors positions on both calls and puts, the predictability channel may be off-set.[5] Building upon this context, our paper seeks to contribute additional evidence regarding the predictive power of options trading volume around analyst recommendations, particularly its ability to forecast stock returns via the tipping channel. To do so, we exploit a 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 for both calls and puts. This database allows us to extend previous literature which has looked at the (aggregate) role of options trading volume before news arrivals by uncovering a clearer pattern on the role of investors' preferences and informed trading around analysts' announcements. Our variable of interest is the directional open buy call-put volume (OB) ratio constructed as the ratio between the numbers of call and put contracts purchased by non-market makers to open new positions, similar to Pan and Poteshman (2006) and Weinbaum et al. (2022). The directionality of the options trades on each type of contract allows us to discern whether trades correspond with the direction of upcoming returns from recommendation revisions, thereby providing further evidence to accurately validate the analyst tipping hypothesis.

Analyzing a sample of recommendation revisions from May 2005 to June 2021, we observe that the OB ratio increases (decreases) in the days leading up to analyst recommendation upgrades (downgrades), attaining its highest (lowest) value on the day of the announcement. Next, we empirically document that the directional options trading volume ratio, OB, positively forecasts the two-day cumulative abnormal returns ($CAR[0, +1]$) tied to the recommendation announcement,

[5]For instance, options investors would purchase a call (put) or sell a put (call) options before an unscheduled events when their expectations on the future stock market price are bullish (bearish) or they possess some private valuable information (e.g. Buraschi and Jiltsov, 2006; Han, 2008). Additionally, an optimistic investor can choose to buy calls or sell puts, whilst a pessimistic investor to buy puts or sell calls. Overall, when working with option trading aggregated volume, investors' positions on both calls and puts are aggregated, and the channels at work might be off-set or blurred.

in the week leading up to the announcement. Notably, when we zoom into the pre-announcement week, we consistently document a significant positive relationship between OB on the day preceding the recommendation announcement and subsequent stock returns. Hence, we uncover evidence that options traders are executing orders in the right direction for the upcoming analysts' revisions. In addition, using an ordered probit model, our analysis shows that OB predicts not only the future returns of recommendations but also the direction and magnitude of these revisions. Such findings validate the presence of tipping practices prior to analyst recommendation changes.

We then assess the effectiveness of FINRA Rule 2241 in curbing tipping practices. Specifically, Rule 2241(g) mandates that financial firms are required to create, uphold, and enforce policies and procedures aimed at preventing selective distribution of research reports to certain traders or customers ahead of others who are also entitled to receive such reports. While guidelines for selective dissemination of research existed previously, the 2007-2008 global financial crisis underscored the need for formal codification, a process highlighted in the 2008 proposal (FINRA Regulatory Notice 08-55). Despite the proposal, incidents of guideline violations occurred.[6] These guidelines were formally codified for the first time in December 2015 through the enactment of Rule 2241 (e.g. Markov et al., 2017).

Employing a difference-in-differences approach for the years 2013-2017 and using all other non-analyst unscheduled events as a control sample, we observe a halt in the predictive power of the OB ratio. Further analysis indicates that, in the period following the rule implementation, the OB ratio does not predict future recommendation returns. Our results show that Rule 2241 has been effective in curbing the systematic tipping practice in the post-regulation period. Our

[6]For example, in 2009, Goldman Sachs provided "trading ideas" on a variety of stocks to a select group of top clients. Similarly, in 2014, Citigroup organized "idea dinners" attended by some of its institutional clients and trading personnel. For further details, refer to Section 2.

findings are robust to sub-sampling exercises, additional analyses including a placebo test, and the inclusion of several control variables accounting for other option markets measures, firm-specific and analyst characteristics, and concurrent information.

In this paper, we combine several strands of literature to explore the analyst tipping hypothesis. Unlike previous research adopting aggregate volume measures, we employ directional options trading volume around analyst announcements to more precisely pinpoint the tipping channel, ruling out potential alternative explanations. Importantly, the enactment of Rule 2241 provides a quasi-experimental framework that strengthens our investigation. Our findings offer direct, causal evidence of prior information leakage from analysts, thereby reinforcing the validity of the tipping hypothesis. In addition, our evidence in the analysts' domain, contributes to the ongoing academic debate on the predictive information content of the options market for stock returns (see, e.g. Cremers and Weinbaum, 2010; Xing et al., 2010; Lin and Lu, 2015; Goncalves-Pinto et al., 2020).

Our study contributes to the literature examining information content in the options market, especially on options trading volume, around both scheduled (e.g. Jin et al., 2012; Ge et al., 2016; Weinbaum et al., 2022) and unscheduled corporate events (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).[7] Furthermore, 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).[8]

[7]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. Weinbaum et al. (2022) looked at both unscheduled and scheduled events.

[8]We are also linked to the more general literature on the lead-lag relation between the option and stock markets and on the stock returns predictability by exploiting information extracted from the option market (see Pan and Poteshman,

Our work also extends the literature that examines the phenomenon of information leakage from analysts, especially on the practice of tipping option traders and its relationship with the regulatory environment (see Irvine et al., 2007; Hayunga and Lung, 2014; Lung and Xu, 2014; Lin and Lu, 2015; Markov et al., 2017; Kadan et al., 2018; Wang et al., 2022; Bondarenko and Muravyev, 2022). Finally, we answer calls from the literature for evaluating the efficacy of Rule 2241 in preventing selective tipping practices (e.g. Markov et al., 2017). We thus contribute to the general body of research investigating impact of regulatory changes on analyst activities, such as the NASD Rule 2711 and NYSE Rule 472 (e.g. Barber et al., 2006; Barniv et al., 2009; Chen and Chen, 2009; Kadan et al., 2018; Guan et al., 2012; Corwin et al., 2017), and MiFID II directive (e.g. Fang et al., 2020; Guo and Mota, 2021; Lang et al., 2023). Therefore, our evidence has regulatory implications, being particularly relevant for regulators in their ongoing process to enhance the integrity and efficiency of capital markets.

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 data employed and variables measurement. Section 4 reports the empirical findings related to the tipping hypothesis. Section 5 presents the results related to the difference-in-difference analysis around the FINRA Rule 2241. Section 6 concludes the paper. Supplementary results are relegated to the paper Appendix.

2 Theoretical background

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 (see, e.g. Black, 1975;

2006; Cremers and Weinbaum, 2010; Xing et al., 2010; Johnson and So, 2012; An et al., 2014; Weinbaum et al., 2022, among others).

Easley et al., 1998; Chakravarty et al., 2004; Pan and Poteshman, 2006; Boyer and Vorkink, 2014). It is also well-known that options are used for hedging positions and preferred given the absence of short selling constraints (see, e.g. Black, 1975; Easley et al., 1998; Cao, 1999; Pan and Poteshman, 2006; Cao and Wei, 2010; Johnson and So, 2012; Bondarenko and Muravyev, 2022). Given these characteristics associated with the options market, we would expect the options market to be the venue where informed investors would trade about the underlying asset.[9] 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.[10] In this context, 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; Golez and Goyenko, 2022).[11]

As far as the analysts activity is concerned, analyst recommendations represent the culmination of their research activities, serving as their ultimate judgment of a stock and constituting their most significant output (e.g. Schipper, 1991; Barber et al., 2006). Existing empirical evidence demonstrates that announcements of analyst recommendation revisions have a considerable market impact and that recommendation upgrades (downgrades) are associated with positive (negative)

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

[10]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.

[11]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, 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.

stock returns on the day of the announcement (e.g. Womack, 1996; Francis and Soffer, 1997; Jegadeesh et al., 2004; Loh and Stulz, 2011; Bradley et al., 2014; Kecskés et al., 2017). Such a view is also shared by the US Security Exchange Commission (SEC).[12] Therefore, recommendation revisions constitute market-moving events that option traders could potentially exploit by trading in advance, provided they have foreknowledge of the forthcoming revisions.

In fact, a body of research has investigated trading patterns in the stock market around the time of analyst announcements. 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. Similar patterns have been observed in option trading, where option volume has been found to predict returns around analyst announcements (see Doran et al., 2010; Hayunga and Lung, 2014). Various studies have explored this phenomenon to determine if it aligns with the tipping hypothesis, among other alternative theories, aiming to clarify the relationship between analyst announcements and options trading (see Lung and Xu, 2014; Lin and Lu, 2015; Markov et al., 2017; Kadan et al., 2018). Overall, the prevailing view among these studies is that their results align with the tipping hypothesis, that is, analysts may share insights about forthcoming recommendation revisions with options traders, and this information leakage prior to analyst announcements influences trading activities and, thus, stock returns.[13]

In our paper, we shed new light on this prevailing tipping hypothesis and contribute to the above strands of the literature by exploiting a novel directional option volume database. Contrary

[12] For more information, see, for example `https://www.sec.gov/about/reports-publications/investor-publications/analyzing-analyst-recommendations`.

[13] In the literature, three primary hypotheses have been proposed to explain the interaction between analyst recommendations and options trading: (i) tipping, (ii) reverse tipping, and (iii) common information (see Lin and Lu, 2015). See subsection 5.3 for a more detailed discussion.

to the use of aggregate volume in previous research, the case for tipping becomes more evident when there is alignment between the direction of the pre-announcement option trading and post-announcement returns. This approach allows for a more accurate analysis, potentially uncovering more revealing evidence of information leakage ahead of analyst announcements. Our work aligns closely with the studies conducted by 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 directional option trading volume to study their information content about future stock prices around both scheduled and unscheduled corporate news announcements. They uncover a predictability pattern for open buy option trading on news days and ahead of unscheduled events. Thus, this theoretical background and previous studies motivate our first two hypotheses:

1) *informed investors trade in the options market exploiting their private information, therefore their signed trading volume should predict future equity returns.*

Put simply, the volume of long options (reflected in the open buy ratio) should convey information about future stock returns both in the period leading up to and on the days of analyst recommendation announcements. The second is that:

2) *the tipping channel is what most likely infers the predictability of option trading volume and future stocks returns around analysts' recommendations.*

2.1 Regulatory environment

In 2015 the SEC approved the new FINRA Rule 2241 (Research Analysts and Research Reports) that consolidates and expands upon the Self-Regulatory Organization (SRO) rules, i.e., NASD Rule 2711 and NYSE Rule 472. Rule 2241 was implemented in two stages with certain provisions becoming effective on September 25, 2015, and the rest on December 24, 2015. In general, the new rule retained the core provisions of the SRO rules, but expanded the requirements by imposing an overarching provision that requires members to establish, maintain and enforce written policies to identify and manage analyst conflicts of interest. Importantly, Rule 2241 introduces a new provision concerning the selective dissemination of research reports. Specifically, Rule 2241(g) mandates that firms must develop, implement, and uphold written policies and procedures that are reasonably designed to prevent the selective distribution of a research report to internal trading personnel or to a specific customer or group of customers ahead of other customers whom the firm has determined are eligible to receive the research report.[14] Prior to the implementation of Rule 2241, the practice of brokerages providing advance information about their recommendations to clients was not deemed illegal (see Markov et al., 2017; Kadan et al., 2018). Nonetheless, Rule 2241 represented the formal codification of pre-existing guidelines on the selective dissemination of research. Put differently, these guidelines were already effective prior to their formal codification in 2015, and explicitly mentioned in a 2008 proposal that ultimately led to Rule 2241.[15]

Brokerage firms engage in tipping practices because they have economic incentives and they

[14]For detailed information on the provisions of Rule 2241, please refer to the official FINRA Rulebook, accessible at: https://www.finra.org/rules-guidance/rulebooks/finra-rules/2241?rbid=2403&element_id=11946. Additionally, pertinent insights regarding this regulation can be found in FINRA's Regulatory Notice 15-30, available at: https://www.finra.org/rules-guidance/notices/15-30.

[15]See, Regulatory Notice 08-55, FINRA Requests Comment on Proposed Research Registration and Conflict of Interest Rules, published on October 14, 2008.

place a high value on their relationships with institutional clients. At least until the formal codification of these guidelines, there were instances where brokerage firms did not fully adhere to the principles of equitable information dissemination, or believed their actions were in compliant.[16] For instance, in 2009, Goldman Sachs distributed trading tips, termed "trading ideas", on several stocks to select top clients. During this period, other brokerage firms were similarly extending such trading insights.[17] The investigations into Goldman Sachs' trading "huddles" revealed a degree of uncertainty among Goldman analysts and others regarding the boundaries of permissible activities.[18] Another instance involved the "idea dinners" hosted by Citigroup Global Markets.[19]

Between 2005 and 2014, FINRA found that Citigroup did not fulfill its supervisory obligations in preventing the potential selective dissemination of non-public research to clients and its sales and trading staff. The discussion above indicates that before the implementation of Rule 2241, which formally codified the guidelines on selective dissemination, brokerage firms often did not adhere to these principles. Consequently, the impact of Rule 2241 is not immediately apparent, leading us to formulate our third hypothesis:

[16] We have no way to distinguish whether it is the analyst or someone else in the analyst's firm that may be tipping the institutions. Nor can we tell if an analyst's firm is aware that tipping occurs. We simply note that there are economic incentives for sell-side analysts to provide tips and that we find evidence consistent with its occurrence (see Irvine et al., 2007).

[17] For more details, see *The Wall Street Journal* article published on Aug. 24, 2009, "Goldman's trading tips reward its biggest clients" at https://www.wsj.com/articles/SB125107135585052521.

[18] Huddles referred to a practice at Goldman Sachs where research analysts convened to share their prime trading ideas with the firm's traders, who subsequently relayed these insights to a select group of premium clients. See, SEC Press Release, SEC Charges Goldman, Sachs & Co. Lacked Adequate Policies and Procedures for Research "Huddles", published on April 12, 2012, https://www.sec.gov/news/press-release/2012-2012-61htm.

[19] In November 2014, FINRA fined Citigroup Global Markets Inc. $15 Million for supervisory failures related to equity research and for involvement in IPO roadshows. Citigroup's failure to supervise certain communications by its equity research analysts involved, for instance, the so-called "idea dinners" hosted by Citigroup equity research analysts and attended by some of Citigroup's institutional clients and trading personnel. At these dinners, Citigroup research analysts discussed stock picks, which, in some cases, were inconsistent with the analysts' research. Despite the risk of improper communications at these events, Citigroup did not adequately monitor analyst communications or provide analysts with adequate guidance concerning the boundaries of permissible communications. See, FINRA News Release, FINRA Fines Citigroup Global Markets Inc. $15 Million for Supervisory Failures Related to Equity Research and Involvement in IPO Roadshows, published on November 24, 2014 https://www.finra.org/media-center/news-releases/2014/finra-fines-citigroup-15-million-failures-related-equity-research.

3) *if the tipping practice is the main predictability channel at work for stock returns around analysts' recommendations, the FINRA 2241 regulatory intervention aimed at curbing this practice should reduce, and ideally eliminate, such predictive ability.*

Documenting evidence supporting the effectiveness of Rule 2241 strengthens the tipping hypothesis, especially since the rule's implementation offers a quasi-experimental setting.

3 Data and variables measurement

We employ multiple databases. Directional options volume data are from the International Securities Exchange (ISE). Analyst recommendations, and related data are obtained from the Institutional Brokers' Estimate System (IBES). Other options related variables are computed using data from the OptionMetrics. Stocks returns and market data are collected from Center for Research in Security Prices (CRSP) and; institutional ownership information from Thomson Reuters (13F) Institutional Holdings; and accounting data from COMPUSTAT North America. The sample period for our study, dictated by the availability of options volume data from ISE, spans from May 2005 to June 2021. We provide more details on our data sources in the following subsections.

3.1 Abnormal stock returns

To assess the predictability of abnormal returns from option volume around analyst recommendations we conduct an event study. For this analysis, we compute the daily abnormal returns using the Fama and French five-factor model Fama and French (2015) augmented with the momentum factor Carhart (1997) namely, the Fama-French six-factor model (FF6). We focus on the two-day cumulative abnormal return starting on the recommendation release day, denoted as CAR

[0,+1]. Day 0 is the recommendation announcement day. In cases where the recommendation is announced after the market closes (at 16:00), we consider the following trading day as day 0 for our analysis. Finally, for estimating expected returns and deriving the factor loadings, we estimate the model with 256 daily returns in the estimation window [-260, -5].

3.2 Directional options volume data

ISE provides daily buy and sell trading volume for each option series, distinguishing between trades that open new option positions and those that close existing ones. We restrict the sample to include only individual equity options, dropping the options on exchange-traded funds (ETFs) and indexes. For each option, the 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 into four groups based on options market participants: customer, proprietary, professional customer, and broker/dealer.[20] In the main analysis of the paper, we adopt trading volume belonging to the customers and proprietary categories.[21] To examine option trading activity around analyst recommendations, we follow previous studies (see Pan and Poteshman, 2006; Weinbaum et al., 2022), and compute the daily directional open buy call-put

[20]The ISE data include volumes due to trades of both firm traders and public customers. Firm volumes are further broken down into proprietary and broker/dealer volumes. Regarding the difference among categories, for instance, according to the ISE documentation, if a retail trader enters an option order through a broker, the broker will designate the order as a customer order. When a member like Morgan Stanley or Goldman enters a trade on behalf of a large customer, institution or hedge fund, the trade is designated a customer trade. When a member like Morgan Stanley or Goldman enters a trade for their own account, the trade is designated as firm trade. Firm trades can be proprietary trades, executed on behalf of their own trading account or for another Broker/Dealer who is not a member of the exchange. A professional customer is a high-activity customer. We exclude broker/dealer from our analysis following Weinbaum et al. (2022).

[21]Robustness checks adopting different trading volume categories are reported in the paper Appendix.

volume ($OB_i(t)$) ratio as:

$$OB_i(t) = \frac{OB_i^C(t)}{OB_i^C(t) + OB_i^P(t)}$$

where $OB_i^C(t)$ and $OB_i^P(t)$ are the numbers of call and put contracts purchased by non-market makers to open new positions on date t and for stock i.[22] Here $t = -5, \ldots, -1, 0$ represents the trading day relative to the analyst recommendation announcement. We also compute a weekly variant of the directional OB ratio, by averaging the non-missing daily ratios separately over the two weeks preceding the analyst recommendation:

$$OB_i\left(t_{week}\right) = \overline{OB_i\left(t\right)}, \quad t_{week} = [-10, -6] \text{ or } [-5, -1]$$

The directionality of OB ratio is instrumental in assessing the predictability of stock returns in response to analyst recommendations. It allows us to verify whether the observed changes in option trading patterns align with the upcoming movements in stock returns.[23]

3.3 Analyst recommendations data

We extract data on analyst recommendation from IBES detail files. IBES employs a 5-tier rating system, where 1 represents "Strong Buy" and 5 denotes "Sell" (*ireccd* item). In line with previous literature, our focus is on recommendation revisions, as these are known to carry market-

[22] 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.

[23] According to Weinbaum et al. (2022), for unscheduled news events, long option strategies earn higher returns, whereas for scheduled news events, the returns on long (short) option positions are reduced (increased) due to the drop in implied volatility on the scheduled event date which affects option prices negatively. This would render the short option strategy more profitable, therefore suggesting that option traders would sell puts rather than buy calls ahead of scheduled news. Hence, a short option volume measure should predict returns before scheduled news. On the other hand, traders should prefer long option positions ahead of unscheduled news releases or on the news day itself. Given this background, we adopt long option volume as our main directional option trading variable as it is informative about future stock returns before unscheduled news and on news days.

moving information (e.g. Jegadeesh et al., 2004; Barber et al., 2007; Loh and Stulz, 2011). A recommendation is considered a change if the broker has either upgraded or downgraded the stock within the last two years. For instance, if an analyst currently issues a "Hold" recommendation (*ireccd* = 3) after previously recommending "Strong Buy" (*ireccd* = 1), it constitutes a downgrade.

3.4 Data matching and screening

Given that the main focus of our paper is on return predictability from option volume around analysts' announcements, our analysis is centered to options on individual stocks. We thus merge the ISE data with CRSP, and we restrict the sample to U.S. common stocks (CRSP share code 10 or 11).[24] Our central analysis targets the trading days in the week leading up to the recommendation announcement, as well as the announcement day itself, spanning $t = -5, \ldots, -1, 0$. We require non-missing ISE data, at least for days $t = -1$ and $t = 0$.

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 the recommendations from small potentially less influential brokers; ii) we remove stocks if their price is less than $5 during the period [-10,10] trading days; iii) we exclude recommendations if there is an earnings announcement within a window of [-5,+5] trading days around their release, where day 0 represents the recommendation announcement date; iv) we remove observations if there is a recommendation

[24]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.

for the same firm by a different analyst in the period [-5,+5] trading day window. Finally, we match the remaining analyst recommendation data with the option trading data from the ISE. This sample is then combined with data from COMPUSTAT and Thomson Reuters (13F) Institutional Holdings to construct the variables relevant for our multivariate analysis. These variables are discussed in detail in Appendix A. The sample selection procedure is outlined in Table B1 in Appendix B. Furthermore, the descriptive statistics for the main OB variable, option control variables, and firm and analyst characteristics utilized in our study are presented in Table B2 in Appendix B. It is important to note that the availability of data for OB and other option-related variables varies for each day.

Finally, for our control sample, we have gathered data on non-analyst related unscheduled events from *RavenPack News Analytics*, focusing exclusively on events with a relevance score of 75 or higher, indicating significant firm relevance in the news story and with an Event Novelty Score (ENS) of 100, ensuring we consider only the most novel news stories about a firm (see, e.g. Bushman and Pinto, 2023).[25] Our event selection criteria were based on RavenPack's categorization, focusing on the "Topic" of business and the "Group" of events encompassing acquisitions-mergers, assets, bankruptcy, credit-ratings, equity-actions, exploration indexes, investor-relations, labor-issues, marketing, order-imbalances, partnerships, products-services, and regulatory.

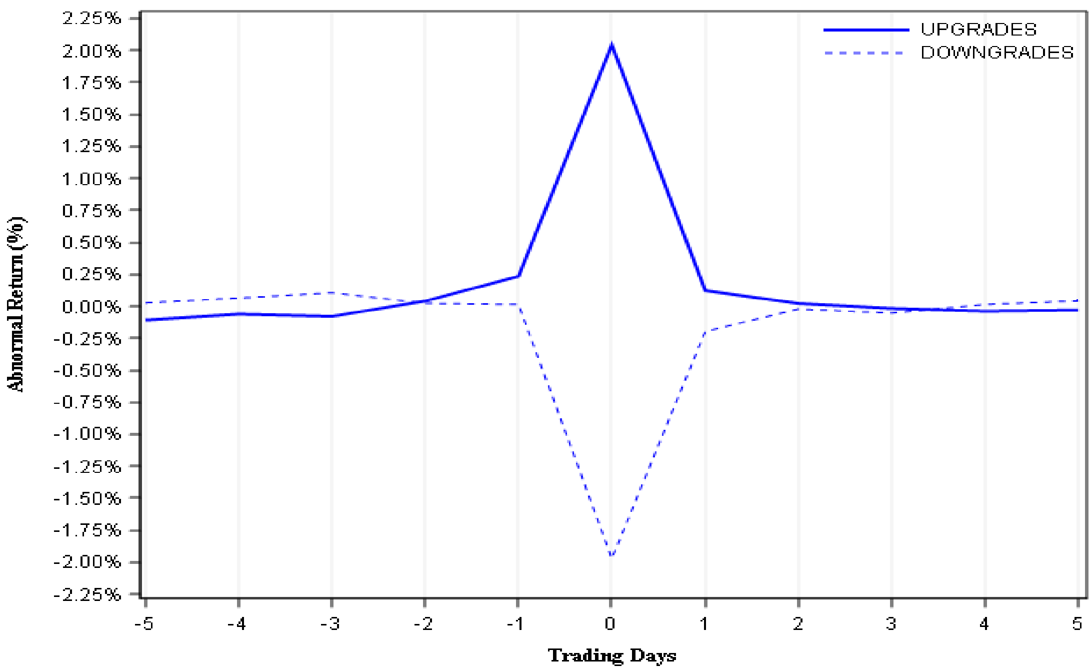
3.5 Abnormal returns, and options volume around analysts' announcements

We first investigate the return behavior over the $[-5, +5]$ event window surrounding the analyst recommendation revisions. Figure 1 shows the average daily abnormal returns separately for recommendation upgrades and downgrades. A market reaction is observed on the event day (day

[25] RavenPack's relevance scores range from 0 to 100, with scores above 75 denoting high relevance. ENS evaluates the novelty of a news item within a 24-hour period, with a score of 100 assigned to initial reports of an event, thereby prioritizing articles that are likely to introduce new information about a firm.

0), which is the day of the recommendation announcement, for both upgrades and downgrades. The corresponding abnormal price change, is 2.04% and -1.97% for upgrades and downgrades, respectively. The level of the AR resolves in one day after the announcement, for both upgrades and downgrades.

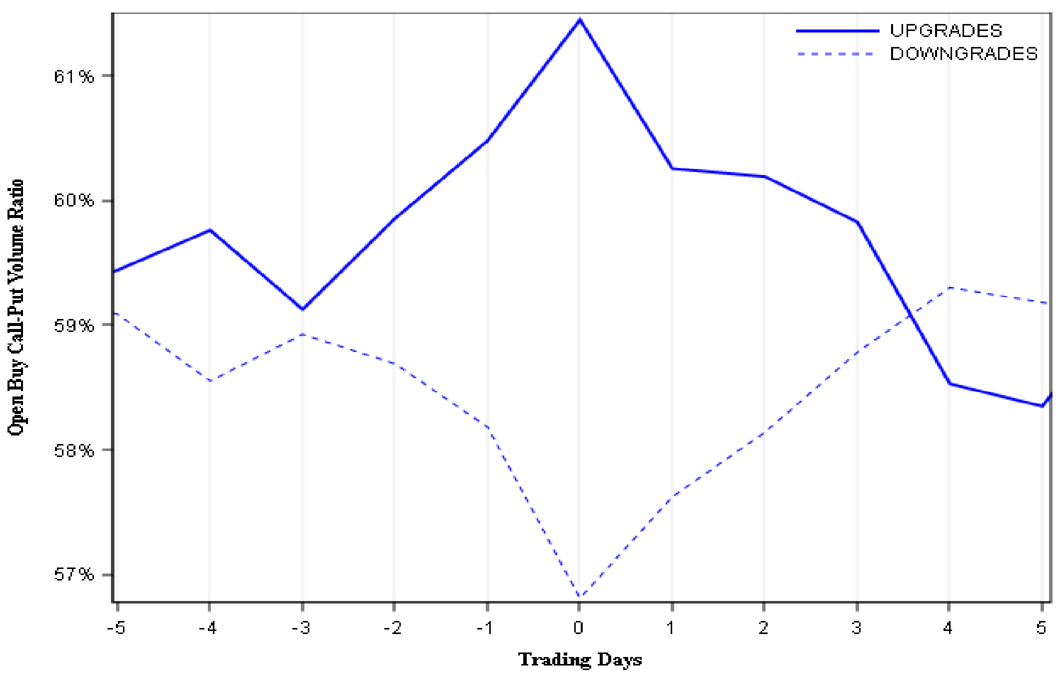
Figure 1: **Abnormal returns around analysts recommendations**



Notes: This figure shows the average daily abnormal stock returns (AR) over the $[-5, 5]$ event window, where day 0 is the recommendation announcement day. Results are presented separately for recommendation upgrades (solid line) and downgrades (dotted line). The figure presents the values on the vertical line and the trading days on the horizontal line. Our sample is from May 2005 to June 2021.

Next, to provide a first insight on how OB reacts to recommendation revisions, Figure 2 plots the daily average OB ratio over the $[-5, 5]$ period. This is done separately for upgrades and downgrades, representing positive and negative analyst news announcements, respectively. We observe that the call-put option trading volume ratio starts to rise 2 days before an upgrade, peaking on the day of the recommendation announcement. This captures the higher trading pressure associated with call option purchased around announcements of positive news. On the other hand, the ratio drops the day before a downgrade reflecting the greater number of trades in put options. The largest drop is on day 0. Overall, call-put open buy volume ratios increase (decrease) before positive (negative) analysts' announcements. The peak (drop) in trading volume resolves in the days following the upgrade (downgrade). This graphical analysis offers preliminary evidence in support of our hypothesis that the open buy volume ratio is predicting returns on news days. It suggests that options traders are more active and options volume is informative both on the news days and the days preceding them, consistent with the findings of Weinbaum et al. (2022).

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



Notes: This figure presents average daily values of the call open buy volume as a percentage of total open buy volume over the $[-5, 5]$ event window, where day 0 is the recommendation announcement day. Results are presented separately for recommendation upgrades (solid line) and downgrades (dotted line). 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.

4 Options volume, returns predictability, and analysts recommendations

The graphical evidence of the previous section suggests that investors engage in trading activities ahead of analyst recommendation revisions, and their trades align with the direction of upcoming recommendation changes. In this section, we empirically test the role of informed directional option trading for returns' predictability around analyst recommendations, placing a particular emphasis on the tipping hypothesis. To do so, we utilize the open buy (OB) ratio to study whether an order flow related to purchases of options is informative in predicting returns around analyst recommendations. We estimate the following regression models for the weeks and days leading up to recommendation revisions, respectively:

$$\begin{aligned}\text{CAR}_i[0,1] &= \beta_{OB}\overline{OB_i(t)} + \beta OptionCONTROLS_{i,t} + \gamma FirmCONTROLS_{i,t} \\ &+ \delta AnalystCONTROLS_{i,t} + YearFE + FirmFE + \epsilon_{i,t},\end{aligned} \tag{1}$$

$$\begin{aligned}\text{CAR}_i[0,1] &= \beta_{OB}OB_i(t) + \beta OptionCONTROLS_{i,t} + \gamma FirmCONTROLS_{i,t} \\ &+ \delta AnalystCONTROLS_{i,t} + YearFE + FirmFE + \epsilon_{i,t}\end{aligned} \tag{2}$$

where $t = [-10, -6]$ or $[-5, -1]$ in Equation 1, and $t = -5, \ldots, -1, 0$ in Equation 2, for stock i. $\text{CAR}[0, 1]$ is the two-day cumulative abnormal return based on the Fama-French five-factor model (FF5) Fama and French (2015) augmented with the momentum factor (see Carhart, 1997) with day 0 being the recommendation announcement day t. $\overline{OB_i(t)}$ is the open buy call-put volume ratio for stock i for the corresponding trading week, while $OB_i\,(t)$ denotes the ratio for the corresponding trading day. If the OB ratio is predictive of future abnormal returns, we expect at least one of the coefficients β_{OB} to be positive and statistically significant, particularly on the day preceding the announcement, $t = -1$, as suggested by Weinbaum et al. (2022).[26]

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). These variables are constructed using data from OptionMetrics. More specifically, IV is the OptionMetrics ATM 30-day implied volatility.[27] $SPREAD$ is calculated as the difference between an ATM IV call and ATM IV put (see Bali and Hovakimian, 2009; Cremers and Weinbaum, 2010). $SKEW$ 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). Specifically, $SPREAD$ 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. $SKEW$ reflects informed traders buying OTM put options, therefore measuring the left shape of the IV and being found to contain negative predictive information for future stock returns (see Lin and Lu, 2015). Hence, following existing literature, we add these implied options trading measures as control variables in our empirical analysis. We incorporate the values of IV, $SPREAD$, or $SKEW$ for the corresponding week or day, as applicable. Weekly values of IV, SPREAD, or SKEW are calculated as the simple averages over the corresponding week.

We also include firm control 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

[26]Regardless of whether the expected return is positive or negative, the coefficients β_{OB} should be positive if OB is predictive. A positive return expectation prompts option traders to buy more calls, resulting in an increase in the OB ratio. Conversely, if a negative return is anticipated, traders are inclined to purchase more puts, leading to a decrease in the OB ratio.

[27]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.

over the week before the analysts' announcement (REV), the firm's momentum during the last six months (MOM), the firm's market capitalization ($MKTCAP$), and the 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 the number of analysts following the firm (AF), 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 the number of years the analyst is following a specific firm, i.e. the analyst firm experience ($EXPER$). Moreover, previous studies have indicated that analysts often release other estimates simultaneously with recommendations. For instance, Kecskés et al. (2017) show that recommendation revisions that are supported by earnings forecasts are more informative. Additionally, it has been shown that target prices provide distinct information not subsumed by recommendations or earnings forecasts (e.g. Brav and Lehavy, 2003; Asquith et al., 2005). Thus, we include two indicator variables to account the simultaneous release of earnings forecast and target price estimates by the same broker within the three-day window around the announcement date, namely EF and TP, respectively. More details on the variables are reported in Appendix A.

We estimate the model including year and firm fixed effects to control for shocks affecting the macroeconomic environment and for any time-invariant unobserved differences among firms. All continuous variables are winsorized at the 1st and 99th percentiles to mitigate the impact of outliers. Finally, the model is estimated using double-clustered standard errors along firm and time (quarter-year) dimensions to account for cross-sectional and serial correlations in the residuals (see, e.g. Petersen, 2009).

4.1 Empirical results

First, we are interested in the role of OB to predict future stock returns around analysts' recommendations. To this aim, we test whether the predictive ability of OB is greater in the week before the announcement ($t = [-5, -1]$), compared to the further week before the announcement ($t = [-10, -6]$). Then, we focus on the coefficients and significance of β_{OB} with respect to the days before and on the announcement day $(t = -5, \ldots - 1, 0)$. The results are reported in Table 1. We present the results for the univariate regression model in Equation 1 that includes only fixed effects in Panel A. The results for the multivariate model augmented with control variables are presented in Panel B. Columns 1 and 2 present the weekly results, while Columns 3 through 8 show the daily results.

We observe that the coefficient of the weekly OB ratio is found to be significant only in the week preceding the announcement day, i.e., $t = [-5, -1]$. An increase in the OB ratio in the trading week before the announcement is associated with an increase in the stock returns on the event day. Notably, 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 remain robust upon the inclusion the addition of several control variables in the multivariate setup, as shown in Panel B of Table 1. Hence, from this first empirical exercise, we observe that the predictive information content of OB for future stock returns around analysts' announcements is entirely placed in the five days before the event day. Next, our objective is to determine on which of the five days preceding the announcement the information content of the OB ratio is stronger in predicting abnormal returns.

In the univariate setup in Panel A, our predictive regressions indicate that the OB ratio significantly predicts announcement day returns on all days preceding the announcement (Columns

3 to 7), with the largest coefficient observed on $t = -1$. Including the set of control variables in Panel B, we find that OB's significance is strongest (at the 1% level) on the day before the analyst recommendations date ($t = -1$). Conversely, when the set of controls is added, the significance of the OB ratio decreases, or even disappears, on some of the other preceding days. For instance, we detect the impact of OB at a 5% significance level on $t = -5$, and a 10% significance level on $t = -3$ indicating evidence of earlier trades before the announcement day.

Overall, the sign of the OB coefficient is positive, as anticipated. Hence, an increase in the OB ratio in the days leading up to the recommendation announcement date leads to an increase in stock returns on the event date. By looking at the ratio dynamics, a higher ratio corresponds to a greater number of call options being purchased to open new positions relative to put options. This suggests that an increase in the ratio reflects more optimistic expectations among traders, which can be expected to translate into positive stock returns following an analyst's recommendation announcement. The positive sign of the OB coefficient is consistent with the findings of previous literature adopting the open buy ratio (e.g. Weinbaum et al., 2022).[28] Therefore, these findings confirm our first hypothesis. Moreover, in terms of economic significance, a 10% increase in the OB ratio on the day preceding the recommendation, predicts an average abnormal return increase of 2.87% in response to the announcement, as indicated in Panel B.

Focusing on the event day, $t = 0$, we observe that our variable of interest, OB, is positive and statistically significantly at the 1% significance level. When we include the set of control variables, as shown in Panel B, we confirm a similar finding for the OB ratio. The positive sign of the OB coefficient implies that an increase in call options purchases on the recommendations day

[28] To be noted that the ratio in Weinbaum et al. (2022) is computed as the 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.

is associated with an increase in the stock returns on the same day.

These results also suggests that controlling for the other option-based variables commonly associated with options trading information (e.g. $SPREAD$, $SKEW$) does not impact the predictive ability of the OB ratio. Hence, 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. While other option-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 discern the views of investors. In fact, we show that the investors trade on the right direction of the analysts' revisions. The positive sign associated with the OB ratio implies that investors purchase more call options before analysts' recommendations which will indeed predict an increase in stock returns.[29]

Finally, it is worth noting that the trading activity pattern observed from Table 1, regarding the significance and information role of the directionality of the OB ratio, supports the tipping hypothesis. The observed pattern in the week leading up to the announcement day may reflect a combination of informative and non-informative trading. However, the predictive ability of the OB ratio on the day before the release of the analyst recommendation, along with its directional characteristic, suggests that investors' trades are generally aligned with the anticipated direction of recommendation returns. This suggests more strategic, informative trading, possibly hinting at information leakage prior to a recommendation revision, which is in line with our second hypothesis. The tipping channel is in line with earlier studies that utilized non-directional option volume

[29]We perform the same analysis by adopting the ISE signed volume data by customers only and by customers, proprietary and professional customers (CPPC) jointly. We present these findings in Table C1 in the paper Appendix C. See Section 3 for more information about these categories of trading volumes by ISE.

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

	Recommendation Revisions							
Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	t = [-10,-6]	t = [-5,-1]	t = -5	t = -4	t = -3	t = -2	t = -1	t = 0
OB (t)	0.1599	0.4667***	0.2339***	0.1552**	0.1375*	0.1525**	0.3299***	0.8442***
	(0.1124)	(0.1022)	(0.0708)	(0.0771)	(0.0760)	(0.0740)	(0.0690)	(0.0713)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Obs	30,297	30,828	24,596	24,732	24,800	24,969	26,278	27,320
Adj-R2	0.0431	0.0432	0.0513	0.0489	0.0505	0.0504	0.0498	0.0580
Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	t = [-10,-6]	t = [-5,-1]	t = -5	t = -4	t = -3	t = -2	t = -1	t = 0
OB (t)	0.0423	0.4375***	0.1828**	0.1271	0.1371*	0.1089	0.2870***	0.7633***
	(0.1068)	(0.1061)	(0.0806)	(0.0785)	(0.0813)	(0.0780)	(0.0754)	(0.0738)
IV (t)	0.1925	0.3240	-0.2526	0.2766	-0.0364	0.3451	-0.0391	-2.7806***
	(0.3335)	(0.3315)	(0.3728)	(0.3842)	(0.3237)	(0.3531)	(0.3275)	(0.3700)
SKEW (t)	-1.7550*	-2.0058*	-0.4793	-2.0963**	-1.3412	-2.7669**	-2.1199**	2.7584***
	(0.9501)	(1.0646)	(0.9879)	(0.9685)	(1.1919)	(1.0812)	(0.9633)	(0.9717)
SPREAD (t)	7.0531***	8.5604***	2.1032	3.9014***	4.3857*	2.2359	3.8808*	-5.0251***
	(2.0224)	(2.2723)	(1.4359)	(1.4424)	(2.2874)	(1.9473)	(1.9648)	(1.6986)
REV	-0.0387***	-0.0348***	-0.0395***	-0.0388***	-0.0330***	-0.0364***	-0.0358***	-0.0455***
	(0.0069)	(0.0065)	(0.0067)	(0.0066)	(0.0065)	(0.0079)	(0.0062)	(0.0067)
MOM	-0.4594**	-0.4042*	-0.4567*	-0.4855*	-0.4712*	-0.3571	-0.2993	-0.5513**
	(0.2165)	(0.2299)	(0.2394)	(0.2430)	(0.2414)	(0.2310)	(0.2468)	(0.2380)
MKT CAP (ln)	-0.5275***	-0.5280***	-0.5107***	-0.4244***	-0.4929***	-0.5220***	-0.5511***	-0.6610***
	(0.0909)	(0.0821)	(0.0948)	(0.0860)	(0.0911)	(0.0954)	(0.0919)	(0.0959)
AF (ln)	-0.0765	-0.0886	-0.0658	-0.1023	0.0208	-0.0791	-0.0771	-0.0409
	(0.1470)	(0.1489)	(0.1814)	(0.1769)	(0.1839)	(0.1622)	(0.1725)	(0.1619)
IO	-0.3041	-0.2837	-0.3024	-0.1658	-0.3372	-0.1337	-0.4756	-0.5204
	(0.2678)	(0.2712)	(0.2840)	(0.2692)	(0.2542)	(0.2940)	(0.3030)	(0.3131)
BM (ln)	-0.0224	-0.0328	-0.0384	-0.0698	-0.0453	-0.0671	-0.0486	-0.0117
	(0.0760)	(0.0730)	(0.0777)	(0.0874)	(0.0814)	(0.0804)	(0.0757)	(0.0775)
BSIZE (ln)	-0.0121	-0.0089	-0.0221	-0.0140	0.0070	0.0074	-0.0119	-0.0077
	(0.0260)	(0.0251)	(0.0266)	(0.0252)	(0.0278)	(0.0255)	(0.0240)	(0.0296)
EXPER (ln)	0.0629***	0.0558**	0.0646***	0.0466*	0.0611**	0.0568**	0.0583***	0.0667***
	(0.0217)	(0.0219)	(0.0223)	(0.0234)	(0.0232)	(0.0257)	(0.0211)	(0.0235)
EF	-0.1382*	-0.1428*	-0.1289	-0.1103	-0.1617**	-0.1372*	-0.1265	-0.1163
	(0.0756)	(0.0758)	(0.0793)	(0.0789)	(0.0686)	(0.0782)	(0.0806)	(0.0765)
TP	0.7282***	0.7316***	0.6880***	0.6943***	0.7080***	0.6989***	0.6848***	0.7563***
	(0.0794)	(0.0818)	(0.0743)	(0.0785)	(0.0781)	(0.0809)	(0.0772)	(0.0763)
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Obs	26,339	26,808	21,304	21,429	21,495	21,601	22,766	23,684
Adj-R2	0.0632	0.0637	0.0691	0.0690	0.0692	0.0704	0.0684	0.0826

Notes: This table presents regression results where the dependent variable is the two-day cumulative abnormal return based on the Fama-French six-factor (FF6) model ($\mathrm{CAR}[0,1]$). Day 0 represents the analyst recommendation announcement day. OB is the open buy call-put option volume ratio. IV is the ATM implied volatility. $SKEW$ is the implied volatility skew. $SPREAD$ is the call-put implied volatility spread. t represents either a trading week, (labeled as $[-10,-6]$ or $[-5,-1]$), or a trading day (labeled as $-5,\ldots,-1,0$) each relative to the day of the analyst recommendation announcement. In the first two columns, the option-related variables are averaged over the corresponding week. REV is the last week's stock return reversal. MOM the firm's momentum over the last six-months. $MKTCAP$ is the market capitalization of the firm. AF is the number of analysts following the stock. IO is the fraction of shares held by institutional investors. BM is the firm book-to-market. $BSIZE$ is the number of analysts employed by the brokerage during the last year. $EXPER$ the number of quarters the analyst has been following the firm. EF and TP are indicator variables for whether earnings forecast and/or a target price were issued with the recommendation. For more detailed definitions of the variables refer to Appendix A. Panel A reports the regression results for the univariate model, whereas Panel B displays the results for the model that includes the control variables. Robust standard errors clustered by time (quarter-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.

measures (e.g. Lung and Xu, 2014; Lin and Lu, 2015; Markov et al., 2017; Kadan et al., 2018). These studies also observed that options investors tend to trade within the five trading days preceding an upcoming revision, supporting the notion that option trading patterns are predictive of imminent analyst recommendation changes.[30]

4.2 The direction and magnitude of recommendation revisions

In this subsection, our aim is to further validate the tipping hypothesis by examining the predictive role of the directional option volume in relation to the direction and magnitude of analyst recommendation revisions. Considering that IBES assigns numeric values to analyst recommendations, ranging from 1 ("Strong Buy") to 5 ("Sell"), we define the magnitude of recommendation revisions such that positive values indicate upgrades, while negative values downgrades. Specifically, for stock i at time t, the magnitude of the recommendation revision is defined as follows:

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

An ordered probit model is employed to determine whether the OB ratio offers any predictive

[30]We also control for the so-called Monday effect. One can argue that specific weekdays and, in particular, trading pressure associated with the weekend can be the driver of our options volume significance especially uncovered the day before the event. Hence, we add a dummy control to our baseline regression which marks one if the recommendation was issued from Friday after the market closure (at 16:00) to Monday until the market closure (at 16:00), and zero otherwise. We present the results in Table C2 in the paper Appendix C. However, even after controlling for such an effect, the significance of our variable holds robust, validating the tipping rationale.

insights into the magnitude of forthcoming recommendation revisions.[31]

$$REC\_REV_{i,t} = \beta_{OB}OB_i(t) + \beta OptionCONTROLS_{i,t} + \gamma FirmCONTROLS_{i,t} + \delta AnalystCONTROLS_{i,t} + \epsilon_{i,t}, \tag{3}$$

where $OptionCONTROLS_{i,t}$ is a vector of control variables as defined in Equation 2.

Table 2: **Recommendation revisions predictability**

	t = [-10,-6]	*t* = [-5,-1]	*t* = -5	*t* = -4	*t* = -3	*t* = -2	*t* = -1	*t* = 0
OB (t)	0.0261	0.0844***	0.0260	0.0570***	0.0146	0.0447**	0.0740***	0.1463***
	(0.0259)	(0.0262)	(0.0204)	(0.0202)	(0.0200)	(0.0204)	(0.0205)	(0.0194)
C1	-0.6985***	-0.6040***	-0.7039***	-0.6488***	-0.6612***	-0.5841***	-0.5907***	-0.7146***
	(0.0784)	(0.0792)	(0.0879)	(0.0875)	(0.0901)	(0.0870)	(0.0827)	(0.0832)
C2	0.2694***	0.3599***	0.2637***	0.3117***	0.3028***	0.3789***	0.3734***	0.2463***
	(0.0782)	(0.0793)	(0.0882)	(0.0877)	(0.0905)	(0.0873)	(0.0831)	(0.0831)
C3	1.2303***	1.3231***	1.2279***	1.2719***	1.2620***	1.3359***	1.3371***	1.2086***
	(0.0792)	(0.0804)	(0.0897)	(0.0889)	(0.0916)	(0.0884)	(0.0844)	(0.0841)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Obs	26,499	26,972	21,429	21,560	21,619	21,729	22,907	23,830
Pseudo R2	0.0133	0.0134	0.0119	0.0129	0.0126	0.0131	0.0127	0.0135

Notes: This table presents the results of ordered probit regressions where the dependent variable is the magnitude of a recommendation revision, $REC\_REV_{i,t}$. OB is the open buy call-put option volume ratio, and the controls are the same as in Table 1. Robust standard errors clustered by firm are reported in parentheses. ***, **, * indicate significance level at the 1%, 5%, and 10%, respectively. The last rows report the number of observations and the pseudo R^2. Our sample is from May 2005 to June 2021.

Table 2 presents the results of the ordered probit model. In the first columns (1) and (2), we show the results corresponding to the OB weekly averages. We confirm a significant and positive estimate on OB only in the week concluding immediately before the recommendation revision, $t = [-5, -1]$. When we focus on the five days before the event day, OB is positively and significantly related to recommendation on $t = -4$, $t = -2$, and $t = -1$. It is also significant on the event day ($t = 0$). These results imply that an increase (decrease) in the OB ratio prior

[31] Revision changes of more than two levels are relatively rare, therefore are pooled together when defining $REC\_REV_{i,t}$.

to the event raises the likelihood of an analyst upgrading (downgrading) the stock on the event day. These findings reveal a clear predictive relationship between the pre-event OB ratio and forthcoming revisions, which provides further empirical support for the tipping hypothesis.

5 The impact of FINRA Rule 2241

In the preceding sections, our analysis has uncovered evidence that aligns with the tipping hypothesis. Throughout our entire sample period, the OB ratio demonstrates predictive ability for upcoming returns associated with the release of analyst recommendations. In this section, we aim to establish further evidence for the existence of tipping focusing on the impact of the FINRA Rule 2241 on tipping practices and their variations across our sample period. The effective date for Rule 2241 varied, with some provisions taking effect on September 25, 2015, while the remainder came into force on December 24, 2015. Given our research focus on the provision directly related to tipping, that is Rule 2241(g), we select December 24, 2015, as the pivotal implementation date.[32]

If our earlier documented results are indeed attributable to tipping and the new Rule 2241 was effective in curtailing information leakage, then we would expect to see a reduced or potentially non-existent predictive ability of the OB ratio in the period following the rule's introduction. Therefore, our objective in this section is twofold. First, we aim to enhance our confidence in attributing our earlier findings to tipping behavior by documenting the impact of this exogenous regulatory event on our empirical results. Second, we aim to provide empirical evidence and new insights on the impact of this regulatory shift.

To offer empirical evidence regarding the impact of Rule 2241, we concentrate on the years

[32] See FINRA's Regulatory Notice 15-30, available at: https://www.finra.org/rules-guidance/notices/15-30.

surrounding the regulatory change and employ the following model:

$$
\begin{aligned}
&\mathrm{CAR}_i[0,1] = \beta_1 OB_i(t) + \beta_2 RULE2241 \times OB_i(t) \\
&+ \beta OptionCONTROLS_{i,t} + \gamma FirmCONTROLS_{i,t} \\
&+ \delta AnalystCONTROLS_{i,t} + YearFE + FirmFE + \epsilon_{i,t},
\end{aligned} \tag{4}
$$

where $RULE2241$ is an indicator variable that takes the value one if the recommendation announcement date is after Dec 24, 2015. Our main examination spans the period from January 1, 2013, to December 31, 2017. Additionally, we provide results for the period concluding on December 31, 2016, thereby restricting the post-analysis period to one year. This relatively narrow window allows us to mitigate the potential impact of confounding factors. If Rule 2241 was successful in containing tipping activities, it would likely diminish the predictive ability of the OB ratio. Consequently, we expect the coefficient on $RULE2241 \times OB$ to be negative, that is, $\beta_2 < 0$, in the days leading up to the recommendation announcement ($t = -5, \ldots, -1$). Conversely, the Rule should not influence the OB ratio on the day of the announcement itself ($t = 0$).

Results are presented in Table 3. Our findings consistently show negative and statistically significant coefficients for the interaction term $RULE2241 \times OB$, for the weekly OB ratio (Column 1) and the OB ratio on the day immediately before the recommendation announcement (Column 6). This pattern holds for both the period ending in 2016, as shown in Panel A, and the period ending in 2017, as detailed in Panel B. Conversely, the coefficients for the interaction term on the announcement day (Column 7) are not statistically significant, indicating no impact on the day of the announcement itself. These findings suggest a substantial reduction in tipping activities in the two years immediately following the implementation of Rule 2241. Overall, the above empirical findings lend support to the tipping hypothesis. Our results show that tipping occurred more systematically before in the pre-rule period.

Table 3: **The impact of FINRA Rule 2241**

Panel A: Period 2013 - 2016							
	(1) t = [-5,-1]	(2) t = -5	(3) t = -4	(4) t = -3	(5) t = -2	(6) t = -1	(7) t = 0
OB (t)	0.4294**	0.1208	-0.1575	0.1081	0.4218**	0.2767*	0.5763***
	(0.1769)	(0.1892)	(0.1447)	(0.1763)	(0.1510)	(0.1330)	(0.1908)
$RULE2241 \times OB(t)$	**-1.2632*** **	**-0.4346**	**0.0019**	**-0.6880** **	**-0.3386**	**-1.1309** **	**-0.0217**
	(0.3687)	**(0.3108)**	**(0.2995)**	**(0.2711)**	**(0.2830)**	**(0.4353)**	**(0.3391)**
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	5,587	4,093	4,126	4,150	4,148	4,539	4,807
Adj-R2	0.1460	0.1471	0.1315	0.1482	0.1760	0.1636	0.1798

Panel B: Period 2013 - 2017							
	(1) t = [-5,-1]	(2) t = -5	(3) t = -4	(4) t = -3	(5) t = -2	(6) t = -1	(7) t = 0
OB (t)	0.4611**	0.1450	-0.1263	0.0393	0.4031***	0.2713**	0.5564**
	(0.1780)	(0.1923)	(0.1320)	(0.1697)	(0.1364)	(0.1291)	(0.1958)
$RULE2241 \times OB(t)$	**-0.9562** **	**-0.4943** *	**-0.1165**	**-0.2976**	**-0.5301** **	**-0.6813** **	**-0.0967**
	(0.3570)	**(0.2498)**	**(0.2168)**	**(0.2170)**	**(0.2394)**	**(0.2984)**	**(0.2648)**
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	6,569	4,831	4,864	4,922	4,903	5,360	5,659
Adj-R2	0.1380	0.1354	0.1304	0.1388	0.1635	0.1571	0.1682

Notes: This table presents regression results where the dependent variable is the two-day cumulative abnormal return based on the Fama-French six-factor (FF6) model ($\mathrm{CAR}[0, 1]$). Day 0 represents the analyst recommendation announcement day. OB is the open buy call-put option volume ratio. $RULE2241$ is an indicator variable that takes the value one if the recommendation announcement date is after Dec 24, 2015. All the other control variables are defined as in Table 1.. The regressions are estimated with year and firm fixed effects. Robust standard errors clustered by time (quarter-year) 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-R2. The sample period begins on January 1, 2013. Panel A presents regression results up to December 31, 2016, while Panel B shows the results for the period ending on December 31, 2017.

5.1 Difference in differences (DiD) analysis

To determine the causal impact of Rule 2241, we employ a difference in differences (DiD) methodology. Considering that the OB ratio is predictive for all unscheduled events, as established by Weinbaum et al. (2022), we select all other unscheduled events outside the analysts' domain as our control sample. This approach allows for a more precise evaluation of the specific effects of Rule 2241 on the OB ratio in the context of analyst recommendations. We have gathered data on unscheduled events from $RavenPack$. These events cover a broad spectrum, including mergers and acquisitions (M&As), credit rating changes, equity actions, and more. Our analysis covers the period surrounding the implementation of Rule 2241, from January 1, 2013, to December 31, 2016. Additionally, we provide results for a longer post-rule period, concluding on December 31, 2017. The model used is:

$$
\begin{aligned}
&\mathrm{CAR}_i[0,1] = \beta_1 OB_i(t) + \beta_2 TREAT \times OB_i(t) \\
&+ \beta_3 RULE2241 \times OB_i(t) + \delta RULE2241 \times TREAT \times OB_i(t) \\
&+ \beta OptionCONTROLS_{i,t} + \gamma FirmCONTROLS_{i,t} \\
&+ YearFE + FirmFE + \epsilon_{i,t},
\end{aligned}
\tag{5}
$$

where $TREAT$ is an indicator variable that takes the value 1 if the event is analyst recommendation. Our focus is on the triple interaction term $RULE2241 \times TREAT \times OB$, which is intended to capture the incremental effect resulting from the implementation of Rule. If Rule 2241 was successful in reducing tipping activities, then we expect the coefficients of $RULE2241 \times TREAT \times OB$ for the days leading up to the recommendation announcement ($t = -5, \ldots, -1, 0$) to be negative, i.e., $\delta < 0$. We do not expect any impact on the day of the recommendation release ($t = 0$).

We also present estimates of the model using the entropy balancing technique to address the potential covariate imbalance between the control and treated sample. The entropy balancing technique allows us to maintain the whole sample and ensures a balance in the covariates between the treatment and control groups by re-weighting the observations. This weighting aims to achieve virtually identical post-weighting means and variances for the freezing and non-freezing observations (see Hainmueller, 2012). The covariates adopted for the weighting include the OB ratio, as well as the firm characteristics we included in our earlier analysis: stock return reversal (REV), momentum (MOM), market capitalization ($MKTCAP$), analyst following (AF), institutional ownership (IO), and the book-to-market ratio (BM).

We report the DiD results in Panel A of Table 4. We observe negative coefficients for the triple interaction term, $RULE2241 \times TREAT \times OB$. The weekly coefficient (Column 1) and the coefficients on days $t = -2$ (Column 5) and $t = -1$ (Column 6) are statistically significant indicating a discernible negative impact on the predicting ability of the OB ratio in the post-rule year. Notably, no effect is observed on the recommendation announcement day, $t = 0$. In Panel B of Table 4, we repeat the analysis using the entropy balancing technique, yielding a very similar outcome that further corroborates the findings presented in Panel A.

Overall, the findings displayed in Table 4 reveal a significant decrease in the predictive ability of OB in the days leading up to the recommendation announcement following the implementation of Rule 2241. No effect is noted on the day of the recommendation announcement itself. These results suggest that Rule 2241 effectively curtailed information leakage related to forthcoming recommendation revisions, thereby validating our third hypothesis. By extending the sample period to include the year 2017, our analysis remains broadly consistent (see Table C3 in the Appendix). Although the results in Panel A of Table C3 might be slightly weaker compared to those in Panel

Table 4: **The impact of FINRA Rule 2241. DiD results 2013 – 2016.**

Panel A: DiD

	(1) t = [-5,-1]	(2) t = -5	(3) t = -4	(4) t = -3	(5) t = -2	(6) t = -1	(7) t = 0
$OB(t)$	0.1505*	0.0351	-0.0085	0.0313	0.0180	0.1368***	0.3552***
	(0.0712)	(0.0559)	(0.0523)	(0.0373)	(0.0255)	(0.0454)	(0.0434)
$TREAT \times OB(t)$	0.1820	0.1173	0.0402	0.0405	0.2795**	0.1158	0.1788
	(0.1680)	(0.1764)	(0.0980)	(0.1420)	(0.1176)	(0.1374)	(0.1590)
$RULE2241 \times OB(t)$	-0.0218	-0.0024	0.0547	0.0359	0.1986**	-0.0123	0.1598*
	(0.0853)	(0.0812)	(0.0770)	(0.0698)	(0.0709)	(0.0760)	(0.0813)
$RULE2241 \times TREAT \times OB(t)$	**-0.3659****	**-0.2659**	**-0.2154**	**-0.3279**	**-0.4031*****	**-0.4984****	**-0.1191**
	(0.1550)	**(0.1744)**	**(0.1908)**	**(0.2127)**	**(0.1309)**	**(0.2001)**	**(0.1160)**
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	40,375	31,113	31,116	31,342	31,474	33,414	33,953
Adj-R2	0.0448	0.0524	0.0504	0.0545	0.0539	0.0515	0.0709

Panel B: DiD with entropy balancing

	(1) t = [-5,-1]	(2) t = -5	(3) t = -4	(4) t = -3	(5) t = -2	(6) t = -1	(7) t = 0
$OB(t)$	0.2057*	0.0681	-0.0201	0.0335	0.0063	0.1866**	0.3859***
	(0.1089)	(0.0788)	(0.0711)	(0.0741)	(0.0392)	(0.0777)	(0.0611)
$TREAT \times OB(t)$	0.1516	0.0619	-0.0324	0.0492	0.3078**	0.0873	0.1447
	(0.1783)	(0.1643)	(0.1121)	(0.1461)	(0.1088)	(0.1592)	(0.1672)
$RULE2241 \times OB(t)$	-0.3498**	-0.0130	0.0639	-0.1120	0.1311	-0.2818**	0.1066
	(0.1534)	(0.1261)	(0.1148)	(0.1221)	(0.1568)	(0.1189)	(0.1356)
$RULE2241 \times TREAT \times OB(t)$	**-0.2816***	**-0.2333**	**-0.1589**	**-0.2570**	**-0.3242****	**-0.4407****	**-0.0305**
	(0.1511)	**(0.1743)**	**(0.2142)**	**(0.2148)**	**(0.1305)**	**(0.2055)**	**(0.1404)**
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	40,375	31,113	31,116	31,342	31,474	33,414	33,953
Adj-R2	0.0980	0.1050	0.0976	0.1050	0.1088	0.1095	0.1232

Notes: This table presents DiD panel regression models where the dependent variable is the two-day cumulative abnormal return based on the Fama-French six-factor (FF6) model ($\mathrm{CAR}[0,1]$). Day 0 represents unscheduled event announcement day. OB is the open buy call-put option volume ratio. $RULE2241$ is an indicator variable that takes the value one if the recommendation announcement date is after Dec 24, 2015. $TREAT$ is an indicator variable that takes the value 1 if the unscheduled event is analyst recommendation. The control sample encompasses all other unscheduled events which do not belong to the analysts' domain (e.g. M&A, credit-ratings changes, equity-actions). Panel A presents the results of regression model in Equation 5. Panel B presents the results for the same model but using the entropy balancing technique. All regression models include option-related and firm-specific control variables, as detailed in Table 1. The regressions are estimated with year and firm fixed effects. Robust standard errors clustered by time (quarter) 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 January 1, 2013, to December 31,2016.

A of Table 4, the application of the entropy balancing technique in Panel B yields to unchanged findings. A noteworthy distinction in Table 4 is the statistical significance of the coefficient for

$RULE2241 \times TREAT \times OB$ on day $t = -5$ (Column 2) further indicating a reduction in the OB ratio's predictive ability.

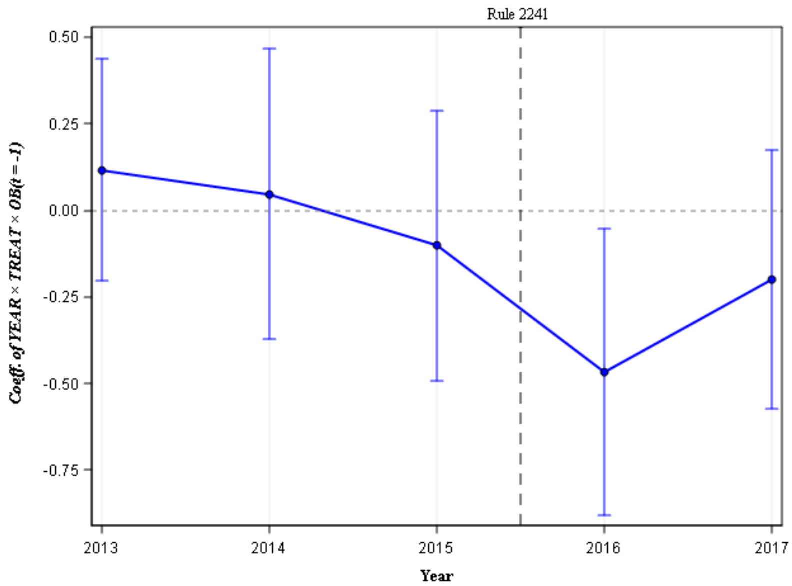
Next, to evaluate the parallel trend assumption critical for the difference-in-differences analysis, we follow the methodology recommended by Angrist and Pischke (2009). To achieve this, we replace the $RULE2241$ indicator variable in model in Equation 5 with year-specific indicators for each year from 2013 to 2017. We then plot the coefficients of the triple interaction term ($RULE2241 \times TREAT \times OB$) for each year, specifically for the day preceding the recommendation announcement, $t = -1$.

These coefficients, along with their corresponding 90% confidence intervals, are depicted in a dynamic parallel trend plot shown in Panel A of Figure 4. Panel B illustrates the dynamic coefficients employing the entropy balancing technique. The coefficients of the triple interaction terms and the year-specific indicators, $YEAR \times TREAT \times OB$ ($t = -1$) become statistically significant and fall below zero for the year 2016—and also for 2017 in the entropy balancing plot—that is, after the implementation date of Rule 2241. These findings serve as evidence that the parallel trend assumption is satisfied, supporting the robustness and causality of our analysis.

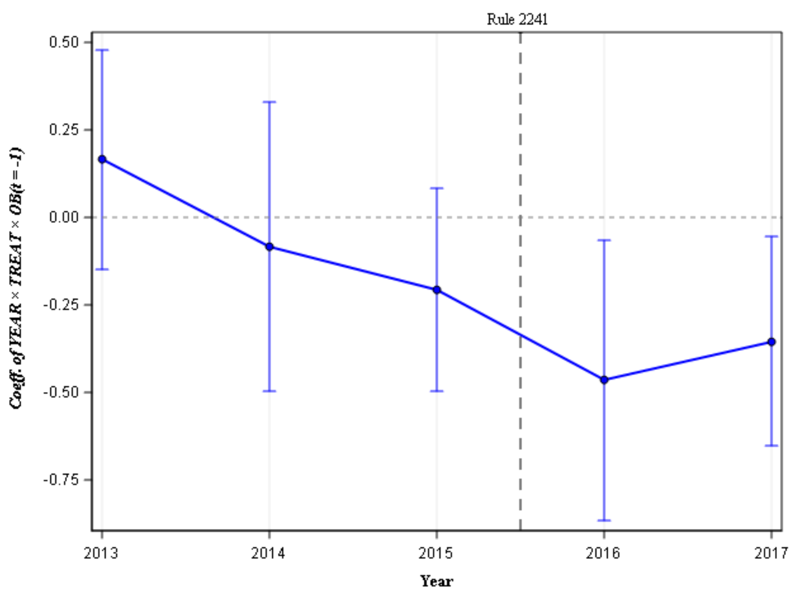
The findings outlined in this section support the effectiveness of Rule 2241 in curbing information leakage before the issuance of analyst recommendation revisions. Additionally, these results offer further empirical support for the tipping hypothesis, complementing the evidence presented in Section 4.

Figure 3: **The effect of FINRA Rule 2241**

(a) DiD



(b) DiD with entropy balance



Notes: This figure displays the coefficients and their associated 90% confidence intervals for the triple interaction term $RULE2241 \times TREAT \times OB$ from model in Equation 5, with the $RULE2241$ indicator variable substituted by year-specific indicators. Panel A depicts the coefficients and their confidence intervals for the day preceding the recommendation announcement, $t = -1$, as per the regression model shown in Table 4, Panel A, column 6. Panel B shows the coefficients obtained through entropy balancing as in Table 4, Panel B, column 6. The sample is from January 1, 2013, to December 31, 2017.

5.2 Tipping pre- and post-FINRA Rule 2241

Finally, of interest is also to study the persistence of tipping behavior in the aftermath of the implementation of FINRA Rule 2241. To investigate potential temporal variations in the predictability of open buy call-put volume, we partition our sample period into three distinct subperiods of approximately equal duration: May 1, 2005, to December 31, 2010; January 1, 2011, to December 23, 2015; and December 24, 2015, to June 30, 2021.

The results are presented in Table 5, Panels A – C, respectively, and reveal that OB predicts abnormal returns during the first two periods but not in the latter period. Conversely, OB remains statistically significant on the recommendation announcement day across all periods. Furthermore, these findings reveal that, following the implementation of FINRA Rule 2241, the OB ratio ceases to predict future returns. This observation suggests that the predictive ability of the OB ratio previously identified was primarily a consequence of tipping practices. Overall, the evidence outlined in this Section, fulfills two objectives: first, it demonstrates the effectiveness of FINRA Rule 2241 by illustrating that the OB ratio's predictive power for future returns diminishes following the rule's implementation; second, it provides further evidence indicating that the OB ratio's predictive ability was predominantly attributable to tipping practices.

5.3 Placebo test: recommendation reiterations

To mitigate potential concerns regarding potential omitted variables affecting our results, we use a placebo test to examine the counterfactual. Our hypothesis contends that options traders, motivated by private information, are more inclined to participate in trading activities when such information provides them with an informational edge, particularly when they anticipate signifi-

Table 5: **Subperiods analysis**

Panel A: 2005 - 2010

	(1) t = [-5,-1]	(2) t = -5	(3) t = -4	(4) t = -3	(5) t = -2	(6) t = -1	(5) t = 0
OB (t)	0.6022***	0.2429*	0.2411*	0.1693	0.1364	0.3970***	0.9320***
	(0.1830)	(0.1347)	(0.1311)	(0.1335)	(0.1326)	(0.1171)	(0.1536)
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	12,240	10,296	10,326	10,356	10,426	10,771	11,094
Adj-R2	0.0463	0.0465	0.0487	0.0526	0.0481	0.0472	0.0663

Panel B: 2011 - 2015

	(1) t = [-5,-1]	(2) t = -5	(3) t = -4	(4) t = -3	(5) t = -2	(6) t = -1	(5) t = 0
OB (t)	0.5518***	0.1338	-0.0860	0.1917	0.2106**	0.3247***	0.6282***
	(0.1209)	(0.1260)	(0.1112)	(0.1257)	(0.0864)	(0.0817)	(0.1149)
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	8,285	6,243	6,253	6,280	6,276	6,762	7,122
Adj-R2	0.1306	0.1409	0.1309	0.1297	0.1509	0.1398	0.1498

Panel C: 2016 - 2021

	(1) t = [-5,-1]	(2) t = -5	(3) t = -4	(4) t = -3	(5) t = -2	(6) t = -1	(5) t = 0
OB (t)	0.1168	0.0295	0.1223	0.0663	-0.1580	-0.1100	0.6165***
	(0.2223)	(0.1698)	(0.1194)	(0.1735)	(0.2147)	(0.1692)	(0.1560)
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	6,283	4,765	4,850	4,859	4,899	5,233	5,468
Adj-R2	0.1157	0.1239	0.1181	0.1199	0.1249	0.1248	0.1423

Notes: This table presents regressions results for three distinct subperiods: May 1, 2005, to December 31, 2010 (Panel A); January 1, 2011, to December 23, 2015 (Panel B); and December 24, 2015, to June 30, 2021 (Panel C). The dependent variable is the two-day cumulative abnormal return based on the Fama-French six-factor (FF6) model ($\mathrm{CAR}_{[0,1]}$). Day 0 represents the analyst recommendation announcement day. OB is the open buy call-put option volume ratio. All the other control variables are defined as in Table 1. The regressions are estimated with year and firm fixed effects. Robust standard errors clustered by time (quarter-year) 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 1, 2005, to June 30, 2021.

cant returns. Conversely, they are less inclined to trade in events characterized by small or uncertain returns. Following the approach described by Kadan et al. (2018), we analyze instances of recommendation reiterations—occasions on which analysts reiterate their previous recommendations—as placebo information events to assess the validity of the tipping hypothesis.[33]

If the tipping hypothesis holds true, we would expect to find no predictive ability of the OB ratio for forthcoming recommendation reiterations. To test this hypothesis, we estimate the model in Equation 2 to reiteration events during the period up to the enactment of Rule 2241, i.e., until December 24, 2015. We identified a total of 6,124 instances of recommendation reiterations, which yielded an average abnormal two-day return of 0.019% (p-value = 0.568). Panel A of Table C4 in Appendix C displays the results. We observe no statistically significant coefficients for the OB ratio either in the week preceding the reiteration, Column 1, or on the days leading up to the reiteration, Columns 2 – 6.

Continuing with our analysis, we investigate the impact of Rule 2241 on the OB ratio's predictive ability for recommendation reiterations. Under the tipping hypothesis, and considering that recommendation reiterations are unlikely to present informational advantages, we would expect to see no effect of the Rule on the OB ratio's predictive ability. Therefore, we apply the model in Equation 5 to recommendation reiterations and results are presented in Table C4 in Appendix C, Panel B. As anticipated, our analysis reveals no statistically significant coefficient for the triple interaction term $RULE2241 \times TREAT \times OB(t)$. Hence, the placebo test results demonstrate an absence of informed trading prior to analyst reiterations. These findings support the conclusions drawn from our main analysis, reinforcing the hypothesis that information leakage occurs specifically prior to recommendation revisions.

Moreover, in the literature, two alternative hypotheses have been proposed, in addition to tip-

[33]For example, the analyst has rated a stock as a "hold" in the past and then issues a recommendation report that maintains the "hold" recommendation for that stock.

ping, to explain the interaction between analyst recommendations and options trading, that are reverse tipping, and common information (see, e.g. Lin and Lu, 2015). The first alternative hypothesis posits that options traders may convey their trading information to analysts, subsequently influencing changes in analysts' recommendations (reverse tipping). The common information hypothesis posits that analysts and options traders may independently gather similar information and base their predictions on the same set of data, but options traders could potentially act on this information more swiftly (common information). Nevertheless, the existing literature documents evidence consistent with the tipping hypothesis.

We argue that the findings in Section 5 support this prevailing view, i.e. the tipping hypothesis, while simultaneously precluding the validity of both the reverse tipping and common information hypotheses. In fact, if analysts were merely responding to the actions of options traders or accessing information simultaneously with them, then the enactment of Rule 2241 would not have influenced these information acquisition processes among analysts. Thus, by documenting compelling causal evidence of Rule 2241's effectiveness, which specifically influences the predictability of the OB ratio in the days preceding the recommendation announcement without affecting its association with same-day returns, the tipping hypothesis stands as the sole plausible explanation.

Moreover, the predictability of OB precisely on the day before a recommendation revision further undermines the reverse tipping hypothesis. Analysts typically refrain from issuing frequent recommendation revisions based on minor valuation changes, as evidenced by the stickiness observed in their recommendations (see, e.g. Bernhardt et al., 2016). This implies that analysts need a considerable amount of information before deciding to revise a recommendation. Additionally, recommendation revisions typically must undergo an internal review process before receiving approval (see, e.g. Womack, 1996).

Furthermore, the control variables adopted in our analysis take into account the potential influence of common information that could potentially drive the results. First, as mentioned before, we exclude recommendations that coincide with an earnings announcement or another recommendation for the same firm within a [-5, +5] trading day window. Second, we include stock reversal (REV) as a control variable, in the week leading up to the analyst's announcement. If common news events were affecting both traders and analysts, such influence would likely be reflected in stock returns, and the inclusion of the reversal variable would capture this effect. Consequently, under such circumstances, we would expect to observe a diminished or potentially non-existent significance associated with our OB variable. Third, the ATM implied volatility (IV), adopted among our controls, could potentially absorb all or a portion of the OB ratio's predictive information if the common information hypothesis was dominant. Nevertheless, our findings show that the OB ratio maintains its significance even after controlling for both stock REV and IV, with the latter, notably, becoming non-significant on the day preceding the announcement (see Table 1).

We conducted further tests for the pre-rule period to examine the potential influence of other information on the predictability of the OB ratio. To this end, we first consider the potential predictive ability of the underlying stocks' trading volume. It is conceivable that certain information about the stock, not captured by its return, could be reflected in its trading volume (e.g. Beaver, 1968; Kim and Verrecchia, 1994). We calculate the abnormal trading volume for the stock during within the trading window of [-5,-1], $CAVOL$, using a mean-adjusted approach, where the reference period for the mean calculation is [-260,-5] days relative to the event. Additionally, it can be argued that stock options can be traded whenever there is a recommendation revision for other firms within the same industry, if investors aim to exploit any industry-based spillover effect. To mitigate concerns that industry-wide effects might be driving our results, we construct two control variables. These variables measure the number of upgrades (or downgrades) within the same industry (2-digit SIC) during within the trading window [-5,-1], $IndUpgrade$ ($IndDowngrade$).

We augment the models in Equations 1 and 2 with these variables and results are presented in Table C5 in Appendix C. The findings are consistent with the main analysis, showing that the OB ratio continues to exhibit predictive power in the days leading up to the recommendation revision. Furthermore, to examine if tipping practices were associated with specific brokerage firms, we incorporated broker fixed effects, with these results are displayed in Panel B. The predictive ability of OB remains unchanged, indicating that tipping practices were most likely a systematic phenomenon rather than limited to specific brokers. We also performed additional untabulated tests to exclude possible contamination of our findings associated with earning announcements. Recall that throughout the paper, our analyses consistently exclude a 10-day window, [-5, +5], surrounding earnings announcements. In our sample, we observe that recommendation revisions are uniformly distributed throughout the rest of the quarter. Finally, to tackle further this potential concern, we add an indicator variable set to one if the analyst recommendation occurs within the two weeks, or month following quarterly earnings announcements. The robustness of our results is evidenced by their continued significance of OB even after the inclusion of these indicators.

6 Conclusion

We investigate the predictive value of options trading volume for future stock returns surrounding analysts' announcement days. We exploit the ISE database on directional options trading volume and the implementation of FINRA Rule 2241 in 2015. First, we find that a measure of option order flow related to open buy (OB) is informative in predicting stock returns around analysts' news days. Interestingly, we uncover evidence that options traders are executing orders in the right direction for the upcoming analysts' revisions. These findings are consistent with informed trading in the options market before analysts' announcements, and with the prevailing tipping hypothesis.

Next, we validate the informed trading channel associated with the tipping hypothesis through a difference-in-differences analysis related to the implementation of FINRA Rule 2241, which targets analysts' tipping practices. Our findings indicate a halt in systematic tipping behavior in the years following the regulation. Consequently, we confirm the prevailing tipping hypothesis regarding the predictive channel of stock returns around analysts' announcements, and demonstrate the efficacy of FINRA 2241 in curbing tipping practices. Our results are corroborated by a rich set of robustness checks.

Our research has substantial implications for academics, regulatory practice, and policy formulation. Options information around news days are crucial for understanding the dynamics of private information flow in financial markets. Informed trading activity is particularly relevant for regulators who are focused on preserving the integrity of financial markets. Furthermore, standard setting is a dynamic process subject to continuous updates and amendments. By evaluating the impact of Rule 2241, we provide valuable feedback that can aid legal experts and regulators in their continuous efforts to monitor and assess the efficacy of their regulatory frameworks.

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Appendix A Variables definitions

A.1 Dependent variables

- $CAR_{0,1}$: two-day cumulative abnormal return based on the Fama and French five-factor model Fama and French (2015) augmented with the momentum factor Carhart (1997) namely, the Fama-French six-factor model (FF6). Day 0 represents the analyst recommendation announcement day. We estimate the abnormal returns using 255 daily returns in the estimation window [-259,-5].

- REC_REV: Represents the magnitude of a recommendation revision, utilizing the IBES 5-tier classification system (*ireccd*). This variable spans from -2 to +2, with recommendation changes exceeding two levels being categorized as either +2 for upgrades or -2 for downgrades.

A.2 Independent variables

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

$$OB_i(t) = \frac{OB_i^C(t)}{OB_i^C(t) + OB_i^P(t)}$$

  where $OB_i^C(t)$ and $OB_i^P(t)$ are the numbers of call and put contracts purchased by non-market makers to open new positions on trading day $t = -5, ... - 1, 0$ and for stock i.

- $OB(t_{week})$ = the average $OB(t)$ over the trading week $t = [-10, -6]$ or $t = [-5, -1]$.

- $IV(t)$: is the average of the ATM call and put implies volatilities. OptionMetrics computes IV using a binomial tree, taking into account discrete dividend payments and the possibility of early exercise and using historical LIBOR/Eurodollar rates.

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

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

- REV: the last week's reversal specifically, the cumulative raw return over the trading day window $[-5, -1]$.

- MOM: the firm momentum computed as the buy-and-hold abnormal return (FF6) over the trading day window $[-125, -6]$ (day 0 the event day).

- $MKTCAP(ln)$: the natural logarithm of the firm market value of equity at the end of the last fiscal quarter prior to the recommendation announcement.

- $AF(ln)$: the analyst following taken as natural logarithm of one plus the number of analysts that issued at least one earnings forecast for the firm prior to the recommendation announcement.

- IO: the institutional ownership taken as the fraction of shares held by institutional shareholders measured at the end of the last calendar quarter before the recommendation announcement.

- $BM(ln)$: the book-to-market taken as the natural logarithm of the book value of equity divided by its market value at the end of the last quarter before the recommendation announcement.

- $SIZE(ln)$: 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 before the recommendation announcement.

- $EXPER(ln)$: the analyst firm experience taken as the natural logarithm of one plus the number of quarters the analyst has been issuing earnings forecasts for the specific firm.

- EF: indicator variable that takes the value 1 if the analyst also issued an earnings forecast for the same firm within the trading day window of $[-5, +5]$, and 0 otherwise.

- TP: indicator variable that takes the value 1 if the analyst also issued a target price for the same firm within the trading day window of $[-5, +5]$, and 0 otherwise.

- $RULE2241$: indicator variable that takes the value 1 if the analyst recommendation was issued after December 24, 2015.

Appendix B Data description

Table B1: **Sample selection**

	All Revisons	
Analysts' Reports Items	**N**	%
All recommendation revisions in IBES	190,861	
Brokers with more than 20 recommendations per year	183,166	
Matched with CRSP	137,181	
No penny stocks	125,333	
No confounding events	59,612	
With return data	56,470	
Total usable recommendations	56,470	100.0%
Matched with ISE	31,286	55.4%
Final sample	31,286	

Notes: This table presents the description of the analysts' recommendation revisions from IBES adopted in our study. In the last row, we show the number of observation in the final sample, following the screening process and after matching with ISE data. Our sample is from May 2005 to June 2021.

Table B2: **Summary statistics**

		N	Mean	St.Dev	25th Pctl	Median	75th Pctl
$\underline{\underline{CAR}}_{0,1]}$		31,287	-0.012	4.081	-1.968	-0.038	1.947
			OB				
$OB(t)$	$t=-5$	24,596	0.595	0.361	0.284	0.652	0.972
	$t=-4$	24,732	0.594	0.364	0.278	0.656	0.976
	$t=-3$	24,800	0.594	0.363	0.278	0.654	0.975
	$t=-2$	24,969	0.595	0.363	0.273	0.655	0.976
	$t=-1$	26,278	0.596	0.365	0.278	0.661	0.979
	$t=0$	27,320	0.593	0.355	0.295	0.644	0.956
			Option Variables				
$ATMt$	$t=-5$	26,072	0.410	0.214	0.267	0.363	0.495
	$t=-4$	26,258	0.413	0.217	0.268	0.366	0.497
	$t=-3$	26,240	0.415	0.218	0.269	0.367	0.500
	$t=-2$	26,348	0.416	0.218	0.270	0.369	0.502
	$t=-1$	27,970	0.417	0.215	0.271	0.370	0.503
	$t=0$	27,973	0.419	0.213	0.273	0.373	0.507
$SKEW(t)$	$t=-5$	26,072	0.061	0.070	0.028	0.046	0.075
	$t=-4$	26,258	0.061	0.071	0.028	0.046	0.075
	$t=-3$	26,240	0.061	0.072	0.028	0.047	0.075
	$t=-2$	26,348	0.062	0.072	0.028	0.046	0.076
	$t=-1$	27,970	0.063	0.075	0.028	0.047	0.078
	$t=0$	27,973	0.063	0.074	0.029	0.047	0.077
$SPREAD(t)$	$t=-5$	26,072	-0.006	0.046	-0.012	-0.002	0.006
	$t=-4$	26,258	-0.005	0.045	-0.012	-0.002	0.006
	$t=-3$	26,240	-0.005	0.048	-0.012	-0.002	0.006
	$t=-2$	26,348	-0.006	0.048	-0.012	-0.002	0.006
	$t=-1$	27,970	-0.006	0.051	-0.013	-0.002	0.006
	$t=0$	27,973	-0.006	0.049	-0.012	-0.002	0.006
			Firm Variables				
REV		31,136	0.327	6.568	-2.877	0.424	3.519
MOM		31,136	-0.017	0.189	-0.117	-0.024	0.071
$MKTCAP$		31,136	$19,695.89$	$38,139.56$	$2,197.29$	$6,401.02$	$18,444.19$
AF		31,136	17.443	7.935	12	17	22
IO		31,136	0.788	0.220	0.697	0.821	0.921
BM		31,136	0.449	0.359	0.207	0.363	0.600
			Analyst Variables				
$BSIZE$		31,136	67.466	63.536	18	47	106
$EXPER$		31,136	38.265	23.167	21	37	54
TP		31,136	0.642	0.480	0	1	1
EF		31,136	0.575	0.494	0	1	1

Notes: This table provides the summary statistics for our sample. $CAR[0,1]$ is the two-day cumulative abnormal return calculated using the Fama-French six-factor (FF6) model. OB is the open buy call-put option volume ratio. IV is the ATM implied volatility, SKEW is the implied volatility skew, SPREAD is the call-put implied volatility spread. tD represents the trading day relative to the day of the analyst recommendation announcement, with day 0 being the announcement day. REV is the last week's stock return reversal. MOM the firm's momentum over the last six-months. MKTCAP is the market capitalization of the firm. AF is the number of analysts following the stock. IO is the fraction of shares held by institutional investors. BM is the firm book-to-market. BSIZE is the number of analysts employed by the brokerage during the last year. EXPER the number of quarters the analyst has been following the firm. EF and TP are indicator variables for whether an earnings forecast and/or a target price were issued with the recommendation. For more detailed definitions of the variables refer to Appendix A. Our sample is from May 2005 to June 2021.

Appendix C Additional results

Table C1: **Stock returns predictability for customers vs customers, proprietary and professional customers**

Panel A: Customers

	$t = [-5, -1]$	$t = -5$	$t = -4$	$t = -3$	$t = -2$	$t = -1$	$t = 0$
$OB(t)$	0.5484***	0.1803*	0.1971**	0.2188**	0.1769**	0.4100***	0.3923***
	(0.1125)	(0.0954)	(0.0902)	(0.0898)	(0.0852)	(0.0893)	(0.0808)
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	19,983	15,115	15,238	15,265	15,350	16,088	16,965
Adj-R2	0.0781	0.0856	0.0811	0.0832	0.0878	0.0888	0.0952

Panel B: CPPC

	$t = [-5, -1]$	$t = -5$	$t = -4$	$t = -3$	$t = -2$	$t = -1$	$t = 0$
$OB(t)$	0.4668***	0.2137**	0.0714	0.1052	0.1669**	0.3306***	0.8207***
	(0.1306)	(0.0991)	(0.1009)	(0.0941)	(0.0810)	(0.0890)	(0.0959)
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	20,533	16,234	16,394	16,409	16,488	17,414	18,166
Adj-R2	0.0772	0.0835	0.0845	0.0808	0.0831	0.0832	0.0940

Notes: This table presents cross-sectional panel regressions where the dependent variable is the two-day cumulative abnormal return ($\mathrm{CAR}_{[0,1]}$) on the analysts' announcement day. In Panel A we present the results for ISE option directional volume belonging only to customers, whereas in Panel B the option directional volume belonging to customers, proprietary and professional customers (CPPC). 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 (quarter) 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.

Table C2: **Stock returns predictability around all recommendations announcements: Monday effect**

	$t = [-5, -1]$	$t = -5$	$t = -4$	$t = -3$	$t = -2$	$t = -1$	$t = 0$
$OB(t)$	0.4208***	0.0785	0.1074	0.1006	0.2001**	0.4161***	0.7811***
	(0.1289)	(0.1102)	(0.1140)	(0.1085)	(0.0951)	(0.0932)	(0.1194)
$OB(t) \times MondayEffect$	0.4013	0.6085**	-0.0419	0.1211	-0.1375	-0.1788	0.0458
	(0.2420)	(0.2388)	(0.1980)	(0.2083)	(0.2302)	(0.1913)	(0.2251)
$MondayEffect$	-0.2860*	-0.3500**	0.0166	-0.0627	0.0158	0.0534	-0.0753
	(0.1504)	(0.1530)	(0.1282)	(0.1262)	(0.1601)	(0.1296)	(0.1392)
$Controls$	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	20,490	16,014	16,168	16,190	16,256	17,173	17,971
Adj-R2	0.0761	0.0834	0.0823	0.0815	0.0827	0.0813	0.0934

Notes: This table presents cross-sectional panel regressions where the dependent variable is the two-day cumulative abnormal return ($\mathrm{CAR}_{[0,1]}$) on the analysts' announcement day. OB is the ISE open buy ratio, and the control variables included are as defined before. In addition, we control for a variable capturing the so-called Monday Effect which marks one if the recommendation was issued from Friday after the market closure (at 16:00) to Monday until the market closure (at 16:00), and zero otherwise. We also add an interaction term which multiplies the OB variable with the Monday Effect dummy. 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 (quarter) 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.

Table C3: **The impact of FINRA Rule 2241. DiD results 2013 – 2017.**

Panel A: DiD

	(1) t = [-5,-1]	(2) t = -5	(3) t = -4	(4) t = -3	(5) t = -2	(6) t = -1	(7) t = 0
$OB(t)$	0.1537**	0.0421	-0.0052	0.0249	0.0140	0.1362***	0.3449***
	(0.0660)	(0.0463)	(0.0420)	(0.0383)	(0.0342)	(0.0472)	(0.0416)
$TREAT \times OB(t)$	0.1235	0.0288	0.0265	0.0162	0.2165	0.1023	0.1753
	(0.1775)	(0.1389)	(0.1338)	(0.1449)	(0.1354)	(0.1528)	(0.1404)
$RULE2241 \times OB(t)$	-0.0174	0.0872	0.0114	-0.0148	0.0910	-0.0397	0.0887
	(0.1228)	(0.0761)	(0.0850)	(0.0721)	(0.0670)	(0.0779)	(0.0767)
$RULE2241 \times TREAT \times OB(t)$	**-0.2332**	**-0.2697***	**-0.2031**	**-0.1333**	**-0.2591**	**-0.3387***	**-0.0533**
	(0.1836)	**(0.1609)**	**(0.1874)**	**(0.1793)**	**(0.1698)**	**(0.1728)**	**(0.1531)**
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	47,153	36,369	36,372	36,605	36,815	39,205	39,796
Adj-R2	0.0481	0.0550	0.0556	0.0578	0.0557	0.0564	0.0719

Panel B: DiD with entropy balancing

	(1) t = [-5,-1]	(2) t = -5	(3) t = -4	(4) t = -3	(5) t = -2	(6) t = -1	(7) t = 0
$OB(t)$	0.2287**	0.1044	-0.0170	0.0215	0.0213	0.1849**	0.3704***
	(0.1018)	(0.0734)	(0.0728)	(0.0728)	(0.0398)	(0.0691)	(0.0561)
$TREAT \times OB(t)$	0.1074	-0.0026	-0.0284	0.0239	0.2394**	0.0874	0.1620
	(0.1589)	(0.1504)	(0.1052)	(0.1434)	(0.0937)	(0.1416)	(0.1578)
$RULE2241 \times OB(t)$	-0.2592*	0.0149	0.0091	-0.0847	0.0387	-0.1785*	0.0516
	(0.1433)	(0.1055)	(0.0915)	(0.1020)	(0.1128)	(0.0932)	(0.1110)
$RULE2241 \times TREAT \times OB(t)$	**-0.2526***	**-0.2880****	**-0.1869**	**-0.1208**	**-0.2807***	**-0.3484****	**-0.0497**
	(0.1224)	**(0.1273)**	**(0.1459)**	**(0.1515)**	**(0.1370)**	**(0.1430)**	**(0.1289)**
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	47,153	36,369	36,372	36,605	36,815	39,205	39,796
Adj-R2	0.0940	0.0997	0.0952	0.1018	0.1024	0.1064	0.1168

Notes: This table presents DiD panel regression models where the dependent variable is the two-day cumulative abnormal return based on the Fama-French six-factor (FF6) model ($\mathrm{CAR}[0,1]$). Day 0 represents unscheduled event announcement day. OB is the open buy call-put option volume ratio. $RULE2241$ is an indicator variable that takes the value one if the recommendation announcement date is after Dec 24, 2015. $TREAT$ is an indicator variable that takes the value 1 if the unscheduled event is analyst recommendation. The control sample encompasses all other unscheduled events which do not belong to the analysts' domain (e.g. M&A, credit-ratings changes, equity-actions). Panel A presents the results of regression Model 5. Panel B presents the results for the same model but using the entropy balancing technique. All regression models include option-related and firm-specific control variables, as detailed in Table 1. The regressions are estimated with year and firm fixed effects. Robust standard errors clustered by time (quarter) 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 January 1, 2013, to December 31,2017.

Table C4: **Placebo test: recommendation reiterations**

Panel A: Recommendation reiterations before Rule 2241

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	t = [-5,-1]	t = -5	t = -4	t = -3	t = -2	t = -1	t = 0
$OB(t)$	0.0026	-0.1026	-0.0641	0.0691	-0.0388	0.1034	0.4568***
	(0.1615)	(0.1672)	(0.1197)	(0.1119)	(0.1252)	(0.1154)	(0.1206)
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	4,737	3,817	3,839	3,849	3,851	3,959	4,000
Adj-R2	0.0406	0.0242	0.0445	0.0396	0.0322	0.0453	0.0441

Panel B: DiD

	(1) t = [-5,-1]	(2) t = -5	(3) t = -4	(4) t = -3	(5) t = -2	(6) t = -1	(7) t = 0
$OB(t)$	0.1229*	0.0771	-0.0362	0.0501	0.0153	0.1093**	0.3856***
	(0.0677)	(0.0581)	(0.0511)	(0.0368)	(0.0226)	(0.0393)	(0.0481)
$TREAT \times OB(t)$	0.0438	-0.5546*	-0.0791	0.3173	0.2678	0.0558	0.1179
	(0.2978)	(0.3140)	(0.1949)	(0.3042)	(0.2399)	(0.2583)	(0.2627)
$RULE2241 \times OB(t)$	-0.0850	-0.0253	-0.0334	-0.0314	0.1497*	-0.0394	0.0580
	(0.1243)	(0.0952)	(0.0819)	(0.0966)	(0.0716)	(0.1291)	(0.0992)
$RULE2241 \times TREAT \times OB(t)$	**0.2098**	**0.1846**	**0.5619**	**0.3206**	**-0.0467**	**0.3733**	**0.1539**
	(0.4549)	**(0.6551)**	**(0.4529)**	**(0.4020)**	**(0.4741)**	**(0.3030)**	**(0.3822)**
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	30,363	24,114	23,977	24,157	24,246	25,611	25,858
Adj-R2	0.0622	0.0723	0.0632	0.0686	0.0710	0.0695	0.0896

Notes: This table presents regression results where the dependent variable is the two-day cumulative abnormal return based on the Fama-French six-factor (FF6) model ($\mathrm{CAR}[0,1]$) around recommendation reiterations. Day 0 represents the analyst recommendation announcement day. OB is the open buy call-put option volume ratio. $RULE2241$ is an indicator variable that takes the value one if the recommendation announcement date is after Dec 24, 2015. All the other control variables are defined as in Table 1. The regressions are estimated with year and firm fixed effects. Robust standard errors clustered by time (quarter-year) 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-R2. Panel A presents regression results before December 2015, while Panel B DiD results of regression Model 5 for the period January 1, 2013, to December 31,2016.

Table C5: **Robustness checks**

Panel A: Additional control variables

	(1)	(2)	(3)	(4)	(5)	(6)	(5)
	t = [-5,-1]	t = -5	t = -4	t = -3	t = -2	t = -1	t = 0
OB (t)	0.5259***	0.2205**	0.0983	0.1695*	0.1699**	0.3773***	0.8109***
	(0.1107)	(0.0946)	(0.0860)	(0.0937)	(0.0814)	(0.0773)	(0.0918)
$CAVOL$	0.0051	0.0084	-0.0004	-0.0048	0.0087	-0.0110	0.0452*
	(0.0214)	(0.0266)	(0.0257)	(0.0286)	(0.0270)	(0.0217)	(0.0260)
$IndUpgrade$	0.0432***	0.0401***	0.0458***	0.0467***	0.0449***	0.0407***	0.0392***
	(0.0087)	(0.0093)	(0.0085)	(0.0083)	(0.0087)	(0.0091)	(0.0094)
$IndDowngrade$	-0.0337***	-0.0344***	-0.0361***	-0.0316***	-0.0354***	-0.0353***	-0.0328***
	(0.0082)	(0.0080)	(0.0085)	(0.0083)	(0.0079)	(0.0080)	(0.0070)
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	20,525	16,539	16,579	16,636	16,702	17,533	18,216
Adj-R2	0.0595	0.0644	0.0660	0.0668	0.0642	0.0623	0.0786

Panel B: Additional control variables and broker fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(5)
	t = [-5,-1]	t = -5	t = -4	t = -3	t = -2	t = -1	t = 0
OB (t)	0.5247***	0.2289**	0.1132	0.1692*	0.1830**	0.3514***	0.7928***
	(0.1122)	(0.0937)	(0.0851)	(0.0949)	(0.0856)	(0.0771)	(0.0893)
$CAVOL$	0.0044	0.0087	-0.0014	-0.0052	0.0055	-0.0131	0.0418
	(0.0209)	(0.0262)	(0.0257)	(0.0277)	(0.0270)	(0.0218)	(0.0256)
$IndUpgrade$	0.0417***	0.0381***	0.0432***	0.0448***	0.0425***	0.0383***	0.0374***
	(0.0089)	(0.0096)	(0.0085)	(0.0084)	(0.0094)	(0.0096)	(0.0096)
$IndDowngrade$	-0.0350***	-0.0361***	-0.0378***	-0.0330***	-0.0364***	-0.0363***	-0.0352***
	(0.0082)	(0.0084)	(0.0085)	(0.0086)	(0.0084)	(0.0083)	(0.0071)
Controls	YES	YES	YES	YES	YES	YES	YES
Broker FE	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	20,525	16,539	16,579	16,636	16,702	17,533	18,216
Adj-R2	0.0642	0.0693	0.0700	0.0709	0.0690	0.0668	0.0835

Notes: This table presents regression results where the dependent variable is the two-day cumulative abnormal return based on the Fama-French six-factor (FF6) model ($CAR[0, 1]$). Day 0 represents the analyst recommendation announcement day. OB is the open buy call-put option volume ratio. $CAVOL$ is the abnormal trading volume during within the trading window $[-5, -1]$. $IndUpgrade$ ($IndDowngrade$) are the number of recommendation upgrades (downgrades) within the same industry (2-digit SIC), during the within the trading window $[-5, -1]$. The analysis covers the pre-rule period from May 1, 2005, to December, 24, 2015.