

Analyst Price Target and Retail Option Trading*

Shuaiqi Li[†]

Abstract

This paper examines the short-term reactions of the option market to the release of analysts' price targets. I find that a larger target return, defined as the log ratio of the price target to the current stock price, is associated with increased buy (sell) volume of call (put) options on the announcement day. This effect is mainly driven by small orders rather than large ones. In addition, target returns tend to be upward biased and negatively predict stock returns. These findings suggest that retail investors naively interpret higher target returns as positive news, leading them to buy (sell) call (put) options. Consistent with demand-based option pricing theory, I find that risk-neutral skewness increases with target returns on the release day and reverses in the following two days. In the cross-section, stocks with higher consensus target returns tend to exhibit lower delta-hedged option returns in the subsequent month.

Keywords: Option Trading, Option Return, Analyst, Price Target.

*The data used in this white paper was made available through The Options Institute, the educational division of Cboe Exchange, Inc., in connection with The Options Institute Research Grant Program. Learn more about The Options Institute Research Grant Program at www.cboe.com/optionsinstitute/about_us/research_grant.

The author is an independent contractor and not an employee or agent of Cboe Exchange, Inc. or any affiliates of Cboe (collectively, 'Cboe') with respect to this white paper. The author is solely responsible for the content of and any positions taken in this white paper. Although Cboe may have been consulted in the development of the white paper, Cboe does not have control over the content of the white paper, and it does not necessarily represent the views of Cboe. Cboe does not assume any responsibility or liability for any errors or loss from use of this white paper. Cboe does not make any claim, prediction, warranty or representation whatsoever, expressly or impliedly, as to the results to be obtained from the use of the information or the fitness or suitability of the information for any particular purpose to which it might be put.

[†]City University of Hong Kong, shuaiqli@cityu.edu.hk.

1 Introduction

Financial analyst reports are a crucial channel through which information is incorporated into asset prices. Analysts issue price targets, recommendations, and earnings-per-share (EPS) forecasts in their reports, which reflect their views on stocks. A large literature studies how analyst reports contribute to stock price formation and how investors trade in the stock market following their release.¹ Due to the embedded leverage and the ability to circumvent short-sales constraints, options are often perceived to attract informed traders and contain information that can predict stock returns.² In this sense, option prices may incorporate the relevant fundamental information from analyst reports more timely and accurately than stock prices. On the other hand, retail investors play an important role in individual stock option markets (Bryzgalova, Pavlova, and Sikorskaya (2023); Lemmon and Ni (2014)). They are commonly viewed as non-sophisticated investors who are less capable of discerning biases in analyst reports compared to institutional investors.³ This paper investigates option market reactions to information contained in analyst reports.

This paper focuses on analyst price targets, which provide option investors-especially retail investors-with the most concise and explicit input to evaluate potential gains from their option investments. As pointed out by McLean, Pontiff, and Reilly (2024), EPS forecasts do not give investors a clear course of action. While stock recommendations give investors suggestions on buy or sell actions, they do not come with explicit numbers to help option investors make investment decisions. For instance, it is unclear how

¹See Brav and Lehavy (2003), Stickel (1995), Womack (1996), Barber, Lehavy, McNichols, and Trueman (2001), Malmendier and Shanthikumar (2007), Savor (2012), and McLean, Pontiff, and Reilly (2024).

²See Easley, O'hara, and Srinivas (1998), Pan and Poteshman (2006), Bali and Hovakimian (2009), Johnson and So (2012), Ge, Lin, and Pearson (2016), Muravyev, Pearson, and Pollet (2022).

³See Malmendier and Shanthikumar (2007), and Mikhail, Walther, and Willis (2007) for evidence in the stock market.

much greater the implied return is for a strong buy compared to a buy recommendation. Although price targets are commonly used as proxies for market expectations regarding future returns, they are well-documented to be upward biased (Brav and Lehavy (2003); Palley, Steffen, and Zhang (2024)). I hypothesize that if naive retail investors take price targets at face value without adjusting for this bias, they will perceive firms with larger target returns as having higher future returns. When this perception is combined with retail investors' lottery preferences in option markets,⁴ they tend to respond to price target releases by buying (selling) call (put) options on those firms. Under the framework of demand-based option pricing theory (Garleanu, Pedersen, and Poteshman (2008)), this demand pattern would increase the expensiveness of call options while decreasing their future returns.

Consistent with the hypothesis, I find that target return negatively predicts cross-sectional delta-hedged call option returns in the following month.⁵ The significance remains robust even after controlling for well-established option return predictors in the literature. A strategy that long call options with lowest target returns and short those with highest target returns generates an average monthly profit of 1.44%, with an annual Sharpe ratio of 2.91. This profitability is comparable to some well-known option return predictors in the literature, such as idiosyncratic volatility in Cao and Han (2013). While option bid-ask spreads reduce profitability, the strategy remains profitable when investors pay 25% of the quoted spreads, which is around the cost faced by algorithmic traders in option markets as shown in Muravyev and Pearson (2020).

⁴For studies on lottery preference in option markets, see Bauer, Cosemans, and Eichholtz (2009), Boyer and Vorkink (2014), Byun and Kim (2016), and Blau, Bowles, and Whitby (2016) among others.

⁵The delta-hedged position is rebalanced daily so that the portfolio is not sensitive to the stock price movement. The option expensiveness is thus measured in the perspective of market makers who hedge at a high frequency.

The effects of price targets on put options are more ambiguous: On one hand, if retail investors sell more put options on firms with higher target returns, this could exert downward pressure on current put option prices and increase future returns; On the other hand, when they purchase more call options and drive up call prices, arbitragers would exploit the put-call parity and also increase the expensiveness of put options. Thus, determining the net effect on put option returns becomes an empirical question. I find that while target return still negatively predicts put option returns, the effect is weaker than that for call options: the difference in put option returns between stocks with the lowest and highest target return is 0.81% per month. Although this difference is statistically significant, its magnitude is less than two-thirds of what we observe for call options. Furthermore, a long-short quintile strategy becomes unprofitable when investors pay 25% of the quoted spreads.

Another finding is that target return negatively predicts cross-sectional future 12-month stock returns, confirming that analyst price targets tend to be upward biased, as documented in the literature. The above finding that call options written on firms with higher target returns tend to be more expensive suggests that option investors do not fully account for the bias. To further investigate option market reaction to price target releases, I analyze the trading volumes of call and put options from various trading accounts in the Cboe Open-Close Volume dataset on the target release day. I find that larger target returns are associated with greater buy (sell) volume of call (put) options. This pattern is particularly strong in the most recent period, during which option trading has gained popularity among retail traders. The results remain similar in the subsample where price targets are released during pre-market hours,⁶ suggesting that the findings are not driven by option trading in anticipation of analyst information

⁶The entire option volumes on that day occur after target releases.

releases (Hayunga and Lung (2014)) or by analyst tipping (Lin and Lu (2015)).

To better isolate the trading behavior of retail investors from total volumes, I analyze option volumes splitted by order sizes. Compared to large institutional investors, retail investors are more likely to place small option orders. I find that the above trading pattern is mainly driven by small orders, while it is insignificant among large orders. The finding is consistent with that retail investors naively interpret higher target returns as positive news by buying (selling) call (put) options.

I further analyze how target release can affect the shape of the implied volatility (IV) curve. Bakshi, Kapadia, and Madan (2003) show that risk-neutral skewness is closely related to the shape of the IV curve. Since risk-neutral skewness involves a long position in calls and a short position in puts, it measures the expensiveness of call relative to put options. A more positive skewness is associated with a more right-skewed IV curve. If retail investors respond to target release by buying call and selling put, firms with larger target returns are expected to exhibit higher risk-neutral skewness on the release day. Indeed, I find this true in the data. In addition, the increase in skewness reverses in the two days following the release, consistent with a demand-pressure story. This provides a channel through which analyst bias could manifest itself in option-implied moments.

This paper contributes to the literature on how financial markets react to information contained in analyst reports. Brav and Lehavy (2003) examine how stock prices and volumes react to the release of price target. Malmendier and Shanthikumar (2007) and Mikhail, Walther, and Willis (2007) investigate the direction and profitability of small and large trades following analysts' stock recommendations. McLean, Pontiff, and Reilly (2024) explore whether retail investors in stock market respond to analysts' revisions in price targets, recommendations, and EPS forecasts. This paper focuses on

the response of option market participants, particularly retail investors, to price target releases.

This paper also contributes to the literature on lottery preferences. Kumar (2009) documents retail investors' lottery preference in the stock market. Boyer and Vorkink (2014) point out that due to embedded leverage, individual stock option markets provide an even more ideal arena than stock market for studying lottery preference. Bauer, Cosemans, and Eichholtz (2009) document that gambling and entertainment appear to be retail investors' motives for trading options, and that they incur losses on options investment due to overreaction to past stock returns. I argue that the upward bias in price target, combined with its straightforwardness in evaluating future option performance, can trigger the lottery preference of retail investors, who are prevalent in option markets and inexperienced in accounting for the bias.

The rest of this paper is organized as follows. Section 2 describes the data. Section 3 investigates how target returns predict cross-sectional option and stock returns. Section 4 examines option trading volumes on the price target release day. Section 5 concludes.

2 Data

This paper uses data from the OptionMetrics Ivy DB database from January 1996 to December 2020, which provides daily closing bid and ask quotes for U.S. equity options. I extract analysts' price target information from the I/B/E/S. Daily signed option trading volumes come from Cboe Open-Close Volume dataset. I obtain information about stock prices from CRSP. My sample includes only common shares (CRSP share codes of 10 and 11). I obtain firm accounting information from Compustat.

I compute delta-hedged option return at monthly frequency following Bakshi and

Kapadia (2003):

$$r_{t,T}^{Option} = \frac{O_T - O_t - \sum_{n=0}^{N-1} \Delta_{t_n} [S_{t_{n+1}} - S_{t_n}] - \sum_{n=0}^{N-1} e^{r_f(t_{n+1}-t_n)} [O_{t_n} - \Delta_{t_n} S_{t_n}]}{|O_t - \Delta_t S_t|},$$

where: O is the price of call or put option; O_t is the option price at formation date t , which is typically the third Friday of each month; O_T is the final payoff of the option at expiration date T , which is typically the third Friday of the subsequent month; Delta-hedged positions are rebalanced at each of the business dates $t_n, n = 0, 1, \dots, N - 1$, with $t_0 = t, t_N = T$; Δ_{t_n} is the delta of option at date t_n provided by OptionMetrics; S_{t_n} is the stock price at date t_n ; r_f is the daily risk-free rate.

To enhance option tradability, I pick at-the-money strikes that are closest to the current underlying stock prices and have both call and put left after applying the following filters: First, I remove options with 0 open interest or bid price; Second, I delete options whose ask prices are lower than bid prices; Third, I discard options with missing implied volatilities or deltas; Lastly, I exclude options with stock-splits during the holding period. Option contracts passing the above filters tend to be actively traded and have reliable returns.

Next, I construct the main explanatory variable in this paper: target return. I first utilize the mean price target in I/B/E/S unadjusted summary history database, whose coverage starts from March 1999. Since I/B/E/S releases consensus price target statistics once per month (usually on the third Thursday each month), I compute a monthly target return as the log ratio of mean price target to current stock price, and use it to predict cross-sectional option returns that are formed on the third Friday each month.

Panel A of Table 1 presents the summary statistics of the sample merged between

OptionMetrics and I/B/E/S summary. Since the latter starts later than the former, the sample is from March 1999 to December 2020. Target return has an average of 20.58% with a standard deviation of 26.31%, which means that the stock price will increase by 20.58% on average in the following year based on analysts' estimate. Call (Put) option return is -0.80% (-0.98%) per month on average with a standard deviation of 8.56% (6.27%). On average, firms in my sample has a market capitalization of 10.51 billion dollars, and there are 1533 firms per month in the cross-section.

Then, to investigate short-term option market reaction to price target release, I switch to the I/B/E/S unadjusted details file, which provides details such as the exact release time of price targets. If a target is released after market close, I assign it to the next trading day. If there are multiple targets released on the same day, I pick the maximum one assuming that it is the most eye-catching to trigger retail investors' lottery preference. I focus on targets with forecast horizon at 12 months. This dataset starts from February 19, 1999 and ends on March 31, 2022. I compute daily target return as the log ratio of price target to the stock price on the target release day and use it to explain option volumes on that day. To alleviate the concern that option trading is driven by other major firm events instead of target release, I exclude observations with earnings announcements within $[-3, +3]$ days around the release.

I use the Cboe Open/Close Volume dataset, which records the information on signed option volumes of the open/close and buy/sell orders from public customers account and firm proprietary account. The categorization of investors as public customers or firm proprietary traders follows the OCC classification. The sum of the two constitute all option end-users. I follow Ni, Pearson, Poteshman, and White (2021) to construct

the net signed option volume for option contract j on trading day t , as follows:

$$NetVolume_{j,t} = Volume_{j,t}^{OpenBuy} - Volume_{j,t}^{CloseSell} - Volume_{j,t}^{OpenSell} + Volume_{j,t}^{CloseBuy}$$

Then I aggregate put and call options, respectively, into stock-day-level by summing up all available puts/calls written on the same stock on target release days. I exclude options with fewer than 3 days to expirations. I compute net volumes using public customers, firm proprietary accounts, and their combination, respectively. I am particularly interested in the volume of public customers account, where retail option trading takes place in. Public customers account also include the trading volume of institutional investors. A good feature of the data is that public customers volumes are further broken down into trade size buckets: small (fewer than 100 contracts), medium (100-199 contracts), and large (greater than 199 contracts). This helps differentiate retail trading from institutional trading as retail investors tend to place small orders. Therefore, I further compute net volumes with the three buckets in public customers account. I use the net volume of small orders to proxy for retail trading and use that of large orders to approximate institutional trading.

I merge the Cboe Open/Close Volume dataset with daily IBES database to obtain daily option volumes on target release days. The overlapped period of the two datasets is from February, 1999 to March, 2022. The sample only includes stocks whose options are traded at the Cboe exchange, because otherwise their option volumes are not recorded in the Cboe dataset.⁷ Panel B of Table 1 displays the summary statistics of option volumes.

To examine how price target release affects the shape of IV curve, I construct daily

⁷In option return prediction exercise, I do not restrict to options traded at Cboe.

risk-neutral skewness following Bakshi, Kapadia, and Madan (2003). I extract the 30-day implied volatilities from the OptionMetrics Volatility Surface database and convert them into option prices, which I then use to compute the option-implied skewness.

3 Target Return and Cross-Sectional Option Return

This section investigates how target return predicts cross-sectional option returns. Section 3.1 examines the return predictability using the Fama and MacBeth (1973) regression. Section 3.2 explores the profitability by forming long-short portfolios and evaluates the impact of transaction cost. Section 3.3 checks the stock return predictability of target return to confirm the upward bias in price target.

3.1 Cross-sectional Regressions

I run the following monthly Fama-MacBeth regression,

$$r_{i,t+1}^{Option} = \alpha_t + \gamma_t \cdot Target\ Return_{i,t} + \theta_t \cdot Controls_{i,t} + \epsilon_{i,t+1},$$

where: $r_{i,t+1}^{Option}$ is stock i 's call/put option return in month $t + 1$. $Target\ Return_{i,t}$ is the latest available target return of stock i . To ensure the robustness of the regression results, I include a variety of well-established option return predictors as controls. The choice of control variables largely follows Heston, Jones, Khorram, Li, and Mo (2023): I use the log market capitalization on the third Friday; Following Cao and Han (2013), I calculate idiosyncratic volatility as the standard deviation of the residuals of a 22-day rolling regression using Fama-French 3 factors; I measure the slope of implied volatility term structure (IV term spread) following Vasquez (2017); The smirk of the implied

volatility curve (IV smirk) is computed as the difference between the IV of a 30-day call with delta of 0.3 and that of a 30-day put with delta of -0.3 ; To get the volatility difference in Goyal and Saretto (2009) (IV - HV), I compute the log difference between the historical volatility estimated from rolling one-year daily stock returns and at-the-money IV.

Table 2 reports the time-series averages of the coefficients in Fama-MacBeth regressions, together with their t -statistics in parentheses corrected for heteroskedasticity and autocorrelation, following Newey and West (1986) with 12 lags. Independent variables are winsorized at 1% level in each month. In column (1), the variable Target Return negatively predicts call return with a coefficient of -0.033 and a t -statistic of -12.75 . After adding controls in column (2), its coefficient reduces to -0.014 but remains highly significant with a t -statistic of -4.92 . When used alone to predict put return in column (3), Target Return has a coefficient of -0.021 . Even though the magnitude is two thirds of that in column (1), it is highly significant with a t -statistic of -9.13 . It remains significant after controls in column (4) with a coefficient of -0.007 , half of that in column (2). The comparison between coefficients suggests that target return has a stronger negative effect on call return than on put return.

The interpretation of the negative relation is that stocks with higher target returns in the cross-section tend to have more expensive call/put options and thus lower delta-hedged option returns in the following month.

3.2 Portfolio Sort

In this section, I employ portfolio sort to examine the performance of the option strategies formed by target return and evaluate the impact of transaction costs. I form

long-short portfolios of call and put options, respectively. I long the options of stocks with lowest target returns and short those with highest target returns. Portfolios are equally weighted.

Panel A in Table 3 presents the average monthly portfolio returns in percentage. The (%) symbol after a variable means that it is reported as a percentage. To generate an increasing pattern of option returns, I sort firms into quintiles by *negative* target return. When I use call options, a long-short strategy generates a monthly return of 1.44% with a t -statistic of 13.60. If I use put options, the long-short profit is 0.81% with a t -statistic of 11.37. Although still highly significant, its magnitude is about two-thirds of that of call options. This reconfirms the stronger negative effect of target return on call return than on put return in Table 2. Thus, implementing the strategy with call options is more profitable.

I then analyze the profitability over different sub-periods. Figure 1 plots the five-year moving averages of monthly returns of call options (Panel A) and put options (Panel B). For both call and put, the performance is positive and significant in all five-year subsamples. The call strategy is more profitable than put strategy in all times. Also, put strategy tends to be more profitable in the second half of the sample than in the first half, while call strategy is relatively balanced with high profitability in both early and later sample periods.

I further evaluate the strategy performance by comparing it with other option return predictors examined in the empirical options literature. When I implement the strategy with call options in Panel B of Table 3, the monthly average return of target return is larger than that of IV Smirk and slightly below idiosyncratic volatility. It has an annual Sharpe ratio of 2.91. The strategy has limited crash risk: It has a positive skewness of 0.32 and a minimum monthly return of -5.89% . Thus, there is no evidence that its

profitability can be explained by the exposure to downside risk.

So far, I assume that options can be bought and sold at the midpoint of bid and ask quotes. To examine the effects of transactions costs, I assume that the transaction cost of trading an option is some fraction of the quoted spread. I consider fractions ranging from zero (trades take place at the midpoint) to 100% (trades take place at the bid or ask quote), with three values in between (25%, 50%, and 75%). To mitigate the effects of transactions costs, I also sort firms into more extreme deciles rather than quintiles.

Table 4 presents the average monthly returns of long-short strategies under different spread ratios. When I use call options, the strategy remains profitable when investors pay 25% of the quoted spread, which is about the transaction cost faced by algorithmic traders as documented in Muravyev and Pearson (2020). Even though still significant, the profit is more than halved: If I sort by deciles, the profit drops from 2.30% per month to 1.03%. The strategy is no longer profitable when investors pay 50% of the quoted spread. When I implement with put options and sort by quintiles, the strategy becomes nonprofitable even under 25% threshold. Therefore, reducing transaction cost is essential to maintain the profitability.

3.3 Cross-sectional Stock Returns

To confirm whether price target is indeed upward biased as documented in previous literature, I run the following monthly Fama-MacBeth regression,

$$r_{i,t+1 \rightarrow t+12}^{Stock} = \alpha_t + \gamma_t \cdot Target\ Return_{i,t} + \theta_t \cdot Controls_{i,t} + \epsilon_{i,t+1},$$

where: $r_{i,t+1 \rightarrow t+12}^{Stock}$ is stock i 's future-12-month log return, which aligns with analyst's forecast horizon. I include standard control variables in stock literature: I compute the

stock’s exposure to market risk β using rolling-1-year daily stock returns; logarithm of market cap and logarithm of book-to-market ratio as in Fama and French (1992); operating profitability and investment factor in Fama and French (2015); stock momentum in Jegadeesh and Titman (1993); past month stock return; idiosyncratic volatility as in Ang, Hodrick, Xing, and Zhang (2006).

Table 5 reports regression results. When used alone, target return negatively predicts stock return with a coefficient of -0.372 and a t -statistic of -6.66 . After adding controls in column (2), its coefficient reduces to -0.203 but remains highly significant with a t -statistic of -5.79 . The negative effect is consistent with the findings in the literature that analyst price target tends to be upward biased and is negatively related to future stock return.

4 Option Trading Volumes

This section investigates short-term option market reactions to analyst’s price target release. Section 4.1 examines call and put option volumes on the release day. Section 4.2 separates retail trading from institutional trading by order size. Section 4.3 explores how target release can affect the shape of IV curve.

4.1 Call and Put

In order to examine option market reaction, I regress daily call and put volumes, respectively, on daily target return in a panel regression on firm-days with target release. I separately look at volumes from public customers account, firm account, and total volume. Retail trading takes places via public customers account. I include time- and firm-fixed effects, and cluster standard errors at the firm- and day-level. To reduce

the impact of extreme outliers, I winsorize dependent and independent variables at 1% level. The choice of control variables follows those in McLean, Pontiff, and Reilly (2024), which include the day $t - 1$ stock return, lagged weekly return, lagged monthly return, day $t - 1$ return squared, lagged weekly return squared, lagged daily return variance over the last month, last month's stock turnover, and log market capitalization. I standardize all independent variables to facilitate interpretation.

Table 6 presents regression results. In column (1) ((4)), target return is positively (negatively) associated with the total volume of call (put) options: a one-standard-deviation increase in target return leads to 6.672 (-6.402) number of contracts increase in call (put) volume. The sign is consistent with the hypothesis that retail investors naively take higher target return as positive news without adjusting for the upward bias by buying (selling) call (put) options. The economic magnitude is sensible given that the average daily volume of call (put) is -25.81 (-32.85). Total volume matters for option pricing under demand-based option pricing framework. Thus, target return should be positively related to call option expensiveness and negatively predict call return, which is consistent with the findings in Section 3.1.

After I split total volume into those from public customers account and firm account, the buy (sell) volume for call (put) is entirely driven by customer volume, where retail trading occurs, as shown in column (2) ((5)). The volume of firm account, where sophisticated investors trade, does not or oppositely respond to target return as shown in column (3) ((6)), suggesting that experienced option traders are able to adjust for the bias contained in price target.

To check the robustness of this pattern, I run the same panel regressions using different sub-periods in Table 7. The tendency to buy call options exists in half of all sub-periods, both in the early and later half of the sample. The effect is especially

strong during the most recent 2020-2022 period, during which option trading gained popularity among retail traders. This corresponds to the rise of long-short profitability in Panel A of Figure 1. On the other hand, the tendency to sell put options mainly exists in the first half of the sample and almost disappears in the second half except during 2014-2016 period. This can explain why the profitability of put strategy in Panel B of Figure 1 is low in early sample periods, because firms with higher target returns in the short leg tend to face larger selling pressure on put options that causes higher put returns. When the selling effect almost disappears in the second half of the sample, the put-call parity becomes the dominant effect and long-short profitability increases.

To rule out the possibility that my results are driven by option trading in anticipation of analyst information releases or by analyst tipping, I restrict the sample to days on which price targets are released during pre-market hours. The entire option volumes thus occur after target releases on those days. This cleanly measures option market reaction after observing price targets. Table 8 displays the results. All the previous patterns hold in the pre-market subsample. The coefficients related to call options are very close to those in the whole sample in Table 6. Even though the t -statistics drop slightly due to smaller sample size, they remain highly significant in columns (1) and (2).

4.2 Retail Option Trading

In addition to retail trading, public customers account also includes trading volumes of institutional investors. To further isolate retail volume from institutional volume, I follow the method in stock literature and assume that retail investors place smaller orders than institutional investors. I break down customer volume into three size buckets

(small, medium, and large) and run the same panel regressions to explain those volumes in Table 9.

In column (1), a one-standard-deviation increase in target return leads to 4.281 contracts increase in call volume of small orders. The magnitude drops to only 1.288 for medium size order in column (2) but remains significant. When volume of large order is the dependent variable in column (3), the coefficient is close to 0 and no longer significant. The decreasing pattern of coefficients is consistent with the story that retail investors who tend to place small orders react more aggressively to larger target return by purchasing more call options, while sophisticated institutional investors who tend to use large orders react less. The pattern of put options is similar, except that the coefficient of large order in column (6) is also significant, even though its magnitude is around half of that of small order in column (4).

4.3 Shape of IV Curve

If option traders react to target release by buying call and selling put, this demand pattern will increase the expensiveness of call relative to put written on the firm, which would make the firm's IV more right-skewed. To test this conjecture, I regress the daily *change* of risk-neutral skewness on target return in panel regressions of Table 10.

In column (1), a one-standard-deviation increase in target return causes a 0.005 increase in $\Delta Skew_t$, which is the change of risk-neutral skewness on the same day as target release. The coefficient is highly significant with a coefficient of 5.92. The positive sign is consistent with the conjecture, because risk-neutral skewness consists of long positions on call options and short positions on put options. Therefore, more expensive call relative to put would lead to an increase in skewness.

To test whether the effect would reverse as predicted by the typical demand-based story, I further use as dependent variables the skewness in future 5 days following the release. The coefficients switch to negative in columns (2) and (3), and they add up to -0.005 , which cancels out the coefficient 0.005 in column (1). The result suggests that the demand-pressure effect would completely reverse in 2 days following target release.

Overall, the findings indicate that when naive retail investors respond to higher target return without adjusting for its upward bias by buying call and selling put, their option demands make the risk-neutral skewness more positive and the IV curve more right-skewed.

5 Conclusion

This paper examines option market reactions to the release of analyst price targets by investigating the trading volumes of call and put options on the release day. Compared with analyst recommendations and EPS forecasts, price targets provide a more straightforward metric for retail investors to evaluate the potential profits of their option investments. This feature, combined with naive retail investors' incapability to adjust for the upward bias in price targets, may trigger their lottery preferences and create a channel for analysts' biases to affect option pricing.

I document evidence that larger target returns are associated with increased buy (sell) volumes of call (put) options on target release days. This effect is mainly driven by investors placing small orders, who tend to be retail investors. The findings are consistent with that retail investors naively interpret higher target returns as positive news by buying (selling) call (put) options. The effect becomes especially strong in recent period when option trading is more accessible to retail traders. Additionally, my

findings cannot be explained by option trading in anticipation of analyst information releases or by analyst tipping.

A consequence of the buying pressure on call and the selling pressure on put is that call options become more expensive relative to the puts written on the same firm. I find that risk-neutral skewness increases with target returns on the release day and reverses in the following two days. Therefore, a larger target return corresponds to a more right-skewed implied volatility curve on the target release day.

In the cross-section, stocks with higher consensus target returns tend to exhibit lower call option returns in the following month, consistent with the notion that buying pressure on call options triggered by upward-biased price targets makes calls more expensive. A long-short strategy designed to exploit this relationship can generate an average monthly profit of 1.44% with an annual Sharpe ratio of 2.91. The strategy remains profitable throughout the entire sample period. Transaction cost management is important to maintain its profitability.

References

- Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang, 2006, “The cross-section of volatility and expected returns,” *The Journal of Finance*, 61(1), 259–299.
- Bakshi, G., and N. Kapadia, 2003, “Delta-hedged gains and the negative market volatility risk premium,” *The Review of Financial Studies*, 16(2), 527–566.
- Bakshi, G., N. Kapadia, and D. Madan, 2003, “Stock return characteristics, skew laws, and the differential pricing of individual equity options,” *The Review of Financial Studies*, 16(1), 101–143.
- Bali, T. G., and A. Hovakimian, 2009, “Volatility spreads and expected stock returns,” *Management Science*, 55(11), 1797–1812.
- Barber, B., R. Lehavy, M. McNichols, and B. Trueman, 2001, “Can investors profit from the prophets? Security analyst recommendations and stock returns,” *The Journal of finance*, 56(2), 531–563.
- Bauer, R., M. Cosemans, and P. Eichholtz, 2009, “Option trading and individual investor performance,” *Journal of Banking & Finance*, 33(4), 731–746.
- Blau, B. M., T. B. Bowles, and R. J. Whitby, 2016, “Gambling preferences, options markets, and volatility,” *Journal of Financial and Quantitative Analysis*, 51(2), 515–540.
- Boyer, B. H., and K. Vorkink, 2014, “Stock options as lotteries,” *The Journal of Finance*, 69(4), 1485–1527.
- Brav, A., and R. Lehavy, 2003, “An empirical analysis of analysts’ target prices: Short-term informativeness and long-term dynamics,” *The Journal of Finance*, 58(5), 1933–1967.
- Bryzgalova, S., A. Pavlova, and T. Sikorskaya, 2023, “Retail trading in options and the rise of the big three wholesalers,” *The Journal of Finance*, 78(6), 3465–3514.
- Byun, S.-J., and D.-H. Kim, 2016, “Gambling preference and individual equity option returns,” *Journal of Financial Economics*, 122(1), 155–174.
- Cao, J., and B. Han, 2013, “Cross section of option returns and idiosyncratic stock volatility,” *Journal of Financial Economics*, 108(1), 231–249.

- Easley, D., M. O'hara, and P. S. Srinivas, 1998, "Option volume and stock prices: Evidence on where informed traders trade," *The Journal of Finance*, 53(2), 431–465.
- Fama, E. F., and K. R. French, 1992, "The cross-section of expected stock returns," *the Journal of Finance*, 47(2), 427–465.
- , 2015, "A five-factor asset pricing model," *Journal of financial economics*, 116(1), 1–22.
- Fama, E. F., and J. D. MacBeth, 1973, "Risk, return, and equilibrium: Empirical tests," *Journal of political economy*, 81(3), 607–636.
- Garleanu, N., L. H. Pedersen, and A. M. Poteshman, 2008, "Demand-based option pricing," *The Review of Financial Studies*, 22(10), 4259–4299.
- Ge, L., T.-C. Lin, and N. D. Pearson, 2016, "Why does the option to stock volume ratio predict stock returns?," *Journal of Financial Economics*, 120(3), 601–622.
- Goyal, A., and A. Saretto, 2009, "Cross-section of option returns and volatility," *Journal of Financial Economics*, 94(2), 310–326.
- Hayunga, D. K., and P. P. Lung, 2014, "Trading in the options market around financial analysts' consensus revisions," *Journal of Financial and Quantitative Analysis*, 49(3), 725–747.
- Heston, S. L., C. S. Jones, M. Khorram, S. Li, and H. Mo, 2023, "Option momentum," *The Journal of Finance*, 78(6), 3141–3192.
- Jegadeesh, N., and S. Titman, 1993, "Returns to buying winners and selling losers: Implications for stock market efficiency," *The Journal of finance*, 48(1), 65–91.
- Johnson, T. L., and E. C. So, 2012, "The option to stock volume ratio and future returns," *Journal of Financial Economics*, 106(2), 262–286.
- Kumar, A., 2009, "Who gambles in the stock market?," *The journal of finance*, 64(4), 1889–1933.
- Lemmon, M., and S. X. Ni, 2014, "Differences in trading and pricing between stock and index options," *Management Science*, 60(8), 1985–2001.

- Lin, T.-C., and X. Lu, 2015, “Why do options prices predict stock returns? Evidence from analyst tipping,” *Journal of Banking & Finance*, 52, 17–28.
- Malmendier, U., and D. Shanthikumar, 2007, “Are small investors naive about incentives?,” *Journal of Financial Economics*, 85(2), 457–489.
- McLean, R. D., J. Pontiff, and C. Reilly, 2024, “Retail investors and analysts,” *Available at SSRN*.
- Mikhail, M. B., B. R. Walther, and R. H. Willis, 2007, “When security analysts talk, who listens?,” *The Accounting Review*, 82(5), 1227–1253.
- Muravyev, D., and N. D. Pearson, 2020, “Options trading costs are lower than you think,” *The Review of Financial Studies*, 33(11), 4973–5014.
- Muravyev, D., N. D. Pearson, and J. M. Pollet, 2022, “Is there a risk premium in the stock lending market? Evidence from equity options,” *The Journal of Finance*, 77(3), 1787–1828.
- Newey, W. K., and K. D. West, 1986, “A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix,” .
- Ni, S. X., N. D. Pearson, A. M. Poteshman, and J. White, 2021, “Does option trading have a pervasive impact on underlying stock prices?,” *The Review of Financial Studies*, 34(4), 1952–1986.
- Palley, A. B., T. D. Steffen, and X. F. Zhang, 2024, “The Effect of Dispersion on the Informativeness of Consensus Analyst Target Prices,” *Management Science*.
- Pan, J., and A. M. Poteshman, 2006, “The information in option volume for future stock prices,” *The Review of Financial Studies*, 19(3), 871–908.
- Savor, P. G., 2012, “Stock returns after major price shocks: The impact of information,” *Journal of financial Economics*, 106(3), 635–659.
- Stickel, S. E., 1995, “The anatomy of the performance of buy and sell recommendations,” *Financial Analysts Journal*, 51(5), 25–39.
- Vasquez, A., 2017, “Equity volatility term structures and the cross section of option returns,” *Journal of Financial and Quantitative Analysis*, 52(6), 2727–2754.

Womack, K. L., 1996, "Do brokerage analysts' recommendations have investment value?," *The journal of finance*, 51(1), 137–167.

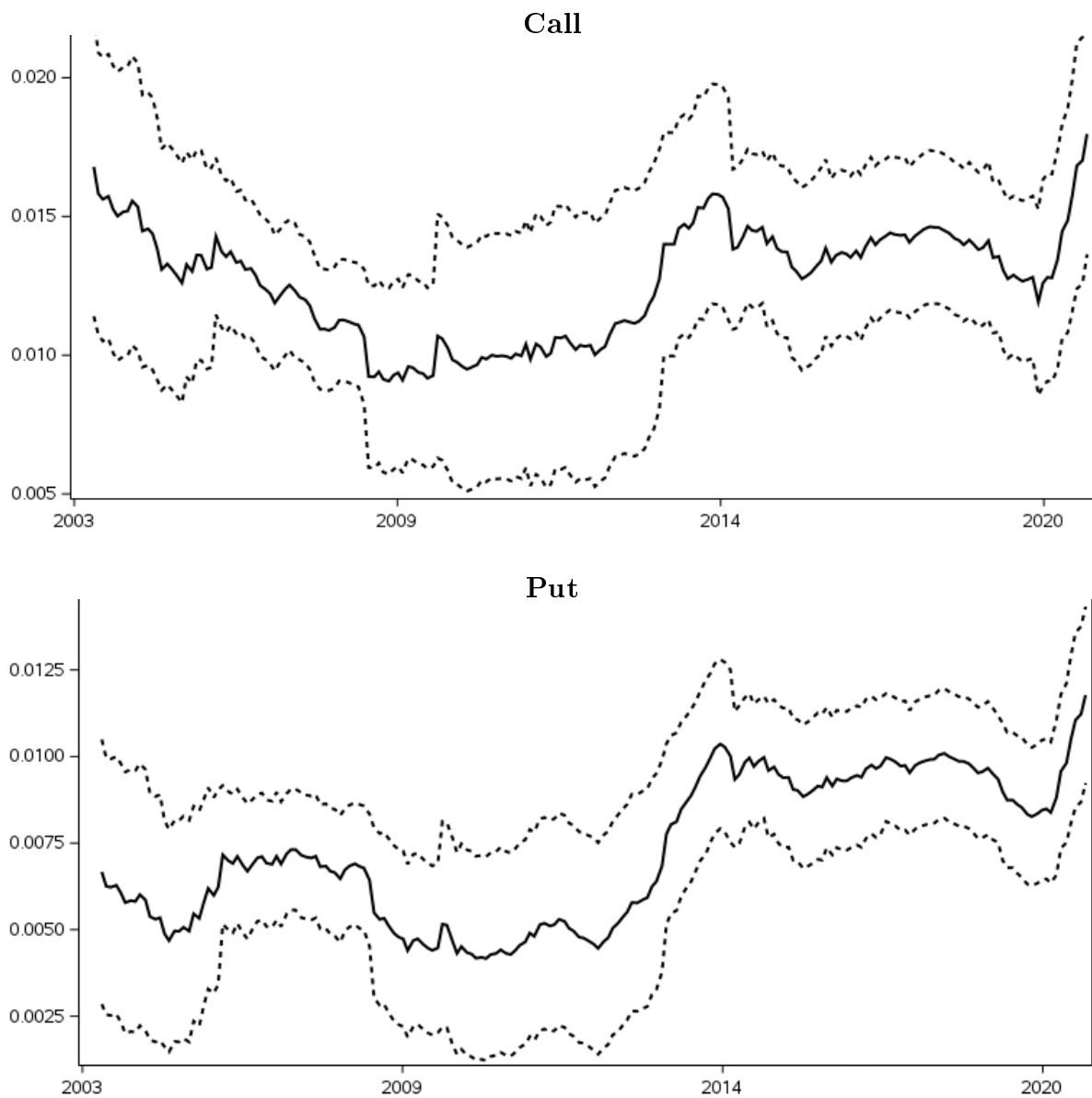


Figure 1: **5-year moving average returns of long-short strategies using call and put.** The upper (lower) panel plots the 5-year moving average returns of the long-short strategy using call (put) and its 95% confidence intervals in dashed lines.

Table 1: **Summary statistics**

In Panel A: Target Return is the log ratio of mean analyst price target to stock price; Call (Put) Option Return is the delta-hedged option return in excess of risk-free rate. All returns are in percentage and at monthly frequency. Sample is from March 1999 to December 2020.

Panel B reports the summary statistics of daily option volumes from different trading accounts on days with analyst issuing price target. The sample is from February 1999 to March 2022.

	Observation	Mean	StdDev	P10	P25	Median	P75	P90
Panel A:								
Target Return (%)	401755	20.58	26.31	-1.65	5.75	14.94	28.77	49.72
Call Option Return (%)	401755	-0.80	8.56	-5.86	-2.86	-0.86	0.88	3.88
Put Option Return (%)	401755	-0.98	6.27	-5.56	-2.97	-1.12	0.55	3.18
Market Cap (in billions)	401754	10.51	35.81	0.35	0.78	2.13	6.85	21.09
Number of Firms each month	262	1533	239	1211	1345	1604	1703	1782
Panel B:								
Total Call Volume	295907	-25.81	986.35	-296	-58	-2	27	225
Customer Call Volume	295907	-35.20	1362.07	-322	-61	-2	21	209
Firm Call Volume	295907	9.39	948.53	-31	0	0	0	65
Total Put Volume	295907	-32.85	728.91	-213	-35	0	10	134
Customer Put Volume	295907	-46.61	1081.59	-219	-36	0	6	106
Firm Put Volume	295907	13.76	853.73	-21	0	0	0	46

Table 2: **Predict cross-sectional option returns**

I run the monthly Fama-MacBeth regression:

$$r_{i,t+1}^{Option} = \alpha_t + \gamma_t \cdot Target\ Return_{i,t} + \theta_t \cdot Controls_{i,t} + \epsilon_{i,t+1},$$

where: $r_{i,t+1}^{Option}$ is firm i 's call (put) option return in next month. Control variables include: the log difference between the historical and at-the-money implied volatilities (Volatility Deviation); idiosyncratic volatility of Fama-French 3 factors in the past month; the difference between the long- and short-term implied volatilities (IV Term Spread); the difference between the implied volatilities of the 30-day call with a delta of 0.3 and the 30-day put with a delta of -0.3 (IV Smirk Slope); logarithm of market cap. Independent variables are winsorized at 1% level in each month. T statistics are Newey-West adjusted with 12 lags. Sample is from March 1999 to December 2020.

	Call Return		Put Return	
	(1)	(2)	(3)	(4)
Target Return	-0.033*** (-12.75)	-0.014*** (-4.92)	-0.021*** (-9.13)	-0.007*** (-3.29)
Volatility Deviation		0.030*** (8.44)		0.026*** (9.50)
Idiosyncratic Volatility		-0.299*** (-7.52)		-0.265*** (-6.07)
IV Term Spread		0.062*** (9.58)		0.044*** (10.44)
IV Smirk Slope		-0.041*** (-7.69)		0.040*** (7.75)
log(Market Cap)		0.001*** (4.74)		0.001*** (4.58)
Intercept	-0.002* (-1.96)	-0.027*** (-4.26)	-0.006*** (-6.25)	-0.028*** (-4.46)
Adjusted R^2	0.019	0.060	0.012	0.058

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: **Portfolio sort**

This table reports the monthly average portfolio returns. In Panel A, I sort portfolios by negative target return in order to generate positive long-short returns. In Panel B and C, I sort call and put option returns, respectively, by the variables in the column names, and evaluate their performance. Portfolios are equally weighted.

Panel A: Univariate sorts by negative target return.

	Low	2	3	4	High	High - Low
Call (%)	-1.84 (-12.12)	-0.69 (-6.74)	-0.58 (-6.67)	-0.51 (-6.32)	-0.41 (-4.04)	1.44 (13.60)
Put (%)	-1.64 (-14.30)	-0.89 (-9.16)	-0.82 (-9.39)	-0.81 (-9.37)	-0.83 (-8.84)	0.81 (11.37)

Panel B: Strategies using call option.

	Target Return	Volatility Deviation	Idiosyncratic Volatility	IV Term Spread	IV Smirk Slope	Market Cap
Mean (%)	1.44 (13.60)	2.30 (21.96)	1.64 (14.75)	1.73 (17.29)	0.80 (11.64)	1.93 (17.65)
Standard Deviation (%)	1.71	1.69	1.80	1.62	1.11	1.77
Sharpe Ratio	2.91	4.70	3.16	3.70	2.49	3.78
Skewness	0.32	1.73	-0.64	0.52	2.28	0.29
Kurtosis	5.32	4.09	4.82	6.27	14.46	5.72
Minimum (%)	-5.89	-1.12	-6.25	-5.76	-1.76	-6.47

Panel C: Strategies using put option.

	Target Return	Volatility Deviation	Idiosyncratic Volatility	IV Term Spread	IV Smirk Slope	Market Cap
Mean (%)	0.81 (11.37)	1.85 (24.29)	1.23 (14.99)	1.37 (20.53)	0.81 (14.96)	1.42 (19.16)
Standard Deviation (%)	1.15	1.23	1.33	1.08	0.87	1.20
Sharpe Ratio	2.43	5.20	3.21	4.39	3.20	4.10
Skewness	-0.29	0.60	-1.32	-0.45	-0.12	-0.05
Kurtosis	5.73	2.22	5.65	4.66	5.04	2.35
Minimum (%)	-5.32	-3.56	-6.42	-4.34	-4.17	-3.44

Table 4: **Transaction cost analysis**

This table reports the average returns of long-short strategies based on target return. I report results for the baseline strategies by quintiles and for strategies that reduce transactions costs by using extreme deciles. I consider sizes of transactions costs ranging from zero to the full quoted half-spread. Intermediate cases include 25%, 50%, and 75% of the quoted option bid-ask spreads.

Panel A: Call return.

	Mid-point	25%	50%	75%	Quoted
Quintiles	1.44 (13.60)	0.43 (4.09)	-0.56 (-5.16)	-1.53 (-12.80)	-2.49 (-18.59)
Deciles	2.30 (15.06)	1.03 (6.86)	-0.21 (-1.34)	-1.41 (-8.61)	-2.60 (-14.58)

Panel B: Put return.

	Mid-point	25%	50%	75%	Quoted
Quintiles	0.81 (11.37)	-0.03 (-0.43)	-0.88 (-11.43)	-1.75 (-19.78)	-2.64 (-25.23)
Deciles	1.35 (14.03)	0.33 (3.44)	-0.71 (-6.92)	-1.78 (-15.25)	-2.88 (-20.99)

Table 5: **Predict cross-sectional stock returns**

I run the monthly Fama-MacBeth regression:

$$r_{i,t+1 \rightarrow t+12}^{Stock} = \alpha_t + \gamma_t \cdot Target\ Return_{i,t} + \theta_t \cdot Controls_{i,t} + \epsilon_{i,t+1},$$

where: $r_{i,t+1 \rightarrow t+12}^{Stock}$ is firm i 's future-12-month log stock return. Control variables include: market beta estimated using rolling-1-year daily stock returns; logarithm of market cap; logarithm of book-to-market ratio; operating profitability; investment factor in Fama and French (2015); stock momentum ($RET_{t-12,t-1}$); past month stock return ($RET_{t-1,t}$); idiosyncratic volatility of Fama-French 3 factors in past month. Independent variables are winsorized at 1% level in each month. T statistics are Newey-West adjusted with 12 lags. Sample is from March 1999 to December 2020.

	(1)	(2)
Target Return	-0.372*** (-6.66)	-0.203*** (-5.79)
β		-0.033 (-1.46)
log(Market Cap)		0.005 (1.17)
log(B/M)		-0.007 (-0.56)
Operating Profitability		0.024* (1.78)
Investment		-0.035*** (-4.24)
$RET_{t-12,t-1}$		0.030 (1.48)
$RET_{t-1,t}$		0.019 (0.53)
Idiosyncratic Volatility		-4.547*** (-7.03)
Intercept	0.056* (1.78)	0.034 (0.34)
Adjusted R^2	0.039	0.125

Table 6: Analyst price target and option volumes

This table reports the results of panel regressions. The dependent variables are a firm's net option trading volumes of puts and calls on days with analyst issuing price target. 'Customer' means the volume of public customers account. 'Firm' means the volume of firm proprietary account. 'Total' is the sum of Customer and Firm. Dependent and independent variables are winsorized at 1% level. Independent variables are standardized. The regressions include firm and time fixed effects, and standard errors are clustered on firm and time. The sample is from February 1999 to March 2022.

	Call			Put		
	Total (1)	Customer (2)	Firm (3)	Total (4)	Customer (5)	Firm (6)
Target Return	6.672*** (5.16)	6.482*** (4.58)	0.221 (0.44)	-6.402*** (-6.28)	-8.052*** (-7.08)	1.060** (2.29)
Stock Return ₋₁	-19.304*** (-10.06)	-22.781*** (-10.64)	2.240*** (3.87)	8.956*** (7.56)	9.829*** (7.63)	-0.416 (-0.85)
Stock Return _{-1,-7}	-14.765*** (-7.94)	-16.911*** (-8.37)	2.492*** (3.80)	12.902*** (9.46)	12.009*** (8.11)	1.558*** (2.69)
Stock Return _{-1,-30}	-9.368*** (-5.59)	-11.267*** (-6.13)	0.487 (0.74)	6.025*** (4.61)	7.483*** (5.22)	-1.536*** (-2.81)
Stock Return ₋₁ ²	-1.254 (-0.92)	0.258 (0.17)	-0.566 (-1.02)	-5.529*** (-4.96)	-5.836*** (-5.11)	0.402 (0.87)
Stock Return _{-1,-7} ²	0.207 (0.13)	1.538 (0.85)	-0.792 (-1.37)	-2.063* (-1.80)	-4.256*** (-3.50)	1.613*** (3.35)
Variance	-4.947* (-1.85)	-7.844*** (-2.60)	2.133*** (2.66)	-3.275* (-1.78)	-3.233 (-1.53)	0.134 (0.19)
Turnover	-7.632** (-2.06)	-6.488 (-1.50)	-1.197 (-1.24)	-12.764*** (-4.41)	-15.926*** (-4.83)	2.184** (2.24)
log(Market Cap)	-35.552*** (-5.14)	-44.763*** (-6.15)	5.747*** (3.72)	-23.624*** (-3.77)	-28.723*** (-4.26)	3.011* (1.71)
Intercept	-22.785*** (-177.37)	-34.091*** (-235.49)	10.920*** (178.44)	-28.607*** (-328.17)	-39.656*** (-402.31)	9.487*** (207.60)
Adjusted R^2	0.017	0.019	0.004	0.034	0.044	0.004

Table 7: **Analyst price target and option volumes by years**

This table reports the coefficients of the variable ‘Target Return’ in the same regressions as in Table 6. The only difference is that I run the regressions during every three year sub-periods from 1999 to 2022.

	Call			Put		
	Total (1)	Customer (2)	Firm (3)	Total (4)	Customer (5)	Firm (6)
1999 - 2001	12.336*** (3.16)	12.835*** (2.68)	-0.521 (-0.33)	-12.063*** (-3.80)	-13.914*** (-3.98)	0.899 (0.78)
2002 - 2004	5.828 (1.62)	5.688 (1.39)	1.340 (0.89)	-15.027*** (-5.65)	-17.879*** (-5.30)	2.275 (1.61)
2005 - 2007	-0.453 (-0.09)	-6.206 (-1.02)	4.091* (1.81)	-10.303** (-2.49)	-16.513*** (-3.72)	2.188 (1.05)
2008 - 2010	7.089** (2.01)	7.821** (1.99)	0.160 (0.09)	-4.092 (-1.32)	-4.797* (-1.74)	1.157 (0.88)
2011 - 2013	-3.613 (-1.17)	-2.802 (-0.81)	-0.926 (-0.62)	-1.142 (-0.42)	-3.503 (-1.13)	1.037 (0.71)
2014 - 2016	8.183** (2.26)	8.384** (2.13)	1.038 (0.78)	-4.882** (-2.32)	-6.212** (-2.22)	0.406 (0.32)
2017 - 2019	4.582 (1.13)	3.820 (0.91)	-1.459 (-1.16)	-5.568* (-1.81)	-5.644 (-1.42)	-0.340 (-0.31)
2020 - 2022	15.310*** (4.07)	15.849*** (3.86)	-1.402 (-1.23)	-4.498 (-1.47)	-5.299* (-1.75)	0.106 (0.10)

Table 8: **Analyst price target and option volumes: pre-market subsample**

The regression specifications in this table are the same as those in Table 6, except that the sample is restricted to firm-days on which analyst price target is released before regular trading hours.

	Call			Put		
	Total (1)	Customer (2)	Firm (3)	Total (4)	Customer (5)	Firm (6)
Target Return	6.118*** (3.82)	6.454*** (3.62)	-0.314 (-0.53)	-4.712*** (-4.03)	-6.441*** (-4.96)	1.207** (2.19)
Stock Return ₋₁	-18.160*** (-8.26)	-21.485*** (-8.84)	2.213*** (2.99)	7.761*** (5.55)	8.088*** (5.56)	0.090 (0.16)
Stock Return _{-1,-7}	-14.615*** (-6.67)	-17.179*** (-7.10)	2.657*** (3.30)	12.371*** (7.56)	11.867*** (6.74)	1.126 (1.60)
Stock Return _{-1,-30}	-10.755*** (-5.26)	-12.542*** (-5.68)	0.447 (0.57)	5.130*** (3.30)	5.756*** (3.64)	-0.871 (-1.35)
Stock Return ₋₁ ²	-0.517 (-0.30)	0.903 (0.47)	-0.590 (-0.88)	-5.850*** (-4.40)	-6.110*** (-4.32)	0.508 (0.84)
Stock Return _{-1,-7} ²	-0.747 (-0.38)	0.707 (0.32)	-0.675 (-0.93)	-1.225 (-0.88)	-3.675** (-2.44)	1.823*** (3.06)
Variance	-4.179 (-1.24)	-6.679* (-1.73)	1.863* (1.92)	-2.797 (-1.33)	-3.618 (-1.45)	0.316 (0.36)
Turnover	-7.169* (-1.66)	-6.974 (-1.37)	-1.072 (-1.08)	-15.906*** (-4.91)	-17.858*** (-4.81)	1.519 (1.27)
log(Market Cap)	-34.323*** (-4.37)	-44.027*** (-5.32)	6.178*** (3.42)	-24.265*** (-3.70)	-28.894*** (-4.02)	2.135 (1.10)
Intercept	-19.596*** (-45.53)	-30.123*** (-63.87)	10.429*** (78.90)	-29.154*** (-88.25)	-39.725*** (-112.52)	9.256*** (76.24)
Adjusted R^2	0.014	0.016	0.004	0.036	0.046	0.003

Table 9: **Analyst price target and option volumes: order size**

Dependent variables are option volumes of public customers account splitted by order size into small, medium, and large. Other regression specifications are the same as those in Table 6.

	Call			Put		
	Small (1)	Medium (2)	Large (3)	Small (4)	Medium (5)	Large (6)
Target Return	4.281*** (5.77)	1.288*** (3.89)	0.617 (0.72)	-4.122*** (-7.52)	-1.074*** (-4.72)	-2.107*** (-3.45)
Stock Return ₋₁	-10.658*** (-10.84)	-3.196*** (-8.41)	-6.630*** (-6.04)	4.514*** (7.80)	1.345*** (5.71)	3.131*** (4.09)
Stock Return _{-1,-7}	-11.447*** (-10.62)	-1.638*** (-4.39)	-4.106*** (-3.42)	5.552*** (8.28)	1.662*** (5.87)	3.675*** (4.59)
Stock Return _{-1,-30}	-3.412*** (-3.49)	-1.981*** (-5.25)	-4.768*** (-4.77)	3.498*** (5.44)	0.629** (2.47)	3.189*** (3.90)
Stock Return ₋₁ ²	1.271* (1.65)	-0.244 (-0.74)	-0.801 (-0.83)	-3.267*** (-5.80)	-1.012*** (-4.52)	-1.034 (-1.52)
Stock Return _{-1,-7} ²	1.267 (1.39)	0.221 (0.62)	-0.267 (-0.26)	-2.258*** (-4.11)	-0.517* (-2.07)	-1.158 (-1.59)
Variance	-3.542** (-2.36)	-1.326** (-2.30)	-2.938* (-1.74)	-0.886 (-0.79)	0.066 (0.19)	-1.943* (-1.85)
Turnover	-3.820* (-1.65)	-1.052 (-1.26)	-2.146 (-1.07)	-11.362*** (-6.23)	-2.331*** (-4.41)	-1.722 (-1.22)
log(Market Cap)	-22.776*** (-5.72)	-6.935*** (-5.46)	-13.288*** (-3.80)	-22.167*** (-4.67)	-2.480*** (-3.29)	-0.522 (-0.29)
Intercept	-22.568*** (-380.25)	-3.755*** (-113.75)	-9.552*** (-89.34)	-29.669*** (-759.70)	-4.013*** (-162.95)	-3.863*** (-49.54)
Adjusted R^2	0.035	0.008	0.005	0.100	0.012	0.002

Table 10: **Analyst price target and risk-neutral skewness**

This table reports the results of panel regressions. The dependent variables are the daily changes of a firm's risk-neutral skewness calculated from 30-day implied volatility curve. The sample includes days with analyst issuing price target. $\Delta Skew_t$ is the change of risk-neutral skewness on target release day. $\Delta Skew_{t+n}$ is the change of risk-neutral skewness at n -day ahead. Independent variables are standardized and winsorized at 1% level. Regressions include firm and time fixed effects, and standard errors are clustered on firm and day. The sample is from February 1999 to March 2022.

	$\Delta Skew_t$ (1)	$\Delta Skew_{t+1}$ (2)	$\Delta Skew_{t+2}$ (3)	$\Delta Skew_{t+3}$ (4)	$\Delta Skew_{t+4}$ (5)	$\Delta Skew_{t+5}$ (6)
Target Return	0.005*** (5.92)	-0.003*** (-4.24)	-0.002** (-2.53)	-0.001 (-0.95)	-0.001 (-0.59)	-0.001 (-0.69)
Stock Return ₋₁	0.017*** (15.73)	0.000 (0.13)	0.000 (0.23)	0.001 (1.29)	-0.000 (-0.11)	-0.000 (-0.22)
Stock Return _{-1,-7}	0.001 (1.31)	0.001 (0.49)	-0.002 (-1.47)	-0.000 (-0.08)	-0.002** (-2.19)	0.000 (0.33)
Stock Return _{-1,-30}	0.003*** (3.07)	0.000 (0.03)	0.003*** (3.49)	0.002* (1.93)	0.002** (2.26)	0.002** (2.21)
Stock Return ₋₁ ²	-0.001 (-0.46)	-0.003*** (-2.76)	0.001 (0.83)	0.000 (0.05)	-0.001 (-1.09)	0.001 (1.13)
Stock Return _{-1,-7} ²	-0.001 (-1.20)	-0.000 (-0.46)	-0.001 (-0.53)	-0.001 (-1.11)	0.000 (0.44)	-0.001 (-0.67)
Variance	-0.002 (-1.49)	0.001 (0.93)	-0.000 (-0.03)	-0.001 (-0.43)	0.001 (0.84)	-0.001 (-0.99)
Turnover	0.000 (0.06)	-0.001 (-1.21)	0.001 (1.28)	0.000 (0.11)	-0.001 (-1.04)	0.000 (0.10)
log(Market Cap)	-0.008*** (-3.57)	0.002 (1.00)	0.003 (1.62)	-0.001 (-0.57)	0.002 (0.80)	0.000 (0.10)
Intercept	0.001*** (9.18)	0.001*** (9.74)	-0.001*** (-13.77)	-0.000** (-2.06)	-0.000*** (-3.96)	0.001*** (9.99)
Adjusted R^2	0.033	0.028	0.026	0.024	0.024	0.024

Table A1: **Analyst price target and option volumes: weighted by market cap**

The regression specifications in this table are the same as those in Table 6, except that the regression is weighted by firm market capitalization.

	Call			Put		
	Total (1)	Customer (2)	Firm (3)	Total (4)	Customer (5)	Firm (6)
Target Return	25.637** (2.08)	36.446** (2.49)	-11.625** (-2.49)	-16.771* (-1.83)	-25.955*** (-3.07)	4.442 (0.70)
Stock Return ₁	-97.568*** (-5.26)	-109.187*** (-5.44)	4.939 (0.99)	46.402*** (4.62)	44.423*** (3.89)	3.872 (0.53)
Stock Return _{1,-7}	-55.064*** (-3.09)	-65.464*** (-3.00)	16.743* (1.95)	58.726*** (4.39)	51.815*** (3.54)	17.831** (2.22)
Stock Return _{1,-30}	-14.009 (-0.82)	-19.759 (-1.04)	-8.961 (-0.95)	16.209 (0.95)	18.207 (0.95)	-6.495 (-1.24)
Stock Return ₁ ²	4.020 (0.32)	15.338 (0.97)	-3.877 (-0.83)	-30.379 (-1.52)	-24.688 (-1.36)	-2.371 (-0.35)
Stock Return _{1,-7} ²	30.819** (2.04)	49.836*** (2.79)	-10.914** (-2.11)	-47.460*** (-3.33)	-50.558*** (-3.70)	3.806 (0.86)
Variance	-31.773 (-1.13)	-57.778* (-1.95)	5.645 (0.78)	-2.117 (-0.10)	-17.827 (-0.77)	3.476 (0.46)
Turnover	72.852** (1.96)	105.615** (2.27)	-8.987 (-1.53)	-30.004 (-1.04)	-2.245 (-0.07)	-13.121 (-1.42)
log(Market Cap)	-19.522 (-0.50)	-37.567 (-0.87)	20.226* (1.78)	-36.513 (-1.26)	-22.619 (-0.72)	4.910 (0.43)
Intercept	-83.158 (-1.51)	-66.601 (-1.14)	-26.789 (-1.63)	-164.698*** (-4.10)	-233.582*** (-5.46)	19.065 (1.22)
Adjusted R^2	0.261	0.267	0.216	0.300	0.326	0.222

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$